Influence of an Electronic Medical Record with a Clinical Decision Support System on Inpatient Falls, Nurses' Clinical Experiences, and Decision-Making Processes for Fall Prevention: A Mixed Methods Study

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Abstract

Background: This thesis is informed by the researcher's 25 years of operational management experience in New Zealand (NZ) private hospitals, including leading the design and implementation of an electronic medical record (EMR) with an integrated clinical decision support system (CDSS). International evidence shows that CDSS-enabled electronic health systems have advanced, offering evidence-based recommendations, workflow integration, and improvements in process measures and clinical performance, all with the potential to enhance fall-risk identification and outcomes. However, no NZ studies have explored the impact on inpatient fall management or nurses' clinical decision-making in hospital settings.

Objective: Determine whether replacing a patient management system with an EMR and a CDSS for fall risk assessment affected the incidence of falls, and to explore nurses' clinical experiences and decision-making in fall prevention.

Design: Employed a convergent mixed-methods approach consisting of three studies: a systematic review, a systems analysis, and a qualitative study, guided by the Donabedian Framework (Structure, Process, Outcomes).

Methods

Systematic review: Systematically synthesised empirical evidence on the impact of digital health systems, including EMR and CDSS, on inpatient fall outcomes and nurses' clinical decision-making that followed a deductive analysis.

Systems analysis: Examined whether replacing a patient management system with an EMR and CDSS for fall risk assessment influenced inpatient fall incidence at a private hospital using descriptive and inferential analyses of retrospective system data.

Qualitative study: Explored nurses' experiences with the electronic fall risk assessment CDSS and its influence on fall-related clinical decision-making. A hybrid inductive/deductive approach was used, combining inductive coding with deductive organisation.

Integration of data: Using the mixed-methods synthesis, data from the systematic review, systems analysis, and qualitative study were integrated to develop a

comprehensive understanding of how the EMR with CDSS may influence fall-prevention practices in private hospitals and to inform the overall discussion, conclusions, and recommendations.

Findings: Structural factors, particularly system design, usability, hardware, training, and staffing, influenced nurses' interactions with the EMR and its embedded CDSS, thereby affecting workflow efficiency and data quality. At a process level, the CDSS improved coordination by strengthening communication, shared awareness of patient risk, and fall-related documentation, though use varied. In terms of outcomes, electronic systems enhanced the quality and visibility of fall reporting but did not reduce fall incidence. Nurses primarily relied on clinical judgement, highlighting an ongoing tension between CDSS design and clinical relevance and emphasising the need for nurses' involvement in system design.

Conclusions: This thesis demonstrates that implementing an EMR with CDSS is a major organisational change that affects clinical practice, workflows, communication, and nurses' experiences, indicating that technology alone does not improve patient safety. When systems misalign with workflows or lack clarity and usability, nurses develop workarounds that can compromise data quality, highlighting the need for co-design and ongoing training to support consistent documentation standards and confident use. While electronic systems offer benefits, fall prevention continues to rely on human judgement, vigilance, and engagement. Overall, the findings indicate that EMR with CDSS implementation influences fall prevention through complex interactions among system design, clinical processes, and human factors.

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Abbreviations

ACC	Accident Compensation Corporation
AUD	Australian Dollar
CDSS	Clinical decision support system
EBP	Evidence-based practice
EHR	Electronic health record
EMR	Electronic medical record
FPTK	Fall Prevention Tool Kit
HIMSS	Healthcare Information and Management Systems Society
HIT	Health information technology
HQSC	Health Quality & Safety Commission
INCN	Intensity of Nursing Care Needs
ITS	Interrupted time series
JBI	Joanna Briggs Institute
JHFRAT	Johns Hopkins Fall Risk Assessment Tool
LOS	Length of stay
MELAA	Middle Eastern/Latin American/African
MeSH	Medical Subject Headings
NDNQI	National Database of Nursing Quality Indicators
NHI	National Health Index
NHS	National Health Service
NZ	New Zealand
NZD	New Zealand Dollar
NZPSHA	New Zealand Private Surgical Hospitals Association
PICO	Population, intervention, comparison, and outcome
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCT	Randomised controlled trial

RN	Registered nurse
ROF	Risk of fall
SAC	Severity Assessment Code
SPSS	Statistical Package for the Social Sciences
STRATIFY	St Thomas' Risk Assessment Tool in Falling Elderly
UK	United Kingdom
USA	United States of America

Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor used artificial intelligence tools or generative artificial intelligence tools (unless it is clearly stated, and referenced, along with the purpose of use), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

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Finally, my mum, whom I said goodbye to on this journey, way too soon. I know you questioned why, but I also know that if you could have stayed, you would have been so proud of how it turned out.

Ethics

Auckland University of Technology ethics committee approval was obtained for the following studies within this thesis:

Study 1: Systematic review

Ethical approval was not sought for this systematic review as secondary data was used.

Study 2: Systems analysis

See Appendix B Ethics approval letter - Study 2 (Reference 22/339).

Study 3: Qualitative study

See Appendix E Ethics approval letter - Study 3 (Reference 23/297).

A more detailed explanation of the ethics approval process is provided in the methodology chapter, and the associated documents are available in the accompanying appendices: Study 2 (C and D) and Study 3 (F–H).

Chapter 1 Introduction

This chapter lays the foundation for the thesis by placing it within the wider context of digital health transformation and patient safety. It introduces the problem of inpatient falls, outlines the role of nurses in fall prevention, and considers the emergence of electronic medical record (EMR) with clinical decision support systems (CDSS) as an organisational intervention rather than a purely technical tool. The chapter articulates the study aim, research question, and objectives, and presents the conceptual framework guiding the research.

In the dynamic landscape of healthcare, a nurse's clinical decisions regarding patient care can influence a patient's outcome and experience, whether through their ability to recognise change or through missed care. Each decision can have a significant impact (Recio-Saucedo et al., 2017; Zainal et al., 2025). Clinical decision-making is the process by which a health professional develops a diagnosis, treatment, or management plan for a patient's condition (Shah et al., 2024). Nurses' clinical decision-making can be influenced by factors such as intuition, experience, patient assessment, and the culture of the work environment (Nibbelink & Carrington, 2018). Nursing experience supports the development of intuition that guides decision-making; for example, an experienced nurse would compare patient care experiences to identify patterns (Nibbelink & Carrington, 2018). A patient assessment further informs decision-making by helping the nurse understand the patient's status and needs (Nibbelink & Carrington, 2018). In addition, workplace culture, often expressed through unwritten practices or internal communication norms, can influence clinical decision-making (Braaten, 2015). As healthcare continues to evolve, the growing availability of digital health systems marks a shift in how nurses' clinical decision-making is supported in clinical practice (Shah et al., 2024).

Digital health systems are defined as software that electronically captures, retrieves, presents, and stores patient data (Sheikh et al., 2021). Such systems aim to facilitate effective communication among all healthcare professionals involved in patient care, reducing errors and enabling more effective decision-making by analysing gathered data (Hants et al., 2023). Ensuring that digital health systems integrate seamlessly into clinical workflows, unify patient information, and provide meaningful clinical support

remains essential for realising the benefits without increasing clinical burden (Butcher & Hussain, 2022). Digital health systems range from basic mobile devices and wellness wearables to sophisticated, artificial intelligence (AI)-driven diagnostic tools, EMRs, and CDSS (Australian Institute of Health and Welfare, 2024a).

An EMR serves as a data repository with an integrated CDSS that supports healthcare delivery by providing clinical knowledge and personalised, context-specific recommendations (Grechuta et al., 2024). The CDSS does this by matching patient features with automated, evidence-based clinical guidance and providing nurses with prompts, alerts, and evaluation tools to support their decisions (Dowding et al., 2012; Kwon & Lee, 2024). Importantly, while a CDSS provides valuable guidance, nurses must use their clinical judgment alongside CDSS insights to ensure the best possible care for patients (Ang, 2019; Sutton et al., 2020).

CDSS within EMRs have shown improvements in process measures and clinical performance, and could better identify and prevent falls, a common concern for nurses (Lytle et al., 2015). Hospital falls are the most common and preventable patient safety incidents worldwide, with their occurrence increasing with age; one in three adults aged 65 years and over experiences at least one fall annually (Ozturk & Koc, 2026). To reduce this risk, the World Health Organisation (WHO) (2021a) recommends creating safer environments, enhancing education, expanding research on falls, and developing suitable prevention policies.

This scenario is relevant to the New Zealand (NZ) landscape, with inpatient falls imposing financial and clinical burdens on our health system and causing life-threatening injuries and long-term health issues for those who experience them (Health Quality & Safety Commission [HQSC], 2018). Members of the NZ Private Surgical Hospitals Association (NZPSHA) are actively engaged in long-term planning and partnerships to deliver high-quality planned care (NZPSHA, 2025a). One of these partnerships is with a NZ university, where members annually provide details of their adverse events, including falls, for analysis. To improve the usefulness of these annual adverse event submissions, hospitals rely on accurate reporting, most of which is captured by nursing staff, who are central to identifying, documenting, and responding to fall-related events because of their continuous presence at the bedside. King et al.

(2018) reported that, due to their regular bedside contact and continuous monitoring, nurses serve as vital frontline workers in preventing inpatient falls.

As CDSS become a permanent part of the healthcare landscape, current research comparing their impact is often of low quality, yielding inconsistent outcomes, highlighting the need for more rigorous research (Mebrahtu et al., 2021). Therefore, this study is necessary to contribute to existing knowledge and to assess whether introducing an EMR with CDSS to evaluate patient fall risk in a private hospital affects the number of inpatient falls and influences nurses' clinical decision-making regarding falls. By investing in understanding and improving our systems, we can significantly improve patient care, safety and health outcomes in NZ's healthcare system.

The thesis draws on the researcher's extensive background in operational and executive management within private hospitals across NZ over the past 25 years. During this time, the researcher played a key role in designing and implementing various electronic health systems, including those with integrated CDSS. Anecdotal observations indicate that, after these systems were introduced, it remained unclear whether the initiative enhanced patient safety or influenced nursing practice. Robson (2024) argues that grounding research in the workplace provides a strong rationale and that workplace-based research can offer deeper insights into what is truly happening, potentially making it easier to implement changes based on the findings. Furthermore, Teddlie and Tashakkori (2009) emphasise that providing a pragmatic reason for research guides the formulation of meaningful, real-time questions and methods, highlighting the importance of personal values.

1.1 Thesis aim

This thesis sought to determine whether replacing a patient management system with an EMR with a CDSS for fall-risk assessment in a hospital affected the incidence of falls, and to explore nurses' clinical experiences and decision-making processes related to fall prevention.

1.2 Research questions

The following research questions guided this thesis:

1.2.1 Systematic review (Study 1)

What evidence exists regarding the impact of digital health systems on inpatient fall outcomes and nurses' clinical decision-making in hospital settings?

1.2.2 Systems analysis (Study 2)

Is the implementation of an EMR with an embedded CDSS for fall-risk assessment associated with changes in the incidence of inpatient falls in a private hospital between January 2019 and December 2022?

1.2.3 Qualitative study (Study 3)

How do nurses describe the influence of the EMR with an embedded CDSS on their clinical experiences and decision-making processes related to fall prevention?

1.3 Objectives

The objectives of this thesis are detailed below and were guided by the Donabedian framework.

1.3.1 Systematic review (Study 1)

Systematically synthesise empirical evidence on the impact of digital health systems, including EMRs and CDSS, on inpatient fall outcomes and nurses' clinical decision-making in hospital settings.

1.3.2 Systems analysis (Study 2)

Analyse quantitative fall incidence data before and after implementation of the EMR with an embedded CDSS.

1.3.3 Qualitative study (Study 3)

Explore nurses' clinical experiences and decision-making processes in relation to fall prevention following implementation.

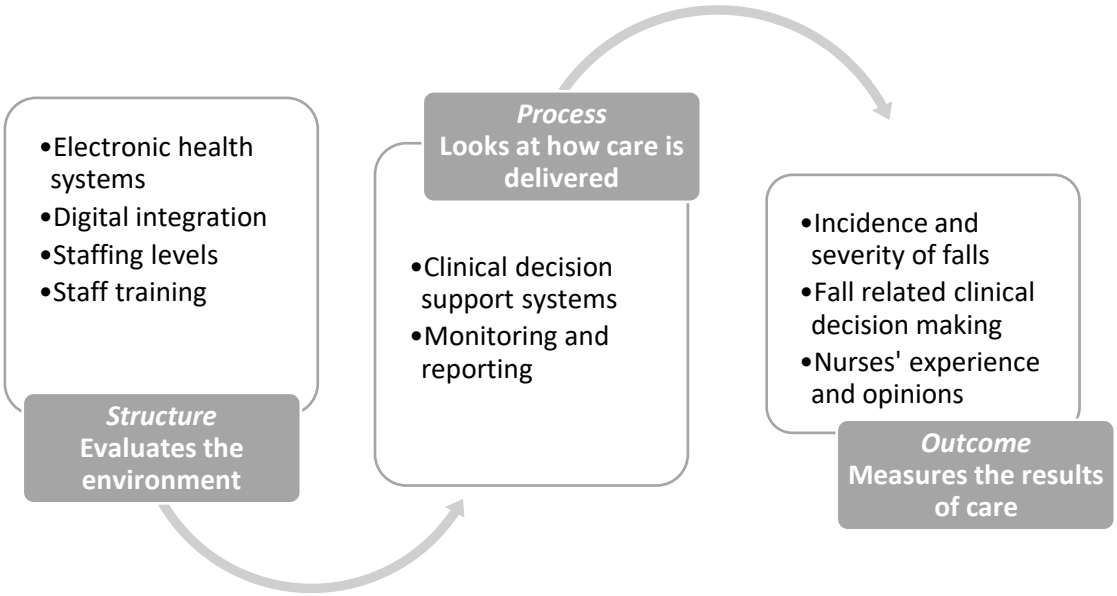
1.3.4 Integration of data

Integrate the three study findings, the systematic review, the systems analysis, and the qualitative study to develop a detailed understanding of how the EMR-embedded CDSS may shape fall-prevention practices in the private hospital setting.

1.4 Conceptual framework

This thesis is informed by Donabedian's Structure-Process-Outcome framework, a widely used model for evaluating healthcare quality (Donabedian, 1988). The framework holds that healthcare outcomes are influenced by structure, which encompasses the environment in which care is delivered, and by process, which concerns how care is delivered. The framework was selected because it offers a suitable lens for examining the implementation of an EMR with an embedded CDSS, enabling consideration of the technological and organisational environment (structure), nurses' clinical decision-making and workflow practices (process), and outcomes such as fall reporting, fall incidence, and nurses' experiences. A more detailed discussion of the framework and its application to this study is provided in Chapter 3. This framework guides the thesis, shaping the analysis and interpretation of the results. Figure 1 presents the conceptual framework for this thesis.

Figure 1. Conceptual framework for this thesis.



Note. Adapted from "The quality of care: How can it be assessed?" by A. Donabedian, 1988, *JAMA: The Journal of the American Medical Association*, 260(*12*), p. 1743. https://doi.org/10.1001/jama.1988.03410120089033

1.5 Context

Costs within NZ's health sector continue to rise, driven by an ageing population, inflation of medical expenses, the emergence of new technologies, and increased demand for healthcare services, a trend likely to continue (Deloitte, 2015). In response to these pressures, New Zealanders access healthcare through a mix of publicly and privately funded services, creating a complex system of service provision and equity (Tenbensel et al., 2023).

New Zealand's private and public hospitals operate in fundamentally different contexts that shape how digital systems function and the extent to which my findings are transferable. Private hospitals are predominantly elective, short-stay surgical environments with predictable caseloads, lower acuity, and minimal emergency demand, supported by stable perioperative nursing teams and modular digital systems tailored to surgical workflows. In contrast, public hospitals manage higher-acuity, complex, and unscheduled presentations, with greater clinical variability, multidisciplinary teams, rotational staffing, and enterprise-scale EMRs that are broader in scope but more complex to use.

Private hospitals are a component of this landscape, with funding primarily from medical insurers, followed by Accident Compensation Corporation (ACC) and Health NZ (New Zealand Private Surgical Hospital Association [NZPSHA], 2025a). In 2025, approximately 1,519,000 adults in NZ held health insurance (Figure NZ, 2025). The NZPSHA was established in 2005 to represent the interests of private hospitals at the government level (NZPSHA, 2025a). NZPSHA reports that its members provide approximately two-thirds of all elective surgery nationally. The association comprises 49 surgical facilities, 215 operating theatres, 5,308 full-time equivalent staff members, and performs approximately 232,323 procedures annually (NZPSHA, 2025b). This study was conducted in a private hospital that is a member of the NZPSHA.

As privately owned facilities, private hospitals in NZ compete in a market environment and often use publicly available information, such as websites, to showcase their services, quality, and patient safety. For example, Franklin Hospital highlights its

endoscopy and surgical services, delivered from “state-of-the-art digital theatres” (Franklin Hospital, 2026). Similarly, Kaweka Hospital promotes a new standard in surgical care by bringing together expert clinical teams (Kaweka Hospital, 2024). Southern Cross Healthcare, the largest group of private hospitals with 18 facilities nationwide (Southern Cross Healthcare, 2026a), also publicly showcases its quality initiatives, emphasising that patient experience and safety are paramount (Southern Cross Healthcare, 2026b). These practices demonstrate the importance placed on transparency, patient experience, and safety within the private hospital sector.

The WHO (2023a) defines patient safety as the absence of preventable harm and the reduction of unnecessary risk to an acceptable minimum, and it remains a significant worldwide problem (Morris et al., 2022). For this study, an inpatient fall is defined as an event in which a patient comes to rest inadvertently on the ground, floor, or another lower level (WHO, 2021a). Patient falls are the most commonly reported adverse events in hospitals (Patey & Corbett, 2016) and pose a significant threat to patient safety (Heikkilä et al., 2022; LeLaurin & Shorr, 2019). Older adults aged 65 years and older are at the highest risk of hospital falls (Giovannini et al., 2022). This vulnerability stems from age-related physiological changes, such as decreased muscle strength, impaired balance, and declining vision, along with chronic conditions such as osteoporosis, arthritis, cardiac issues, neurological disorders, or musculoskeletal diseases (Aranda-Gallardo et al., 2014; Australian Institute of Health and Welfare, 2024b; Dykes et al., 2012; Ye et al., 2020; Yokota et al., 2018). In NZ, approximately 16.6% (828,600 people) are over 65 years of age (Environment Health Intelligence New Zealand [EHINZ], 2023), and this is projected to rise to 1.9 million by 2073, accounting for 28.2% of the total population (Stats NZ, 2024).

In the context of an ageing population, inpatient falls are typically reported as falls per 1,000 bed days (HQSC, 2018). Internationally, reported fall rates vary, with the United Kingdom (UK) reporting between two and eight falls per 1,000 bed days (Morris et al., 2022) and the United States of America (USA) between 3.3 and 11.5 falls per 1,000 patient days (Bouldin et al., 2013). NZ reports an average of eight falls per patient bed day (HQSC, 2018), emphasising that inpatient falls continue to pose a significant risk to patient safety (Cameron et al., 2018; De Jong et al., 2020; WHO, 2021b).

In addition to the impact on patients' health and well-being, the economic burden of falls on healthcare is significant (Finch et al., 2015). In the USA, falls are estimated to cost the equivalent of New Zealand Dollar (NZD) 78 billion annually (Florence et al., 2018), while the National Health Service (NHS) in the UK estimates the cost at approximately NZD 4.5 billion (National Institute for Health and Care Excellence [NICE], 2013). In NZ, falls accounted for 39% of all ACC claims in 2021, resulting in an estimated NZD 1.6 billion cost to the health system (ACC, 2020).

To address patient safety concerns, NZ employs a national adverse events reporting framework for evaluating harm based on the severity of the patient's consequences (HQSC, 2023b). Each incident is assigned a Severity Assessment Code (SAC) rating: SAC 1: Severe (death or harm causing severe loss of function and/or requiring lifesaving intervention), SAC 2: Major (harm causing major loss or function and/or requiring significant intervention), SAC 3: Moderate (harm causing short-term loss of function and/or requiring moderate additional intervention), and SAC 4: Minor (harm causing no loss of function and requiring little or no intervention) (HQSC, 2024). All health and disability providers in NZ are required to report SAC 1 and 2 events to the HQSC. Based on the report covering July 1, 2019, to June 30, 2020, 627 SAC 1 and SAC 2 adverse events were reported nationally, of which 231 were attributed to falls (HQSC, 2020).

1.6 Current strategies

In response to the ongoing risk and increasing incidence of falls, healthcare facilities have adopted various fall-prevention strategies to reduce harm and enhance patient safety. Evidence from randomised controlled trials (RCTs) shows that tailored fall-prevention strategies, especially those involving patients and their families, increase awareness and integration in the care environment, leading to a significant boost in care effectiveness (McLennan et al., 2024). Although older patients are regularly recognised as having a higher risk of falls, translating this evidence into everyday practice remains difficult. This has led to ongoing efforts to encourage the use and systematic implementation of evidence-based clinical practice guidelines for hospital falls throughout the healthcare sector (McLennan et al., 2024).

Clinical guidelines in the UK recommend that all patients aged 65 years and older, and those aged 50–64 years deemed at risk by the clinician, undergo a fall-risk assessment

(NICE, 2013). Although fall-risk assessments aim to identify hospitalised patients at risk of falling, their predictive validity has been questioned, leading to the widely accepted view that all hospitalised adults should be considered at risk during their hospital stay (Shaw et al., 2020). This approach is consistent with the current 'Falls Prevention for Patients' policy implemented at the private hospital where this study took place, which mandates all inpatients undergo "*an individual fall-risk assessment, documentation of a falls score, and implementation of an appropriate prevention plan*" (Private Hospital, 2020, p. 1).

In NZ, many private hospitals adopt the national multifactorial approach to fall prevention (HQSC, 2020) and participate in national benchmarking by reporting their patient fall data quarterly. This fall-prevention initiative is facilitated by a prestigious university in NZ. Benchmarking initiatives enable hospitals to measure and compare clinical outcomes, facilitating shared learning and the application of best practices across organisations (Willmington et al., 2022).

While the clinical consequences of injurious falls are recognised, harm to patients can also occur through associated psychological distress, fear of future falls, extended hospital stays, complaints, and dissatisfaction with care (Morris & O'Riordan, 2017). As healthcare providers seek to mitigate the consequences of inpatient falls, the rapid advancement of digital health technology has transformed approaches to patient safety (Abernethy et al., 2022). Amongst these technological advancements, CDSS represent a shift toward a digital data-driven, proactive approach to fall prevention and patient safety.

1.7 Digital solutions

Digital technologies have become central to everyday life, enhancing global connectivity and accelerating innovation, particularly in digital health (WHO, 2021b). As a result, the concept of digital health has evolved to encompass the electronic capture of data, technical and communication infrastructure, and applications operating within the healthcare ecosystem (McGinnis et al., 2021). Although the concept continues to evolve, there is no single, definitive definition. The differences among EMRs, electronic patient records, and electronic health records (EHRs) remain

debated because they often overlap in function and application (Uslu & Stausberg, 2021).

In NZ, the use of EHRs in secondary care continues to increase. However, adoption varies across hospitals and specialist services, largely due to challenges in achieving full interoperability and seamless data exchange (Deloitte, 2015). An EHR is commonly described as a continuous electronic record of patient health information created through encounters across one or more healthcare settings (Yamada, 2008). Within the public health system, national initiatives such as the Hira Programme were designed to enhance digital health services by improving access to health information. The completion of stage one in June 2024 laid the groundwork for future services such as My Health Record and the digital service hub for digital health information developers (Health New Zealand, 2024).

Alongside EHRs, EMRs represent another digital health system used in NZ. EMRs are similar to EHRs but more localised, operating within a single health facility under the full responsibility of that provider (Waegemann, 1996). While no specific criteria formally define what qualifies as an EMR, the *Privacy Act 2020* (Privacy Commissioner, 2020) outlines guiding principles for the collection, use, disclosure, storage, and access of personal health information. The largest private surgical hospital network in NZ, and the researcher's previous workplace, Southern Cross Healthcare, utilises an EMR called Clinical Workstation, which was specifically designed and configured to meet business requirements. While EMRs primarily serve as repositories for patient data, their ability to store and retrieve historical information enables nurses to monitor patient trends and support clinical decisions informed by the patient's medical history (Hak et al., 2022).

The integration of a CDSS within an EMR represents a significant advancement in digital technology, helping healthcare professionals make real-time clinical decisions by combining clinical knowledge with patient data and providing additional health information, such as timely alerts and reminders (Chen et al., 2023; Khalil et al., 2025). These systems aim to enhance healthcare quality and improve patient outcomes by supporting healthcare professionals and improving workflow efficiency through the standardisation of documentation and care processes, including risk assessments (De

Wildt et al., 2023; Haynes & Wilczynski, 2010; Khalil et al., 2025; Lewkowicz et al., 2020; Mebrahtu et al., 2021; Osheroff et al., 2012; Sutton et al., 2020).

Evidence suggests that CDSS enhance adherence to clinical guidelines, leading to positive health outcomes. For example, a study on a CDSS used for asthma management reported that it improved patient confidence and promoted treatment adherence (Morton et al., 2022). Similarly, a CDSS used in pressure ulcer prevention demonstrated partial effectiveness by improving visual differentiation of pressure ulcers and providing clinicians with patient-specific advice (Kim et al., 2022).

Standard CDSS analyse patient data and provide alerts and reminders to assist nurses in their clinical decision-making (Bright et al., 2012). Based on this definition, the CDSS in this thesis is considered standard because it alerts nurses to the patient's risk level after the nurses complete a fall assessment. In recent years, CDSS have advanced considerably, offering evidence-based recommendations, diagnostic assistance, medication optimisation, workflow integration, and alerts to support their decision-making at the point of care by leveraging advanced artificial intelligence capabilities (Chen et al., 2023; Nankya et al., 2024). As these systems continue to evolve, they hold enormous potential to improve patient outcomes further (Morrison et al., 2021). Importantly, while a CDSS can provide valuable guidance, nurses must use their clinical judgment alongside CDSS insights to ensure the best possible care for patients. (Ang, 2019; Sutton et al., 2020).

Despite their potential benefits, CDSS implementation also presents challenges, including clinician acceptance, system integration, and concerns related to data privacy and security (Kwan et al., 2020). Additional challenges reported in the literature included difficulties integrating with existing workflows, the perceived usefulness of system outputs, technical dependencies on end users, trust in the data, and alignment with users' roles and the clinical environment (Abell et al., 2023; Chen et al., 2023; Mebrahtu et al., 2021). Furthermore, limited technical skills among nurses can affect the effective use of CDSS, although this varies depending on system design: some systems are considered complex, while others are more user-friendly when integrated into clinical workflows (Devaraj et al., 2014; Liberati et al., 2017).

The fall assessment CDSS used in this study lacks dynamic features, such as real-time integration with patient data, but provides alerts based on patient age, comorbidities, surgical procedure, and previous falls, all of which are entered by a nurse. Multifactorial fall-prevention strategies targeting a range of risk factors have been shown to reduce the likelihood of falls, consistent with established fall-prevention practices (Gulka et al., 2020; HQSC, 2020, 2023a). While digital tools such as CDSS support fall-prevention efforts, questions remain about how these systems are implemented in practice, especially about how nurses interact with them and translate their use into real-time clinical actions.

1.8 Implementation

Nurses are a vital part of NZ's healthcare workforce, and as primary users of the CDSS, they play a key role in collecting and inputting patient information. According to the Ministry of Health (2025), there are 66,026 nurses practising in NZ, of whom 5,669 (8.59%) work in private hospital settings. In the private hospital involved in this study, nurses make up the majority of staff in wards and admission or day stay units and are generally responsible for identifying patients at risk and implementing fall-prevention strategies. Nurses also use their professional knowledge, skills, and clinical judgment to assess patients, deliver appropriate care, and regularly review their ongoing needs in accordance with the standards set by the Nursing Council of New Zealand (NCNZ) (NCNZ, 2024). These expectations support continuous competence in nursing practice. While all healthcare professionals share responsibility for ensuring safe patient care, international evidence suggests that nurses are particularly well placed as frontline workers to prevent inpatient falls due to their regular bedside contact and ongoing monitoring (Sutton et al., 2020).

Daily nursing practice is made up of workflows, which provide a structured approach to care delivery and guide how clinical tasks, assessments, communications, and decision-making processes are carried out, promoting safe and effective patient outcomes (Cain & Haque, 2008). The introduction of digital technologies represents one of the strongest drivers of workflow change in healthcare, with the potential to influence how nurses organise, prioritise, and deliver care (Ang, 2019). As CDSS can influence nurses' behaviour at the point of care, it is important to consider how well

they align with existing workflows, as their success depends heavily on this fit (Ozkaynak et al., 2019).

Nursing workflow has been defined as a comprehensive set of activities aimed at achieving patient care objectives (Zheng et al., 2010). While nurses follow best-practice guidelines to minimise risks associated with tasks such as postoperative medication administration, they also engage in other naturally occurring aspects of care, such as building rapport, assessing patients' needs, and evaluating pain and fall risk (Cain & Haque, 2008). Although digital systems offer potential benefits, they also affect nurses' workflows, requiring a balance between computer-based tasks and direct patient care (Wosny et al., 2023).

Despite nurses demonstrating their ability to manage interruptions and multitasking, healthcare managers are encouraged to develop a deeper understanding of nursing workflows to inform strategies and policies that minimise errors and enhance patient safety (Yen et al., 2017). Communication is central to nursing practice and a core component of domain three of their scope of practice (NCNZ, 2024), which outlines nurses' professional responsibility to engage in interpersonal and therapeutic communication with clients (NCNZ, 2024). Evidence from an Australian study highlights the unexpected challenges nurses face when testing digital systems in their workplaces, reinforcing the importance of designers and evaluators actively listening to clinicians who deliver care (Bail et al., 2020).

Beyond workflow considerations, implementing CDSS poses additional challenges related to data privacy and security, as well as potential impacts on nurses and other healthcare providers (Chen et al., 2023). Data privacy involves protecting patient information from unauthorised access, maintaining confidentiality, and complying with regulatory requirements such as the New Zealand *Privacy Act* (2020). In NZ, the Privacy Commissioner is responsible for enforcing this legislation, including Principle 9 on the retention of personal information (Privacy Act, 2020). To address privacy and security concerns, healthcare facilities must implement measures such as encryption, access controls, and compliance with relevant regulations, including the Health Insurance Portability and Accountability Act (Subramanian et al., 2024).

Another unanticipated consequence of CDSS implementation is data sovereignty, the principle that health data are governed by the laws of the country in which they are collected and stored (Hummel et al., 2021). The increasing reliance on cloud-based artificial intelligence systems has raised concerns regarding data storage on offshore servers (Chen et al., 2023; WHO, 2023b). In NZ, data sovereignty is informed by the *Privacy Act* (2020), Māori Data Sovereignty principles advocated by Te Mana Raraunga (2025), and guidance from the Royal Society Te Aparangi (2023) on Indigenous data governance.

Given the significant financial investment required to implement a CDSS, it is essential to consider its technical and ethical implications, as well as its effects on patient safety and nurses' decision-making related to fall prevention. Digital transformation has been associated with improved organisational efficiency, productivity, and decision-making (Vitari & Raguseo, 2016); however, financial investments alone do not ensure successful implementation or cost savings (Zhou et al., 2023). Government investment and national incentive schemes have continued to promote widespread adoption of digital technologies across the USA health system, with certified electronic health record adoption reaching 96% in 2021 (ONC, 2022). Nurses noted advantages, such as real-time access to patient data, but also reported higher workloads and inadequate training, which raise doubts about whether the anticipated quality-of-care improvements were fully realised (Rathert et al., 2017).

Similarly, the Australian Government invested over AUD 1.15 billion in developing the national digital health record, My Health Record, and other digital health infrastructure between 2012 and 2016 (Australian National Audit Office, 2019). Following this implementation, Muhammad and Wickramasinghe (2017) conducted a qualitative review of Australia's My Health Record. They examined users' perceptions and found that it enhanced patient care by providing accessible information, thereby improving clinical decision-making. In NZ, investments in digital health technology have increased in recent years, with Health New Zealand outlining a 10-year digital infrastructure plan to integrate digital health systems, physical systems and healthcare services, creating a more cohesive and efficient structure (Health Informatics New Zealand, 2025). However, in the 2024 budget, the NZ Government announced a NZD 330 million cut to digital health technology funding, despite a broader NZD 16.7 billion increase in the

health sector. The increased funding was mainly for the pharmaceutical management agency, known as Pharmac, which determines the subsidies for medicines used in the community, public hospitals, frontline services, and primary healthcare (Digital Health Association, 2024). This reprioritisation appears to signal a strategic move to meet urgent service delivery requirements. However, it also raises concerns regarding the long-term viability of digital transformation initiatives in NZ's health services.

In summary, NZ faces an ageing population (EHINZ, 2023), and inpatient falls continue to pose significant financial and clinical risks to the healthcare system (HQSC, 2018). In response, many NZ private hospitals engage in long-term quality planning, including the systematic analysis of annual adverse event data, such as falls, to inform continuous improvement initiatives (NZPSHA, 2025a). Nurses are well-positioned to support these initiatives, particularly through their role in fall prevention and the use of CDSS to inform, not replace, their clinical decision-making (King et al., 2018; Nibbelink & Brewer, 2018). As CDSS are intended to support rather than replace nurses' clinical judgment, it is essential that nurses are confident and skilled in their use so that digital health technology and clinical decision-making work together effectively. This study seeks to provide insight into the association between a CDSS, patient outcomes, and nurses' clinical decision-making within a private hospital in NZ.

1.9 Structure of this thesis

1.9.1 Chapter 2: Systematic Review

Chapter 2 presents a systematic review of the literature from 2010–2025, focusing on digital health systems (e.g., CDSS, EHRs, and EMRs), fall management, and clinical decision-making. The review will be guided by the Donabedian framework and organised into three components: structure, process, and outcome.

1.9.2 Chapter 3: Methodology

Chapter 3 explores the researcher's positionality, worldview, and theoretical perspective that shaped the mixed-methods convergent design comprising three studies: a systematic review, a system analysis study analysing data from five health systems, and qualitative semi-structured interviews to capture nurses' experiences and opinions.

1.9.3 Chapter 4: Systems Analysis

Chapter 4 includes descriptive and inferential analysis of retrospective data from five health systems, including a descriptive presentation of nurses' free-text responses recorded within the new EMR.

1.9.4 Chapter 5: Qualitative Study

Chapter 5 provides an analysis of data from semi-structured interviews with nurses working in wards or within the hospital's admission and day stay units.

1.9.5 Chapter 6: Integration of Data

Chapter 6 presents the analysis, which integrates the findings from the three studies: a systematic review (Chapter 2), systems analysis (Chapter 4), and qualitative study (Chapter 5), to provide an integrated interpretation of the findings. This integration is guided by the Donabedian framework's components of structure, process, and outcome.

1.9.6 Chapter 7: Discussion

Chapter 7 synthesises and interprets the thesis findings, explaining their significance by connecting them to the existing literature, theories, and real-world applications.

Chapter 2 Systematic Review (Study 1)

2.1 Introduction

Evidence regarding the link between digital systems and falls is inconsistent. Few studies investigate how nursing clinical decision-making relates to fall outcomes. This review aims to systematically synthesise empirical data on how digital health systems such as EMRs and CDSS affect inpatient fall rates and nurses' clinical decision-making in hospitals.

To provide a structure, the Donabedian framework was used to interpret the literature, examining evidence across the three components: structure, process, and outcome. Within this review, the structural component includes electronic health systems, digital integration, staffing levels, and staff training. The process component includes CDSS and monitoring and reporting, and the outcome component includes fall incidence and severity, as well as nurses' experiences and opinions. Applying the Donabedian framework establishes the current evidence base and informs the study's conceptual and empirical design. Identifying these gaps supports the justification for this study and its aim to broaden existing knowledge.

CDSS are reported to improve the quality of care by assisting healthcare providers in making better decisions through alerts and reminders that prompt specific actions (Olakotan & Yusof, 2021). However, the initial search for this review indicated the literature was insufficient to limit the review solely to CDSS. Consequently, the scope was expanded to include EMRs, EHRs, health information technology (HIT), and CDSS to ensure comprehensive coverage of relevant digital health systems.

2.1.1 Review question

What evidence exists regarding the impact of digital health systems on inpatient fall outcomes and nurses' clinical decision-making in hospital settings?

2.1.2 Objective

This systematic review will support transparent, objective, and repeatable decision-making while ensuring the validity and reliability of the results (Sataloff et al., 2021). Using protocols, search strategies, inclusion and exclusion criteria, methodological

appraisal tools, and computer programmes such as Joanna Briggs Institute (JBI) (JBI, 2025) or Covidence Systematic Review software (Veritas Health Innovation, 2025) enhances the credibility, strength, transparency, and reproducibility of the review by systematically recording, organising, and synthesising data (Munn et al., 2014).

2.2 Design

2.2.1 SPIDER framework

To clearly define the sample (S), phenomenon (PI), design (D), evaluation (E), and research (R), the researcher used the SPIDER framework (Amir-Behghadami, 2024). The SPIDER framework extends beyond the patient/population, intervention, comparison, and outcome (PICO) framework and was specifically designed to optimise the identification of qualitative review questions and to recognise related qualitative and mixed-method studies (Amir-Behghadami, 2024; Cooke et al., 2012). Since this review aimed to synthesise evidence on inpatient fall outcomes and nurses' experiences, the SPIDER framework offered a structured and adaptable method for selecting studies. Table 1 summarises the SPIDER framework.

Table 1. Summary of the SPIDER framework.

SPIDER element	**Study context**
Sample (S)	Adult inpatient falls management data and nurses' perceptions.
Phenomenon (PI)	EHRs of adult inpatient falls management and nurses' clinical decision-making.
Design (D)	Systematic review.
Evaluation (E)	Quality of care using the Donabedian framework: structure, process, outcome.
Research type (R)	Quantitative, qualitative, and mixed-methods studies.

Note. Adapted from "SPIDER as a framework to formulate eligibility criteria in qualitative systematic reviews," by M. Amir-Behghadami, 2024, *BMJ Supportive & Palliative Care*, *14*, e312–e313. https://doi.org/10.1136/bmjspcare-2021-003161

2.2.2 Search strategy

The search was conducted in April 2024 and again in June 2025 to ensure articles relevant to this study were captured. The search used online library databases available through the Auckland University of Technology library, as outlined in the nursing subject guides. The databases searched included Cumulative Index to Nursing

and Allied Health (CINAHL) (via EBSCOhost), Medical Literature Analysis and Retrieval System Online (MEDLINE) (via EBSCOhost), Scopus, and PsycINFO.

The researcher reduced the research question into three concepts: digital systems, fall management, and clinical decision-making. This then generated synonyms, keywords, and controlled vocabulary, including medical subject headings (MeSH) terms. After applying Boolean operators such as AND and OR, the following search strings were identified.

CDSS* OR “clinical decision support system*” OR EMR* OR “Electronic Medical Record*” OR EHR OR “Electronic Health Record*” OR “Health Information system*” OR “decision support systems, clinical”

AND

“fall* prevention” OR “fall* reduction” OR “fall* assessment” OR “fall* risk” OR “fall* management” OR “fall* control” OR “accidental fall*” OR “fall*” OR “fall* assessment tool”

AND

“clinical decision-making” OR “clinical decision-making skill*” OR “clinical judgment” OR “clinical reasoning” OR “decision-making, clinical” OR “diagnostic reasoning” OR “critical thinking” OR “nursing support systems” OR “interactive decision support systems”

Consultation with a senior database specialist librarian was undertaken to verify the search terms and determine whether the findings could be further refined. The librarian confirmed the search was robust and would adequately answer the research question. The supervisory team further validated the search terms and strategy.

2.2.3 Inclusion and exclusion criteria

Table 2 details the inclusion and exclusion criteria for the search strategy.

Table 2. Inclusion and exclusion criteria.

Inclusion	**Exclusion**
English language Peer-reviewed published studies Abstract available Full text Studies that explored/reported on the implementation of digital health systems, such as EHRs, EMRs, HIT or CDSS, and how this influenced adult patient falls or nurses' clinical decision-making regarding falls in a hospital setting Studies published between January 1, 2010 and June 22, 2025	Articles that did not contain empirical data Studies that did not explore/report on the implementation of digital health systems, such as EHRs, EMRs, HIT or CDSS, and how this influenced adult patient falls or nurses' clinical decision-making regarding falls in a hospital setting Studies outside the inclusion dates and inclusion criteria

Note. CDSS = Clinical decision support system; EHR = Electronic health record; EMR = Electronic medical record; HIT = Health information technology.

2.2.4 Search outcome

Once the search criteria were identified, the researcher and supervisors independently applied the search terms to the four selected databases. All studies were screened by title and abstract, and those that did not meet the inclusion criteria were excluded. Full-text included studies were then imported into Covidence and screened in full for eligibility. The researcher, along with the primary and secondary supervisors, used Covidence, a web-based systematic review platform (Veritas Health Innovation, 2025). Covidence allowed the research team to blind-screen the full-text reviews and provided tools to track decisions, document reasons for exclusion, and enhance transparency and reproducibility. The researcher and supervisors independently conducted title, abstract, and full-text screening to ensure rigour. If there was any doubt about whether a study met the inclusion criteria, it was discussed until consensus was reached. The reference lists of all included studies were screened for additional potential studies; any new articles were highlighted, reviewed, and screened as above. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flowchart was used to ensure transparent reporting of the searches conducted (Page et al., 2021). In addition, to enhance the quality and transparency of reporting, a PRISMA-S checklist (Rethlefsen et al., 2021) was completed and reviewed by the researchers' supervisors.

2.2.5 Critical review of studies

All included studies underwent quality assessment using the JBI critical appraisal tools (JBI, 2025). The researcher and a supervisor independently reviewed each study to generate the JBI scores; when discrepancies arose, the researchers met to discuss them until consensus was reached. No studies were excluded based on the JBI scores.

2.2.6 Data extraction

Information required to address the research question was systematically extracted (both quantitative and qualitative data) from each study (key findings relating to adult inpatient hospital electronic falls data, including nurses' perceptions and experiences of fall management and clinical decision-making). Extracted information also included author(s), year of publication, country of origin, study objectives/aim, methodological design, sample characteristics, data collection methods, findings, and implications to practice (Munn et al., 2014).

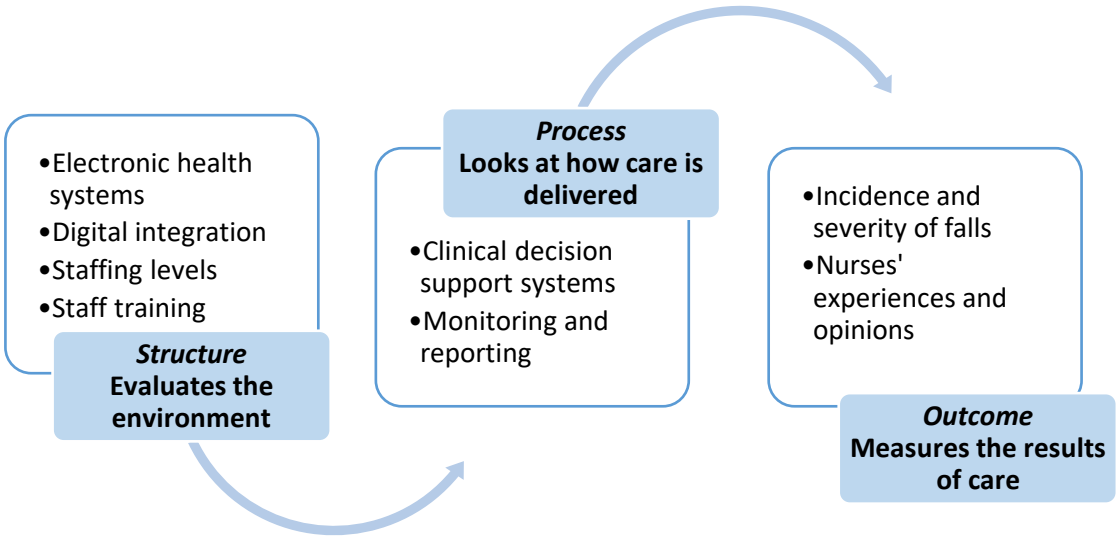
2.2.7 Data synthesis

Although the review covered a broad range of digital health systems and study designs, it was conducted as a systematic review rather than a scoping or mapping review because its primary purpose was to answer a focused review question: What evidence exists regarding the impact of digital health systems on inpatient fall outcomes and nurses' clinical decision-making in hospital settings? The review followed a systematic and transparent process of searching, screening, critical appraisal, and evidence synthesis to identify and evaluate relevant evidence. The scope was broadened from CDSS alone to include EMRs, EHRs, HIT, and CDSS because the preliminary search identified insufficient literature addressing the review question exclusively through CDSS studies. However, the review remained driven by a specific question rather than aiming to map the extent or characteristics of the literature.

Data was synthesised using deductive analysis, which involved applying pre-determined categories to the data, informed by theoretical concepts from the literature (Bingham & Witkowsky, 2022). In this review, the deductive analysis was guided by the Donabedian framework and structured around the three components of structure, process, and outcome, which served as the conceptual framework for the review. Deductive analysis is useful for exploring the existing literature on a

phenomenon of interest and supports a systematic and rigorous approach to data organisation (Bingham & Witkowsky, 2022). Following data extraction, findings from the included studies were explored and collated into categories as defined in Figure 2, aligned with the structure, process, and outcome components.

Figure 2. Deductive analysis categories – Systematic review.



Note. Adapted from "The quality of care: How can it be assessed?" by A. Donabedian, 1988, *JAMA: The Journal of the American Medical Association*, 260(*12*), p. 1743. https://doi.org/10.1001/jama.1988.03410120089033

2.2.8 Definition of categories

Structure

Electronic systems in health facilities are integrated technologies that gather, store, share, and analyse health information (Adjekum et al., 2018). Digital integration in healthcare involves the use of information and communication technologies to manage, process, and share medical data, thereby enhancing the quality of healthcare (Tiriteu et al., 2024). Staffing levels indicate the number of staff members on duty at any given time to provide patient care and are a key metric in workforce management (Griffiths et al., 2020). Staff training involves a structured process to develop nurses' knowledge, skills, and competencies, ensuring safe, effective, and up-to-date clinical practice (Rahmah et al., 2021).

Process

A CDSS is a tool that integrates evidence-based recommendations into daily practice through notifications, such as alerts and pop-up reminders, enabling timely and appropriate interventions (Olakotan & Yusof, 2021). Monitoring and reporting processes are crucial to ensuring quality and safety in nursing, particularly in fall-prevention initiatives (Wilson et al., 2022).

Outcome

The incidence of falls refers to the rate at which patients fall, and the severity of falls describes the level of harm resulting from a fall (HQSC, 2024). Nurses' experiences and opinions were reported based on the feedback provided by the nurse participants during the interviews.

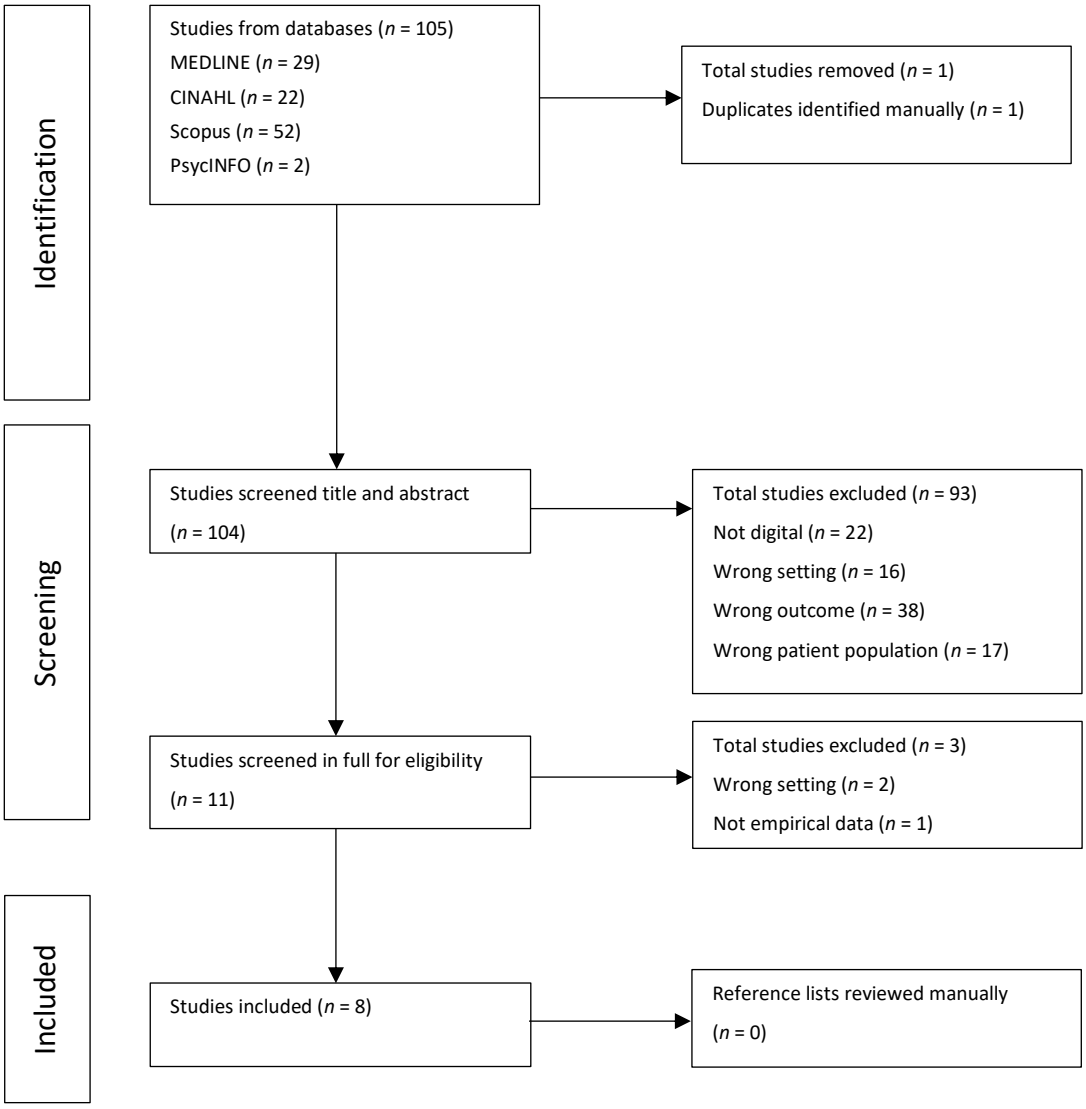
2.2.9 Ethical considerations

Ethical approval was not sought for this systematic review as secondary data was used. However, all included studies had been reviewed by the appropriate ethics committees prior to the commencement of the research.

2.3 Findings

The search identified 105 articles across four databases: CINAHL, MEDLINE, Scopus, and PsycINFO. One duplicate was manually identified and removed. The researcher and supervisor then conducted a title and abstract screening of the 104 studies; 93 were excluded for not being digital (*n* = 22), having the wrong setting (*n* = 16), having the wrong outcome (*n* = 38), or having the wrong patient population (*n* = 17). The remaining 11 studies were then imported into Covidence and screened in full for eligibility. Following the full-text review, a further three studies were excluded: two were from the wrong setting, and the third was not empirical research. This resulted in eight studies being included in this review. The reference lists of the included studies were screened for additional studies, but none were identified. Figure 3 details the PRISMA flowchart, summarising the searches conducted.

Figure 3. PRISMA flowchart.



2.3.1 Data extraction

Error! Reference source not found. summarises the information extracted from the selected articles.

2.3.2 Characteristics of included studies

The studies included one observational study (Carroll et al., 2022), two ITS studies (Cho et al., 2021; Dowding et al., 2012), one RCT (Dykes et al., 2010), and four cohort studies (Furukawa et al., 2011; Walker-Czyz, 2016; Ye et al., 2020; Yokota et al., 2018). Among the eight studies, six were conducted in the USA (Carroll et al., 2022; Dowding et al., 2012; Dykes et al., 2010; Furukawa et al., 2011; Walker-Czyz, 2016; Ye et al., 2020), one in Japan (Yokota et al., 2018), and one in Korea (Cho et al., 2021).

The studies varied in sample size, with some focusing on specific groups and others covering broader populations. Two studies (Carroll et al., 2022; Yokota et al., 2018) reported data from a single health facility, with patient populations of 35,709 and 25,039, respectively. Ye et al. (2020) included the largest sample, with 265,225 participants across 69 health facilities. Dykes et al. (2010) conducted an RCT with 10,264 patients, randomly assigning participants to an intervention or control group. Meanwhile, Cho et al. (2021) examined 42,476 admissions across six units, focusing on falls and fall-related injuries. Furukawa et al. (2011) used data from 3,048 units across 509 hospitals, providing a system-wide perspective.

Using Joanna Briggs' critical appraisal assessments, the researchers obtained critical appraisal scores for each study. Carroll et al. (2022) scored 6/10 (observational study); Cho et al. (2021) scored 8/9 (ITS); Dowding et al. (2012) scored 5/9 (ITS); Ye et al. (2020) scored 8/11 (cohort); Yokota et al. (2018) and Walker-Czyz (2016) each scored 7/9 (cohort); Furukawa et al. scored 8/11 (cohort); and Dykes et al. (2010) scored 8/13 (RCT). Overall, these scores suggest a mostly moderate-to-high-quality evidence base, with more recent ITS and cohort studies showing stronger results, older ITS designs scoring lower, and a moderate-quality RCT highlighting the complexity of assessing digital interventions.

2.3.3 Structure

The structural element of the Donabedian framework evaluates the environment in which care is delivered. These themes were electronic health systems, digital integration, staffing levels, and staff training.

Electronic health systems

Eight studies reported on electronic health systems. Among the eight studies reviewed, three different electronic health systems were used to assess the impact on patient falls and nurses' experiences. EHRs were utilised by Dowding et al. (2012), Walker-Czyz (2016), Ye et al. (2020), and Cho et al. (2021). An EMR was used in the studies by Carroll et al. (2022), Furukawa et al. (2011), and Yokota et al. (2018). Dykes et al. (2010) used HIT.

EHRs were found to assist with fall documentation and risk assessment, offering features such as nursing documentation tools and fall-monitoring modules (Cho et al.,

2021; Dowding et al., 2012; Walker-Czyz, 2016; Ye et al., 2020). Even though the four studies used the same electronic health system, they examined different elements. Dowding et al. (2012) focused on fall-risk assessments and fall rates as key outcomes. Walker-Czyz (2016) and Ye et al. (2020) reported decision support functionalities, including electronic care plans and fall assessment tools. Cho et al. (2021) created a localised fall-prediction tool that replaced the St. Thomas' Risk Assessment Tool in Falling Elderly Inpatients (STRATIFY) and provided daily alerts to nurses.

Three studies used an EMR system (Carroll et al., 2022; Furukawa et al., 2011; Yokota et al., 2018). Furukawa et al. (2011) used the National Database of Nursing Quality Indicators (NDNQI) and healthcare information and management systems to examine the association between nurses' adoption of the system and patient outcomes. This study found EMR implementation was associated with changes in patient outcomes, particularly higher rates of total and injurious falls in the early years. However, the negative impact of EMR on patient outcomes lessened over time, with no significant relationship observed by year three. With respect to the implementation's effect on nurses, the study found nurse staffing levels were negatively associated with patient outcomes, whereas nursing skill mix was positively associated with patient outcomes. Carroll et al. (2022) and Yokota et al. (2018) sought to determine whether an EMR-based fall-risk screening tool reduced falls. However, only one study investigated whether the use of HIT decreased inpatient falls (Dykes et al., 2010).

Seven of the eight available studies focused on outcomes such as fall rates and risk assessments (Carroll et al., 2022; Dowding et al., 2012; Dykes et al., 2010; Furukawa et al., 2011; Walker-Czyz, 2016; Ye et al., 2020; Yokota et al., 2018), rather than on nurses' interactions with the electronic health systems. Cho et al. (2021) was the only study to examine both the impact of an electronic analytic tool for predicting fall risk on patient outcomes and nurses' behaviours. They focused on how the fall-prediction tool might influence nursing behaviour, with the aim of ensuring that patients received the required regular interventions. The results were inconclusive but showed the intervention group conducted more comprehensive, multifactorial patient assessments than the control group, though interventions in both groups were limited.

Digital integration

Five studies reported on digital integration (Carroll et al., 2022; Cho et al., 2021; Dowding et al., 2012; Dykes et al., 2010; Walker-Czyz, 2016). Dowding et al. (2012) examined digital integration during the implementation of Kaiser Permanente Health Connect and reported no decrease in falls. Walker-Czyz (2016) described the adoption of an integrated EHR and its effects on various aspects of nursing care. Dykes et al. (2010) developed the FPTK, a HIT tool that merges existing communication and workflow practices into a digital platform. Building on this, Carroll et al. (2022) examined the integration of an automated ROF prediction model within the EMR, compared it with the manual JHFRAT, and emphasised the advantages of automation in risk assessment. Lastly, Cho et al. (2021) focused on fall prevention by embedding a predictive model into an EHR system, enabling nurses to receive risk predictions automatically and therefore provide proactive patient care.

Four studies showed that digital integration in healthcare can vary in scope, from extensive organisational EHR implementations, some of which used a phased approach, to specialised workflow tools, such as fall assessments and risk prediction (Dowding et al., 2012; Dykes et al., 2010; Furukawa et al., 2011; Walker-Czyz, 2016). Digital integration also provided support functionalities embedded within the systems (Carroll et al., 2022; Cho et al., 2021).

Although digital integration was not explicitly mentioned in the studies, two studies implied its involvement (Furukawa et al., 2011; Ye et al., 2020). Furukawa et al. (2011) explored the integration of EMR functionalities across varying levels of sophistication, while Ye et al. (2020) described the use of machine learning algorithms to develop a predictive tool for fall risk. Despite the lack of direct mention, the use of EMR/EHR functionalities and predictive tools in these studies reflects the concept of digital integration in practice.

Staffing levels

Five studies reported on staffing levels (Cho et al., 2021; Dowding et al., 2012; Furukawa et al., 2011; Walker-Czyz, 2016; Yokota et al., 2018). Furukawa et al. (2011) and Cho et al. (2021) both discussed staffing levels. Furukawa et al. (2011) developed a conceptual framework that included nurse staffing as a key element and measured

nurse staffing levels and skill mix. The findings indicate that implementing EMR might lead to fewer total nurse hours-per-patient-day, with all three EMR stages linked to decreased nurse demand, especially during the first year after implementation. Significant reductions were seen among licensed practical nurses, licensed vocational nurses, and unlicensed assistive personnel, although registered nurse hours remained stable. Over time, staffing patterns evolved, with registered nurse (RN) hours rising in year three of EMR stage one, and licensed practical and vocational nurse hours increasing in the same period three. In contrast, Cho et al. (2021) reported that the implementation of an electronic analytical tool designed to predict fall-risk reduced inpatient fall rates in a South Korean hospital but did not influence staffing levels, as these were determined by government-mandated staffing structures. Furukawa et al. (2011) similarly noted that EMR adoption may adjust the staffing skill mix by reducing demand for lower-skilled nurses and increasing reliance on higher-skilled staff. Together, these studies highlighted that nurse staffing levels and skill mix can influence patient falls and the effectiveness of fall-prevention strategies, reinforcing the importance of adequate, appropriately balanced staffing to deliver quality care.

Dowding et al. (2012) and Walker-Czyz (2016) examined staffing levels from different angles. Dowding et al. (2012 p616) noted that "*although staffing levels have been identified as a predictor of quality of nursing care, we did not include staffing as an independent variable in the analysis*" (p616). Staffing was excluded because California hospitals had minimum staffing requirements, resulting in little variation in nurse staffing across sites during the study (Dowding et al., 2012). In contrast, Walker-Czyz (2016) argued that insufficient staffing support during adoption might have contributed to higher-than-expected nurse turnover and recommended increasing staffing during implementation to mitigate these risks and reduce turnover. Both studies highlighted challenges in implementing staffing, though neither provides detailed quantitative data on staffing ratios or skill mix.

Yokota et al. (2018) was the only study to specify a staffing ratio (one nurse for every seven patients). Conversely, Ye et al. (2020), Dykes et al. (2010), and Carroll et al. (2022) did not address staffing, indicating variability in how workforce factors were accounted for across the studies.

Staff training

Staff training was referenced in seven of the eight studies reviewed (Carroll et al., 2022; Cho et al., 2021; Dowding et al., 2012; Dykes et al., 2010; Furukawa et al., 2011; Walker-Czyz, 2016; Yokota et al., 2018). Cho et al. (2021) reported on the delivery of a comprehensive three-month pre-deployment training programme on the IN@SIGHT system, followed by peer-to-peer education for unit champions. Implementation of the analytic tool led to reduced fall rates, improved completion of risk assessments, and more multifactorial, risk-targeted interventions. To support accurate reporting, the hospital's nursing department also conducted monthly chart reviews and provided feedback to minimise underreporting of falls. Dykes et al. (2010) implemented an educational programme on fall-risk assessment and prevention. The FPTK provided a patient education handout, and clinician education showed effectiveness only in the short term. Yokota et al. (2018) noted that staff education was provided to maintain the quality of the Intensity of Nursing Care Needs data, in line with national standards and guidelines. However, the study did not describe specific educational processes or outcomes.

Furukawa et al. (2011) noted that anecdotal evidence suggests contract nurses may need to offset nurse time for training during implementation. They also reported that as EMR systems become more sophisticated, inadequate staff training and poor coordination among caregivers may contribute to staffing inefficiencies and increased risk of adverse patient outcomes. Similarly, Dowding et al. (2012) described the education of frontline nursing staff as part of an initiative to reduce hospital-acquired pressure ulcers in all Kaiser Permanente hospitals. While the introduction of an EHR was associated with a reduction in hospital-acquired pressure ulcers, it did not reduce patient fall rates. Walker-Czyz (2016) emphasised the need for evidence-based education with clear standards of care to support patient care and for nurses to maintain control over their work environment during EHR implementation, noting that nurses were trained on the new electronic tool. In contrast, Carroll et al. (2022) provided no details about staff education, instead highlighting the importance of clear model configuration and careful review of data definitions, such as those for falls and fall types. Ye et al. (2020) did not include any details of staff training in their study. The

second component of the Donabedian framework emphasises the process of translating fall prevention strategies into clinical practice.

2.3.4 Process

The process element of the Donabedian framework looks at how care is delivered in clinical practice. These themes were clinical decision-making, monitoring, and reporting.

Clinical decision support systems

All eight of the studies reported on the importance of decision support tools in assisting clinical decision-making regarding falls (Carroll et al., 2022; Cho et al., 2021; Dowding et al., 2012; Dykes et al., 2010; Furukawa et al., 2011; Walker-Czyz, 2016; Ye et al., 2020; Yokota et al., 2018). For instance, Furukawa et al. (2011) reported that the EMR can automate clinical decision-making, potentially improving the prevention and management of patient falls. However, the study also noted that poor implementation and lack of integration may lead to workarounds and dissatisfaction, thereby increasing errors and inefficiencies (Furukawa et al., 2011).

Dowding et al. (2012) reported the CDSS delivered automated recommendations to nurses, integrating decision support directly into their workflow and provided guidance at the time and location of decision-making. They described how the Health Connect system was modified to include flowsheets that prompted nurses to perform appropriate actions in line with the SKIN bundle for hospital-acquired pressure ulcer prevention (Dowding et al., 2012). Furukawa et al. (2011) similarly noted that by stage three of the EMR implementation, the hospital had begun implementing clinical decision support and computerised physician order entry in at least one unit. They observed that the EMR could support nursing care through automated alerts, clinical guidelines, and standardised care processes. Carroll et al. (2022) examined the ROF model, a computerised predictive model that generates a score between 0 and 100 to predict the risk of falls. Compared to the organisation's existing JHFRAT, the ROF model showed similar performance, aligning with the current standard methodology used by the organisation. The performance of the ROF model was similar to that of the JHFRAT in predicting inpatient falls, and the comparison provided sufficient evidence to support a transition to a more automated process (Carroll et al., 2022).

Several studies (Cho et al., 2021; Dykes et al., 2010; Walker-Czyz, 2016; Ye et al., 2020; Yokota et al., 2018) documented the use of fall-prevention tools instead of a specifically defined CDSS to assist nurses in customising interventions based on individual risk assessments. Dykes et al. (2010) investigated how an FPTK that employed HIT supported decision-making and bedside communication. This toolkit was integrated into daily practice through a nurse-completed fall assessment, which generated tailored recommendations aligned to each patient's fall-risk profile. Yokota et al. (2018) evaluated the use of a fall screening tool embedded in the EMR, functioning as a CDSS, to determine whether its implementation reduced falls. Even after the tool was implemented, the nurse had full discretion over whether and when to use it in practice. The likelihood of a fall decreased after the tool was introduced, but actual fall rates did not change. Walker-Czyz (2016) indicated that embedding evidence-based practice (EBP) standards of care within the EHR supported nursing decision-making by providing structured checklists that reinforced standardised care delivery, thereby promoting better compliance with practice standards.

Cho et al. (2021) built on this by exploring how predictive fall-risk analytics affected nursing, resulting in more focused interventions in hospitals. Ye et al. (2020) discussed an EHR-based fall-risk prediction tool, suggesting that the risk assessment reviewed in the study could be immediately deployed in the health system to provide automatic early warnings. While Dykes et al. (2010), Yokota et al. (2018), Walker-Czyz (2016), Cho et al. (2021), and Ye et al. (2020) did not explicitly label their predictive screening tool as a CDSS, their features, such as early warnings and personalised risk factors, align with CDSS principles.

Three studies specifically examined how decision support tools affect fall-related clinical decisions (Dowding et al., 2012; Walker-Czyz, 2016; Ye et al., 2020). Dowding et al. (2012) reported that the EHR included risk assessment tools to identify patients at risk of falling. However, the study found no significant decrease in fall rates attributable to EHR implementation. Likewise, Walker-Czyz (2016) discussed how integrating EBP tools into a bedside nurse's workflow enhances point-of-care decision-making, potentially improving quality. This study also recommended further research to understand how nurses utilise EHR resources in clinical decision-making (Walker-

Czyz, 2016). In agreement, Ye et al. (2020) concluded that a fall assessment tool could be used to provide early warnings to improve fall management.

Predictive analytical tools were used in three studies (Carroll et al., 2022; Cho et al., 2021; Ye et al., 2020). Ye et al. (2020) showed that an EHR-based fall-risk predictive tool provided early alerts and identified individual risk factors, thereby enabling individualised patient interventions. Carroll et al. (2021) expanded on this by comparing the JHFRAT and the ROF, concluding their performance was similar in predicting patient falls, indicating evidence to support the transition to an automated process to support clinical decisions. In addition, Cho et al. (2021) compared the traditional STRATIFY assessment tool with a predictive model, finding that the new model was well received by nurses and improved completion of risk assessments.

Two studies examined decision-making through communication and the integration of existing workflows (Dykes et al., 2010; Yokota et al., 2018). Dykes et al. (2010) reviewed the FPTK, which used a valid fall-risk assessment scale within the HIT and was reported to provide fall-prevention decision support and bedside communication. Yokota et al. (2018) examined how implementing a fall-risk screening tool in an EMR influences fall rates but did not specifically examine its effect on clinical decision-making. They acknowledged that the data relied on nurses' voluntary reports, which may have led to underreporting (Yokota et al., 2018).

Monitoring and reporting

All eight studies reported on monitoring and reporting regarding falls (Carroll et al., 2022; Cho et al., 2021; Dowding et al., 2012; Dykes et al., 2010; Furukawa et al., 2011; Walker-Czyz, 2016; Ye et al., 2020; Yokota et al., 2018). While all studies recognised monitoring and reporting as essential for quality and safety, it was evident that the levels of automation and the extent of their integration into organisations varied across studies. Five studies reported using a database or dashboard for monitoring and reporting (Dowding et al., 2012; Dykes et al., 2010; Furukawa et al., 2011; Walker-Czyz, 2016; Yokota et al., 2018). Furukawa et al. (2011) emphasised the significance of the NDNQI, in which participating hospitals collect and report nurse-sensitive data, such as falls. They used standardised specifications, which produce quarterly benchmarking reports to aid continuous quality improvement. Likewise, Dowding et al. (2012) and

Yokota et al. (2018) described monitoring systems through the Collaborative Alliance for Nursing Outcomes and the Intensity of Nursing Care Needs, respectively, where both systems continuously collected unit-level outcomes. Walker-Czyz (2016) and Dykes et al. (2010) discussed using electronic dashboards to support monitoring and provide unit-level performance data. In both cases, registered nurses were required to report patient and injurious falls across all hospitals.

Different methods were employed in three studies (Carroll et al., 2022; Cho et al., 2021; Ye et al., 2020) for monitoring and reporting. In Carroll et al.'s (2022) study, fall-risk scores were documented in the EMR, making risk levels visible throughout the patient's episode of care, thereby fostering collaborative awareness amongst the care team. Cho et al. (2021) managed underreporting through educational programmes, monthly chart reviews, and feedback systems, emphasising the importance of precise documentation. Meanwhile, Ye et al. (2020) focused on predictive tools rather than formal reporting, prioritising real-time risk communication over retrospective monitoring.

Outcomes

The outcome element in the Donabedian framework measures the results of care. These included the incidence and severity of falls, and nurses' experiences and opinions. Falls-related clinical decision-making was not explicitly reported in the literature and is not referenced in this systematic review.

Incidence and severity of falls

All the studies reported on the incidence and severity of falls (Carroll et al., 2022; Cho et al., 2021; Dowding et al., 2012; Dykes et al., 2010; Furukawa et al., 2011; Walker-Czyz, 2016; Ye et al., 2020; Yokota et al., 2018). However, the impact of electronic health systems on fall incidence and severity varied across studies.

Three studies reported specific incident data (Carroll et al., 2022; Cho et al., 2021; Walker-Czyz, 2016). Carroll et al. (2022) shared detailed incidence data, indicating a fall rate of 0.92% across 35,709 inpatient encounters, and estimated that 700,000 to 1 million falls happen each year in USA hospitals. Carroll et al.'s (2022) study also emphasised severity, noting that approximately 10% of inpatient falls resulted in injury, with unassisted falls associated with more severe injuries. Meanwhile, Cho et al.

(2021) provided detailed data from a controlled ITS analysis, which captured 707 falls and 134 fall-related injuries across 42,476 admissions. Walker-Czyz (2016) reported a statistically significant reduction in fall rates after an EHR was implemented, with the EHR model accounting for 15% of the variance, suggesting a moderate but important impact.

Five studies provided a broader perspective on the impact of falls (Dowding et al., 2012; Dykes et al., 2010; Furukawa et al., 2011; Ye et al., 2020; Yokota et al., 2018). For example, Furukawa et al. (2011) provided standardised measures of fall incidence and severity, including total and injury-related falls per 1,000 patient days, collected quarterly via the NDNQI. Dykes et al. (2010) emphasised the impact of falls on patients rather than the number of individuals reporting serious consequences of injurious falls, including increased hospital costs, longer hospital stays, and declines in functional ability, particularly among older adults. Ye et al. (2020) reported the XGBoost predictive model performed better in the short term, capturing 58% of falls within 30 days, compared with 50% within 30–60 days. Dowding et al. (2012) assessed the incidence of falls but not severity and reported that implementation of the EHR did not decrease fall rates. Yokota et al. (2018) stated that relying solely on a fall-risk screening tool does not reduce fall incidence and that multifactorial interventions are necessary.

Nurses' experience and opinions

Three studies reported on nurses' experience and opinions (Dykes et al., 2010; Walker-Czyz, 2016; Yokota et al., 2018). Before launching the EHR, Walker-Czyz (2016) held focus groups to gather nurses' opinions on how the new tool could enhance nursing practice standards, stating nurses' suggestions were integrated and the tool was revised based on further feedback (Walker-Czyz, 2016). Similarly, Dykes et al. (2010) used qualitative inquiry in the first phase of the study to identify barriers and enablers to fall-risk communication and intervention. Nurses reported that alerts regarding patient-specific fall-risk status and fall-prevention interventions were absent, even though they were necessary at the bedside. This feedback informed the development of the prototype FPTK in phase 2 of the study. Yokota et al. (2018) interpreted nurses' experiences and opinions more literally, noting that because nurses had full discretion over whether and when to use the fall screening tool, any reduction in the probability

of falls likely reflected behavioural changes in how nurses approached fall-related care rather than the direct impact of the tool itself.

Carroll et al. (2022) and Cho et al. (2021) both examined nurses' perspectives on proposed system changes and new systems. Carroll et al. (2022) emphasised that nurses are uniquely positioned to intervene in fall risk and discussed how automating fall-risk assessment could influence their workflow and cognitive load by altering how assessments are completed and integrated into daily practice. Cho et al. (2021) found similarly that nurses were generally willing to use the tool in practice. Although survey responses initially reflected neutral or slightly negative feelings, these perceptions improved over time as nurses experienced how the system supported more individualised fall-preventive interventions for patients.

Furukawa et al. (2011) noted that although their study did not exclusively report nurses' experiences and opinions, poor implementation can lead nurses to develop workarounds, thereby undermining the system's intended benefits. Surveys indicated that EMR systems might disrupt workflow and increase computer time, leading to dissatisfaction and reduced efficiency. Ye et al. (2020) and Dowding et al. (2012) did not report the nurses' experiences or opinions in their studies, leaving a gap in understanding the human factors that affect adoption.

Across the studies, only limited direct nurse commentary was noted. Dykes et al. (2010) noted that nurses explicitly stated alerts indicating patient-specific fall-risk status and corresponding interventions were unavailable at the bedside, despite being clearly needed. Yokota et al. (2018) reported that nurses were observed entering information into the EMR, such as a history of falls, disease-related risks, and activities of daily living risks. The nurses also recorded daily Intensity of nursing care needs data, although their views were interpreted rather than directly quoted. Walker-Czyz (2016) did not present direct quotations from nurses, but the study reported that focus groups with nurses were conducted before EHR implementation to explore how the system could support nursing practice standards. Cho et al. (2021), Ye et al. (2020), and Dowding et al. (2012) provided no direct nurse statements; instead, they described nurses' engagement with the system more generally. Similarly, Furukawa et al. (2011) did not include nurse's quotes, relying on quantitative analysis to assess the effects of

the EMR systems on falls and nurses. Carroll et al. (2022) also offered no direct quotations but described nurses' involvement with fall-risk assessment tools, particularly their responsibility to calculate and document the JHFRAT in the EMR manually.

2.4 Summary

Across the eight studies, data on digital health systems and inpatient falls varied, showing both positive and neutral results. Nonetheless, the overall evidence is limited and of low certainty because few studies separate the impact of CDSS from broader electronic health system changes. There is also limited evidence directly linking CDSS implementation to fall rates and nurses' clinical decisions, mainly because most studies assessed whole electronic health systems or integrated tools, rather than isolating CDSS as a standalone intervention. As a result, outcomes typically reflect the combined effects of system modifications, local setups, and implementation processes, rather than the specific impact of CDSS functionality.

Using the Donabedian framework, reporting on structural factors such as electronic health systems, digital integration, staffing levels, and staff training was inconsistent and lacked detail. All eight studies identified the electronic health system used (EHR, EMR, or HIT), but few offered meaningful details on digital integration, staffing, or training. Only a few reported specific staff ratios or implementation characteristics, limiting the ability to determine whether outcomes were affected by the technology itself or by workforce capacity and organisational support. Although the importance of training was recognised, it was rarely described in detail, and limited implementation support was linked to workarounds and inefficiencies. These gaps further weaken the confidence in attributing observed changes to digital technology, emphasising the low strength and incomplete nature of the structural evidence.

The strongest evidence for process improvements concerns documentation and fall assessment activities, with several studies highlighting the use of alerts, predictive tools, and embedded care plans to support nurses' decisions. Some studies reported improved completion rates for risk assessments. However, direct measurement of clinical decision-making was rare, and most studies relied on indirect indicators, such as assessment completion, documentation patterns, or intervention counts. As a

result, the evidence for CDSS influence on nurses' decision-making is indirect and insufficient. When decision support features were discussed, their effectiveness depended heavily on usability, workflow integration, and implementation quality. Monitoring and reporting processes varied from automated dashboards to manual or voluntary reporting, introducing further inconsistency that complicates the interpretation of fall outcomes.

Outcome findings were similarly mixed. Some studies reported reduced fall rates, while others found no significant difference. Only a few studies provided detailed fall and injury data alongside implementation information, and very few explored nurses' experiences and opinions. Where nurses' involvement was reported, such as through feedback during design or structured support, acceptance and adoption seemed more positive. Conversely, minimal support during implementation was associated with dissatisfaction and the use of workarounds. Overall, the evidence offers limited understanding and little insight into how nurses interact with these systems in real time and how this engagement influences clinical decisions about falls.

No NZ literature was identified that examined how electronic health systems influence fall management or clinical decision-making in hospital settings. There is also no NZ evidence assessing whether implementing an EMR with an integrated CDSS for fall-risk assessment affects fall outcomes or nurses' clinical experiences and decision-making within a private hospital. Accordingly, examining the association between the use of an electronic health system with an integrated CDSS for fall-risk assessment, fall outcomes, and nurses' clinical experiences and decision-making within fall prevention in an NZ private hospital setting is necessary to address this gap.

Chapter 3 Methodology

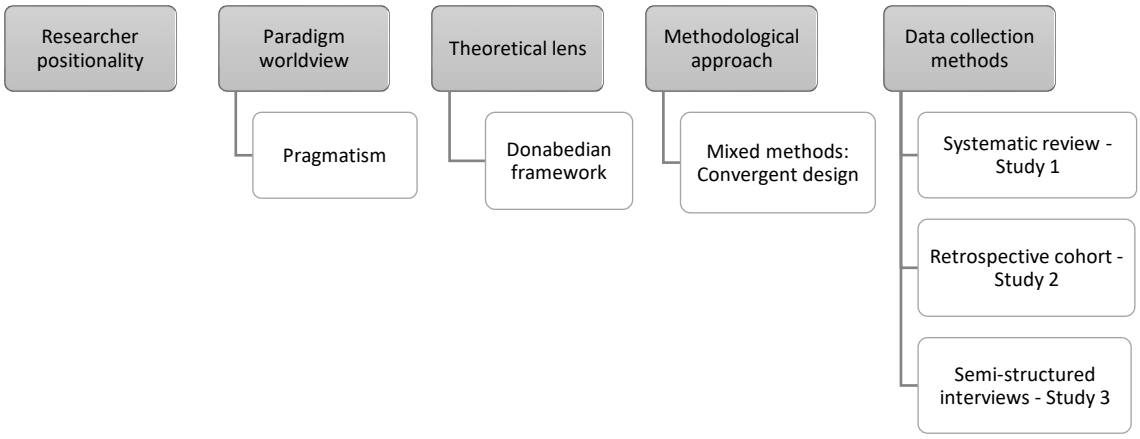
3.1 Introduction

This thesis seeks to determine whether replacing a patient management system with an EMR with a CDSS specifically for fall-risk assessment in a private hospital affects the incidence of falls, nurses' clinical experiences, and decision-making processes related to fall prevention.

This chapter includes a positionality statement to align with the open-science principle of transparency in knowledge production (Savolainen et al., 2023). This statement discloses relevant personal factors that may influence the study and, where necessary, the steps taken to mitigate them, allowing the reader to evaluate how the researcher's ontological perspective may have influenced the study (Steltenpohl et al., 2022).

The chapter also outlines the fundamental elements that guided the design of this study, using an adaptation of Crotty's (1998) framework. Specifically, it discusses the paradigm worldview, pragmatism, the theoretical lens of the Donabedian framework, and the methodological approach using a mixed-methods convergent design. The final section details the data collection methods, with study two being a retrospective cohort study of hospital administrative and patient fall data and study three comprising semi-structured interviews, as detailed in Figure 4.

Figure 4. Summary of thesis design.



Note. Adapted from *The Foundations of Social Research: Meaning and Perspective in the Research Process*, by M. Crotty, 1998, Allen and Unwin.

3.1.1 Research questions

The following research questions guided this thesis.

3.1.2 Systematic review (Study 1)

What evidence exists regarding the impact of digital health systems on inpatient fall outcomes and nurses' clinical decision-making in hospital settings?

3.1.3 Systems analysis (Study 2)

Is the implementation of an EMR with an embedded CDSS for fall-risk assessment associated with changes in the incidence of patient falls in a private hospital between January 2019 and December 2022?

3.1.4 Qualitative study (Study 3)

How do nurses describe the influence of the EMR with an embedded CDSS on their clinical experiences and decision-making processes related to fall prevention?

3.2 Objectives

The objectives of this thesis were as follows.

3.2.1 Systematic review (Study 1)

Systematically synthesise empirical evidence on the impact of digital health systems, including EMRs and CDSS, on inpatient fall outcomes and nurses' clinical decision-making in hospital settings.

3.2.2 Systems analysis (Study 2)

Analyse quantitative fall incidence data before and after implementation of the EMR with embedded CDSS.

3.2.3 Qualitative study (Study 3)

Explore nurses' clinical experiences and decision-making processes in relation to fall prevention following implementation.

3.2.4 Integration of data

Integrate the data from the three studies to develop a comprehensive understanding of how the EMR-embedded CDSS may shape fall prevention practices in the private hospital setting.

3.3 Researcher positionality

In the spirit of transparency, the researcher will share their professional background, which includes a master's degree in nursing and registration as a nurse in both NZ and Australia. With over 25 years of experience in clinical and healthcare management, the researcher worked as a general manager at a private hospital in Auckland from 2008–2021. During that period, an EMR system with CDSS was implemented. From 2021–2024, the researcher then worked as the chief executive officer of a private hospital in Auckland, overseeing clinical governance and information and communication technology, with a focus on patient, staff, and specialist safety. It is important to note that this study was conducted at a different private hospital, not the one directly managed by the researcher.

The researcher's diverse background, covering nursing, hospital management, and executive roles, shaped the research approach. The nursing experience provided insight into clinical care and the practical aspects of fall assessment, prevention, and patient care. The general manager and chief executive officer roles emphasised a problem-focused approach, guided by expertise in implementation, change management, stakeholder engagement, and operational efficiency. Throughout the study, the researcher reflected on her assumptions, values, beliefs, and relationships within the research design and process, carefully and critically considering how these may influence the research. This self-awareness enabled the researcher to actively address and, where possible, reduce potential biases, thereby strengthening the study's credibility and integrity. The qualities described in the positionality section influenced how the researcher interacted and reflected pragmatist principles, emphasising practicality, responsiveness, and the making of a meaningful difference.

3.4 Paradigm worldview – Pragmatism

3.4.1 Alignment with a real-world problem

Pragmatism is suitable for this study because it is grounded in a well-defined real-world problem in clinical practice—the impact of replacing a patient management system with an EMR and a CDSS. According to Kaushik and Walsh (2019), pragmatism helps evaluate a researcher's understanding through their experiences and the beliefs formed from them. In line with Robson (2024), insights from workplace practice can serve as a credible basis for research, enabling the examination of practical issues in healthcare settings. Here, the research problem stems directly from changes in healthcare systems within a private hospital, making pragmatism a fitting foundation.

3.4.2 Methodological flexibility

The pragmatic worldview enabled the researcher to select methods that best addressed the research objectives and questions, rather than being constrained by a single methodological tradition. Pragmatism emphasises adaptable inquiry and supports the use of approaches best suited to explore real-world applications and outcomes (Creswell & Plano Clark, 2018; Teddlie & Tashakkori, 2009). This flexibility facilitated the examination of both patient outcomes and staff opinions following a healthcare system change, allowing the study to analyse nurses' experiences alongside the incidence of falls. As a result, the research problem and methodology are aligned (Creswell & Plano Clark, 2018; Onwuegbuzie & Collins, 2007).

3.4.3 Practical contribution to healthcare practice

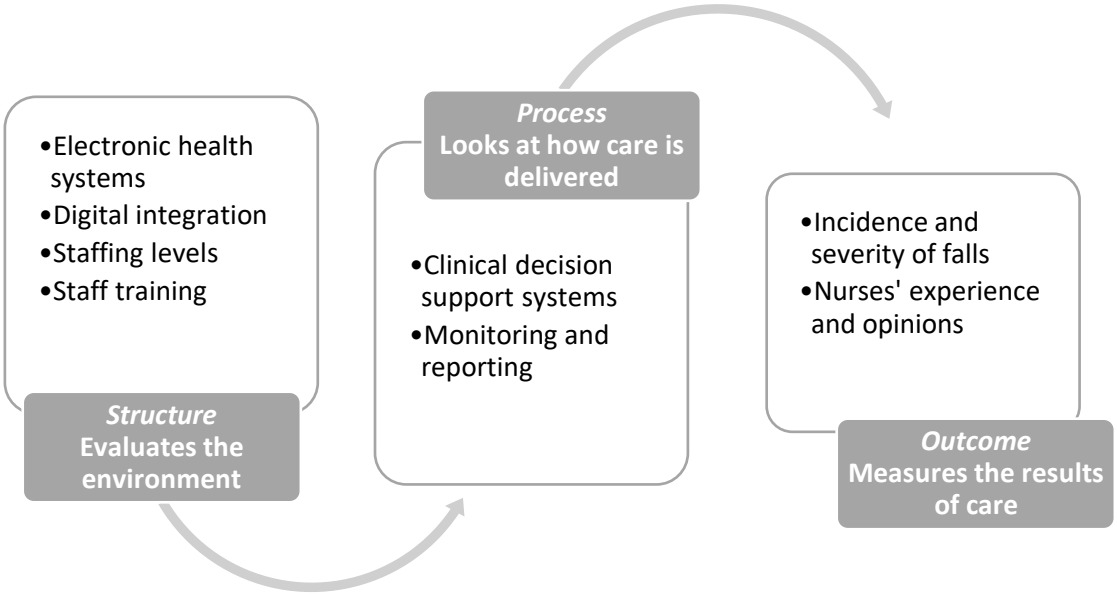
Pragmatic research is committed to creating meaningful improvements through the exploration and evaluation of change (Allemang et al., 2021). In this study, pragmatism supports an emphasis on practical outcomes, including the influence of an electronic system on fall rates, nurses' clinical experiences, and clinical decision-making processes. The use of the Donabedian Framework provides a systematic approach to assessing how changes in an organisation's structures and processes affect patient outcomes. Together, the pragmatic paradigm and the Donabedian Framework ensure that the study delivers a clear, practical evaluation of EMR implementation relevant to private hospital practice.

3.5 Theoretical lens – Donabedian Framework

Avedis Donabedian, a professor specialising in medical care, conducted a review of research on quality assessment and published an article in 1966 titled "*Evaluating the Quality of Medical Care*". In this work, he introduced a framework for evaluating healthcare quality through the triad of structure, process, and outcome (Ayanian & Markel, 2016). This framework can serve as a method for scrutinising health services and assessing the quality of care (Donabedian, 1988). Structural quality is the organisational element that evaluates the environment, encompassing nursing facilities, human resources, and organisational systems (De Rosis, 2024). Process quality evaluates nursing practice and the delivery of care, whereas outcome quality is the result of care and is directly influenced by structural and process controls (Yang et al., 2025).

The Donabedian Framework is appropriate for this study because the implementation of an electronic health system with an integrated CDSS constitutes a structural change within the organisation, alongside staffing levels and staff training. Nurses' use of the risk assessment CDSS and the monitoring and reporting they carry out within their roles reflect processes, and the incidence of patient falls, along with nurses' experience and opinions, can influence patient outcomes. Figure 5 presents the conceptual framework for this study, based on the Donabedian Framework.

Figure 5. Conceptual layout for this thesis.



Note. Adapted from "The quality of care: How can it be assessed?" by A. Donabedian, 1988, *JAMA: The Journal of the American Medical Association*, 260(*12*), p. 1743. https://doi.org/10.1001/jama.1988.03410120089033

The following is an overview of how the Donabedian Framework, and its three components of structure, process and outcome were utilised in this study to answer the research questions.

3.5.1 Structure

Structure refers to the environment in which patient care occurs; in this study, it refers to the private hospital. Understanding the structure helps the researcher assess how the presence of the CDSS influences the environment and whether it enhances the quality of care within the hospital setting.

3.5.2 Process

Process examines how nurses deliver care, including the processes they use and how the CDSS affects daily practice. By examining this, the researcher can understand how the CDSS is integrated into clinical workflows, how its use is monitored and reported on, and whether it improves adherence to fall prevention protocols.

3.5.3 Outcome

Outcome measures the results of the care provided. According to Donabedian's (1988) framework, outcome is the ultimate measure of the effectiveness of the structure and processes in place. By gathering and analysing these data, the study gains a comprehensive understanding of the CDSS's impact on the incidence and severity of falls, as well as whether this influences nurses' experiences and fall-related clinical decision-making within their practice settings.

In summary, the researcher believes that using the Donabedian Framework to assess healthcare quality, along with a pragmatic approach, makes the evaluation more grounded, practical, and adaptable, thereby increasing the relevance and usefulness of the findings. The Donabedian Framework has, however, been criticised for its linear approach, particularly for failing to fully account for factors such as staff dynamics and attitudes (Ameh et al., 2017). This study will adopt a mixed-methods approach that allows researchers to combine detailed staff attitudes and perceptions with system-generated data, providing a more comprehensive understanding of the healthcare delivery system's approach to falls in private hospitals. This method aims to address some of the criticisms of the Donabedian Framework.

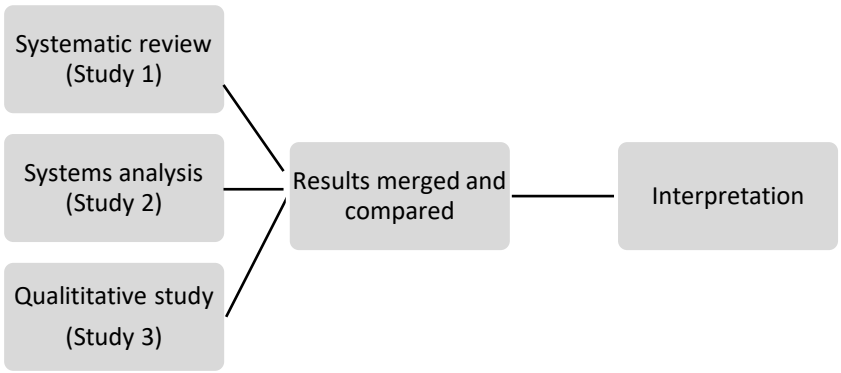
3.6 Methodological approach – Convergent mixed methods design

The mixed-methods design was selected because the research questions cannot be adequately answered using a single methodological approach. The study seeks to determine whether implementing an EMR with a CDSS for fall-risk assessment is associated with changes in fall incidence and to examine how nurses describe their clinical experiences and the decision-making related to fall-prevention. Mixed-methods research is well known for harnessing the strengths of both approaches within a single study (Creswell, 2015; Creswell & Plano Clark, 2018; Dawadi et al., 2021), a feature that is particularly valuable when examining complex healthcare system change (Dawadi et al., 2021). Combining different data types enables thorough exploration and validation, offering a more detailed perspective (Creswell, 2015; Creswell & Plano Clark, 2018; Onwuegbuzie & Collins, 2007; Teddlie & Tashakkori, 2009). This approach also aligns with the study's pragmatic orientation, supporting the use of multiple methods to answer real-world problems.

The researcher initially proposed a sequential design; however, delays in accessing system data and scheduling interviews required a review of the design. A convergent mixed-methods design was subsequently adopted, involving concurrent, equally weighted quantitative and qualitative studies. The quantitative study (system analysis) examines changes in fall incidence following the implementation of the EMR with an embedded CDSS, while the qualitative studies (systematic review and qualitative study) review the wider literature and interviews with nurses to explore nurses' clinical experience and decision-making related to fall prevention. Conducting all the studies concurrently enabled the integration of outcome and process data within the same period, supporting direct comparison and fostering a balanced approach, thereby improving the validity and reliability of the results (Creswell & Plano Clark, 2018; Moon, 2019).

This design also strengthens the application of the Donabedian Framework by enabling a clearer evaluation of how structural change (the implementation of an EMR with CDSS, staffing levels, and staff training) relates to process (the use of CDSS, monitoring, and reporting) and outcome (incidence of falls and nurses' experience and opinions). A summary of the convergent design is presented in Figure 6.

Figure 6. Convergent mixed-methods design.



Note. Adapted from *Designing and Conducting Mixed Method Research* (3rd ed., p. 66), by J. W. Creswell & V. L. Plano Clark, 2018, SAGE.

Building on the outlined methodological approach, the following section describes the data collection methods used to develop the evidence base, including the recruitment of participants and the collection of information.

3.7 Methodology

3.7.1 Setting

This study was conducted at a private hospital in NZ, known for its advanced medical facilities, teamwork, and innovation, which provides a wide range of surgical and medical services.

3.7.2 Systematic review (Study 1)

A systematic review of the literature was undertaken utilising the Donabedian Framework. Chapter 2 provides full details of this process.

3.7.3 System analysis (Study 2)

Aim

This study aims to determine whether replacing a patient management system with an EMR and a CDSS for fall-risk assessment in a private hospital affects the incidence of falls among patients admitted from January 2019 to December 2022.

Objective

To analyse quantitative fall incidence data before and after implementation of the EMR with embedded CDSS.

Population and sample

Data from all patients admitted to the private hospital as inpatients or day stay between January 2019 and December 2022 were included. Patient data were extracted from PiMS from January 1, 2019, to May 4, 2020. The EMR with CDSS was implemented in the private hospital on May 16, 2020. Therefore, this timeframe provides cohorts before (January 1, 2019, to May 4, 2020) and after (May 16, 2020, to December 31, 2022) the CDSS implementation. The fall data were extracted from PayWiz from January 1, 2019, to December 31, 2021, and from Safety Hub from January 1, 2022, to December 31, 2022.

Data sources

The private hospital data analyst extracted data for this study from five hospital systems. Table 3 outlines the data sources and timeframes used. It also includes descriptions and data requested by the researcher from each system.

Table 3. Summary of data sources.

Data source	Description	Data
PiMS January 1, 2019– May 4, 2020	Patient management system prior to the implementation of the EMR Trakcare	Patient identifier, age, admission date and time, discharge date and time, length of stay (hours), length of stay (days), country, postcode, domicile code, ethnicity, procedure code, procedure description, actual procedure, ward
Trakcare May 16, 2020– December 31, 2022	Electronic medical record	Patient identifier, age, discharge date, length of stay (hours), length of stay (days), postcode, ethnicity, procedure code, procedure description, actual procedure, ward, admission time, discharge time, suburb
Trendcare January 1, 2019– December 31, 2022	Workforce planning and workload management system	Ward, date, staffing levels (nursing hours variance)
PayWiz January 1, 2019– December 31, 2021	A technology platform that the private hospital used to record adverse events	Adverse event (falls only), severity code, location of fall, fall category, patient identifier, date of fall
Safety Hub January 1, 2022– December 31, 2022	An online workplace health and safety platform used to record adverse events	Adverse event (falls only), severity code, location of fall, free-text description of fall, date of fall

The inclusion of five systems was a comprehensive approach; however, it introduced overlapping data across periods, resulting in three distinct time periods. Time period one, pre-implementation admission system, with the previous incident management system and staffing system, January 1, 2019–May 4, 2020. Time period two, post-implementation EMR, with the previous incident management system and staffing system, May 16, 2020–December 31, 2022. Time period three, post-implementation EMR, with the current incident management system and staffing system, January 1, 2022–December 31, 2022.

Variables of interest

The variables for this study are categorised according to the Donabedian Framework components: structure, process, and outcome. The variables of interest in Table 4 are listed with their sources and rationales. A more detailed explanation of these variables is provided in Chapter 4.

Table 4. Variables of interest.

Variable	Data source	Rationale for use	DFC
Patient identifier	PiMS Trakcare, PayWiz & Safety Hub	Patient identifier is a unique identifier assigned to every patient who uses health and disability support services in NZ. A unique identifier will enable multiple admission or adverse fall events relating to an individual patient to be linked and aggregated.	P
Year	PiMS Trakcare	Allows the researcher to track health trends (falls) by year (2019–2022).	S
Ward identifier and specialty	PiMS Trakcare	Allows the researcher to track health trends (falls) by specialty.	S
Age	PiMS Trakcare	Collecting this data will provide greater depth to the study's findings.	P
Ethnicity	PiMS Trakcare	Allows the researcher to track health trends (falls) by ethnicity.	P
Post code of usual residence	PiMS Trakcare	Having this data will allow the researcher to determine whether the patients are local to the private hospital. This will relate to distance travelled and access to support networks.	P
Admission date and time	PiMS Trakcare	Used to identify: 1) The patient's timeframe with regards to the CDSS technology 2) The length of time that the patient was exposed to the private hospital environment 3) Whether the patient had extended or sequential admissions for an extended period of time.	P
Discharge date and time	PiMS Trakcare	Used to identify: 1) The patient's timeframe with regards to the CDSS technology 2) The length of time that the patient was exposed to the private hospital environment 3) Whether the patient had extended or sequential admissions for an extended period of time.	P
Length of stay (LOS)	PiMS Trakcare	This can be used as a key explanatory factor. LOS could impact the likelihood of falling. A longer LOS has been associated with increased risk of falling in the private hospital.	P
Procedure description	PiMS Trakcare	The procedure may affect the incidence of falls.	P
Actual procedure description	PiMS Trakcare	The procedure may affect the incidence of falls.	P
Patient identifier	PayWiz	Patient identifier is a unique identifier assigned to every patient who uses health and disability support services in NZ.	P
Ward identifier and specialty	PayWiz & Safety Hub	Allows the researcher to track health trends (falls) by specialty.	S
Date	PayWiz & Safety Hub	Allows the researcher to track health trends (falls) by data.	O

Variable	Data source	Rationale for use	DFC
Adverse events (Falls only)	PayWiz & Safety Hub	This will be used to ascertain the number of falls reported by ward.	O
Adverse events SAC (Falls only)	PayWiz & Safety Hub	This will be used to ascertain the severity of the falls.	O
Adverse events action (Falls only)	PayWiz & Safety Hub	This will be used to identify the fall actions.	O
Ward identifier and specialty	Trendcare	Allows the researcher to track health trends (falls) by specialty.	S
Staffing variance	Trendcare	Allows the researcher to take into account the allocated staffing hours, which are rostered or assigned hours actually scheduled for staff, while required staffing hours are calculated to ensure safety in meeting patient acuity, nurse–patient ratio, and workload demands.	S
Date and shift	Trendcare	Allows the researcher to track the fall by date and the shift in which it occurred.	S
Ward and shift	Trendcare	Allows the researcher to track the fall by location and the shift in which it occurred.	S

Note. CDSS = Clinical decision support system; DFC = Donabedian Framework components; LOS = Length of stay; NZ = New Zealand; SAC = Severity assessment code.

Data management

A data management plan (Appendix C) and Data sharing agreement (Appendix D) were drafted.

Data collection

Before implementing the EMR Trakcare with an embedded CDSS in May 2020, patient admission and demographic data were entered via the patient management system, PiMS. The data for this study were extracted from PiMS and an equivalent dataset from Trakcare. Nurse staffing details were extracted from the workforce planning management system, Trendcare, and adverse event information (falls only) was extracted from the previous technology platform used to record adverse events, PayWiz, and the newly implemented safety platform used to record adverse events. Safety Hub.

Types of data

The quantitative data were extracted from a single system, Trendcare; admission datasets from PiMS and a comparable dataset from Trakcare, the new EMR. The fall data were extracted from the previous system, PayWiz, covering January 2019–December 2021, and from the newly adopted safety platform, Safety Hub, covering January 2022–December 2022. Additional qualitative data were extracted from the free-text description fields in the current incident management system, Safety Hub.

File formats

Once the quantitative data were extracted from PiMS, Trakcare, Trendcare, PayWiz, and Safety Hub, with assistance from the private hospital data analyst, they were imported into Microsoft Excel in comma-separated values format. The two patient demographic datasets (PiMS & Trakcare) and the two fall datasets (PayWiz & Safety Hub) were merged into a single dataset with assistance from the researcher's primary supervisor, a biostatistician.

File organisation

The raw data was saved as a master copy named 'Master copy v1.0.' During data cleaning, subsequent datasets were renamed 'Master Copy v1.1.' The version number continued to increase until the final version was prepared for analysis, which was saved as 'Master copy final v1.0.'

Confidentiality

The encrypted National Health Index (NHI) number was the only patient identifier in the dataset. No other identifiers, such as name, date of birth, or address, were included. Patient confidentiality was ensured through the use of the encrypted NHI number, which served as the sole patient identifier in the dataset. The encryption process was undertaken by the hospital's analyst before data extraction, and the researcher did not have access to the encryption key or any identification.

Quality control

Before the data were made accessible to the researcher, the data analyst confirmed that all datasets were complete and accurate. The researcher did not have input or access to the data during this period. After transferring the comma-separated value format files, the researcher, with her supervisors' support, conducted screening

checks/analysis to address missing data and data entry errors, and to identify outliers. When outliers were identified, modifications were made only after consultation with the supervisors. On several occasions, the researcher and primary supervisor identified significant anomalies, where the researcher consulted the data analyst for clarification.

During this process, the researcher worked with the data analyst to ensure the most appropriate and accurate data extracts were available. Several extracts were conducted before the final one was completed.

Storage and backup

The data is stored securely in accordance with the National Ethical Standards for Health and Disability Research and Quality Improvement (NEAC) (NEAC, 2019), on a secure, password-protected AUT server in compliance with AUT Research Data Storage Guidelines (AUT, 2023). Access to these files is limited to the researcher, Mrs Paula Anne Murray, and her supervisors, Associate Professors Nick Garrett, Mandie Foster, and Professor Nada Signal.

Preservation

Data will be securely stored in an encrypted, password-protected file on an AUT server, and all data will be destroyed 10 years after the publication of this thesis. This aligns with Principle 9, Retention of Personal Information, of the *Privacy Act* (Privacy Commissioner, 2020).

Data cleaning

During data checking and cleaning, several issues were identified in the data extracts. The data analyst was contacted several times, and the researcher was informed that these data fields were not available in the database. The unavailable data fields are detailed in Table 5.

Table 5. Summary of unavailable data fields.

Data type	Timeframe	Unavailable data fields
Admission data	Pre-implementation	Gender
	Post-implementation	Gender
Falls data	Previous system	Time or shift of fall Detailed falls description Detailed actions following the fall
	Current system	Patient identifier Time or shift of fall

Data analysis

Analysis began with descriptive statistics, such as frequencies, to develop an initial understanding of the sample's characteristics and key variables using the Statistical Package for the Social Sciences (SPSS) software version 29.0.2 (IBM, 2023) This step helped the researcher identify patterns and guided the subsequent phases of the analysis. The data were summarised by ward and date, as event time and patient ID were missing in the post-event data (Safety Hub).

Bivariate logistic regression was undertaken to explore statistically significant relationships among key variables and the odds ratios for a fall. The progression from descriptive to inferential analysis, using statistical analyses such as logistic regression, informed the development of a final multivariable model that enhances the validity of the study's results. The researcher's primary supervisor continually reviewed the process to ensure methodological rigour, appropriate model development, and analytical integrity.

Free-text narratives documented by nurses following a fall were analysed descriptively to summarise common fall circumstances and contributing factors, providing contextual support for the quantitative findings. To strengthen the quality and transparency of reporting, the STROBE checklist (von Elm et al., 2007) was completed and reviewed by the researchers' supervisors.

3.7.4 Qualitative study (Study 3)

Aim

This study explored nurses' experiences and opinions regarding the use of the electronic fall-risk assessment CDSS within the EMR and how it influences their fall-related clinical decision-making at a private hospital.

Objective

To explore nurses' experiences and opinions of the electronic fall-risk assessment CDSS and its influence on fall-related clinical decision-making through semi-structured interviews.

Population and sample

A study poster (Appendix I) was emailed to the area managers at the private hospital and circulated across the private hospital wards and the admission and day stay units. The managers agreed to promote the study during staff meetings. Potential participants interested in the study contacted the researcher directly. Once participants contacted the researcher, a participant information sheet (Appendix J) was provided for their review.

Inclusion and exclusion criteria

To ensure participants had adequate experience to respond meaningfully, Table 6 outlines the inclusion and exclusion criteria that were applied:

Table 6. Participants' inclusion and exclusion criteria.

Inclusion	**Exclusion**
• Nurses working in the wards, admissions, and day stay units at the private hospital. • Nurses had to have used the fall assessment tool both before, in paper form, and afterwards, when the fall assessment (CDSS) was embedded into the EMR system. • Participants needed to provide voluntary, informed consent, a sample of which is available in Appendix K.	• Nurses who were employed at the hospital for only one phase of the EMR/CDSS pre- and or post-implementation, as they could not compare both systems. • Did not provide voluntary, informed consent. • Were agency, casual, or temporary nurses who did not have enough exposure to both systems to be aware of the changes.

Purposive sampling process

The following demographic and professional background questions were part of the informed purposive sampling process:

Question 1. What is the origin of your nursing training?

The origin of the training was crucial for understanding the range of educational backgrounds among the participants.

Question 2. How many years of experience do you have as a nurse?

Inquiring about years of nursing experience provided insight into the depth and breadth of the nurse's practical knowledge and skills. This enabled the researcher to distinguish potential perspectives based on the nurses' length of service.

Question 3. How many years of experience do you have working on the ward in the private hospital sector?

This study was conducted in a private hospital; therefore, it was important to understand the participants' experiences in that setting. This understanding helped the researcher ensure that the collected data was relevant.

Question 4. How many years of experience do you have using a fall assessment in the private hospital sector?

Asking participants about their experiences with the fall assessment is important because it provides direct insight into how the CDSS affects their workflow, patient care, and overall opinions. It can also help assess the usability and effectiveness of the fall assessment tool, the practical challenges nurses face, and the benefits observed.

Question 5. How many years of experience do you have using an EMR/CDSS fall assessment in the private hospital sector?

The screening demographic and professional background allowed the researcher to identify and select a diverse range of nurses' experiences to ensure nurses met the inclusion criteria. If participants are intentionally selected to be diverse from the outset, their views may reflect this diversity and provide a nuanced understanding of the phenomenon (Campbell et al., 2020; Thomas, 2022).

Data collection

The private hospital chief executive officer's executive assistant organised the interview dates, times, and venue, selecting a private, comfortable, and confidential location suitable for both the researcher and participants. The researcher offered participants the opportunity to review their transcripts after the interview.

The semi-structured interview guide (Appendix L) was developed based on the study aims. To assess clarity, the interview guide was pilot tested with an experienced nurse who was not involved in the study. The pilot interview was recorded and reviewed, leading to minor refinements in question wording and sequencing. Following each interview, participants were reminded that they could contact the researcher if they wished to clarify or add further information.

The interviews were conducted over three days. The days were allocated by the chief executive officer's executive assistant on days when the hospital was quieter, so as not to affect operations. Following this, the researcher was unable to return because the managers had expressed concern that prolonged exposure might lead to recruitment by the researcher, who managed a sister hospital.

Data management and storage

Both the audio files and transcriptions were stored on a password-protected computer, accessible only to the researcher and her supervisors. All data will be destroyed 10 years after publication. This is in accordance with Principle 9, Retention of Personal Information, of the *Privacy Act* (Privacy Commissioner, 2020).

Data analysis

After all the interviews were completed, the researcher transcribed the de-identified audio files verbatim and stored them as word-processing documents. To ensure rigour, all transcripts were checked by the researcher against the original audio recordings during and after transcription. Minor adjustments to grammar and phrasing were made to improve understanding and readability.

The researcher used a hybrid method to analyse the data, merging initial inductive coding with deductive organisation (Fetters & Molina-Azorin, 2019). Initially, themes were generated inductively from the data, allowing participants' narratives to shape

insights before being refined through iterative review and comparison across transcripts (Barrett & Younas, 2024; Proudfoot, 2023). These themes were then systematically organised deductively according to the Donabedian Framework: structure, process, and outcome, offering a theoretically grounded approach for interpreting the results (Donabedian, 1988). This method was chosen because it acknowledges the subjective nature of qualitative research and participants' experiences (Doyle et al., 2020). To enhance the quality and transparency of reporting in this study, the Consolidated Criteria for Reporting Qualitative Research (COREQ) checklist (Tong et al., 2007) was completed and reviewed by the researchers' supervisors.

While the specific processes for studies two and three have been outlined, the Māori consultation and ethical considerations applied to both studies are described next.

3.7.5 Māori Consultation

Māori consultation on principles and values was incorporated into the research design, methodology, and analysis, in line with the Māori research framework (Tu Kotahi Māori Asthma & Research Trust, 2019). The interview process fostered meaningful relationships and collaboration grounded in trust and mutual respect, consistent with the principle of whanaungatanga (relationships). It was welcoming and respectful, emphasising participants' input and well-being, consistent with the principle of manaakitanga (hospitality and care). This consultation also helped ensure cultural safety in the research, benefiting all participants.

3.7.6 Ethical considerations

Systematic review (Study 1)

Ethical approval was not sought for this systematic review as secondary data was used. **Error! Reference source not found.** details a summary of data from the selected articles.

Systems analysis (Study 2)

Auckland University of Technology Ethics Committee approved the ethics application on December 6, 2022 (Ref 22/339) (see Appendix B).

As part of the ethical approval process, a research data management plan was drafted and presented to the hospital's chief executive officer (see Appendix C), along with a data-sharing agreement (see Appendix D). The hospital accepted both, and the data-sharing agreement was signed.

Qualitative study (Study 3)

Auckland University of Technology Ethics Committee approved the ethics application on October 16, 2023 (Ref 23/297) (see Appendix E).

Following approval from the Auckland University of Technology Ethics Committee, the researcher met with the hospital's chief executive officer to arrange formal access to the hospital. On November 1, 2023, approval was granted (see Appendix F).

All minor suggested changes detailed in Appendix G were implemented. The approval letter can be found in Appendix H.

Eligible nurses were invited to participate voluntarily by responding to a research poster (see Appendix I) distributed by the ward, admissions, and day stay managers. Those who expressed their interest were sent a participant information pack (see Appendix J) by the researcher. Information regarding participants' ability to pause or withdraw from the interview at any time, as well as the researcher's contact details, was provided in the participant information sheet.

Confirmed participants were asked to sign a consent form (see Appendix K). Privacy and confidentiality were maintained throughout recruitment and interviewing, with no identifying information shared with managers or other staff.

Before the interview began, the researcher verbally reminded the participants that they could pause or withdraw at any time. The researcher used the same semi-structured interview questions for each interview (see Appendix L). The participants were offered a koha (gift) to recognise their time and contribution after the interview.

3.7.7 Integration of data

Step one of the convergent design involved confirming the objective of each study, designing the three studies, obtaining the necessary consent, and collecting the data. Step two involved analysing the three datasets (Creswell & Plano Clark, 2018).

Merging of data

In step three, the findings from the systematic review, system analysis, and qualitative study were synthesised using a mixed-methods synthesis approach (Creswell & Plano Clark, 2018). The content of each dataset was reviewed to identify key themes and sub-themes, patterns, and contextual factors. The findings were then compared to determine areas of similarity, difference, and complementarity across the three studies, and a joint display was developed to visually align the results.

Interpretation of merged findings

In step four, the final step of the mixed-methods synthesis approach, data from the three studies (the systematic review, the systems analysis, and the qualitative analysis) were merged (Fetters et al., 2013). The findings were summarised and interpreted in relation to one another to develop integrated themes and an in-depth understanding of the overall findings, formulate a discussion, draw overall conclusions, and formulate recommendations (Teddlie & Tashakkori, 2009). Othman et al. (2020) state that the primary goals of data integration include illustrating, validating, developing, and enriching data. Table 7 outlines the procedural steps for implementing the convergent design.

Table 7. Procedural steps used to implement the convergent design.

	Study 1: Systematic review	Study 2: Systems analysis	Study 3: Qualitative study
Step 1	Objective Systematically synthesise empirical evidence on the impact of digital health systems, including EMRs and CDSS, on inpatient fall outcomes and nurses' clinical decision-making in a hospital setting.	Objective Analyse quantitative fall incidence data before and after implementation of the EMR with embedded CDSS.	Objective Explore nurses' clinical experiences and decision-making processes in relation to fall prevention following implementation.
	Design Systematic review	Design Quantitative and qualitative analysis The data from the systems is primarily quantitative. However, the nurses' free-text narratives within the new incident management system, Safety Hub, capture some qualitative data that is important enough to report.	Design Qualitative analysis The researcher used a hybrid inductive and deductive approach for this qualitative analysis.
	Obtaining approval Approval from the AUT Ethics Committee was necessary before starting each strand. Upon approval, the research proposal was forwarded to the private hospital's research approval committee for local endorsement and authorisation to conduct the study within the private hospital.		
	Data collection Determine the qualitative sample Collect data via database search	Data collection Determine the quantitative sample Collect data by conducting a retrospective cohort study using the private hospital system data (PiMS, Trak Care, Trendcare, PayWiz, and Safety Hub)	Data collection Determine the qualitative sample Collect data using semi-structured interviews
Step 2	Analyses of qualitative data	Analyses of quantitative data	Analyses of qualitative data
	The researcher chose the Donabedian Framework (structure, process, and outcome) as the theoretical framework for this thesis because of its comprehensive structure and insights into healthcare quality, and it offered a strong foundation for analysing and interpreting the findings.		

	Deductive approach using the Donabedian Framework	Retrospective cohort analysis	A hybrid approach for this qualitative analysis, combining inductive coding with deductive organisation.
Merge the three sets of results, using the mixed-methods research synthesis approach			
Step 3	Identify content represented in datasets and compare, contrast, and synthesise the results in a discussion. Identify the differences and similarities Create a joint display to display of the results		
Interpret the merged results			
Step 4	Summarise and interpret the separate results Discuss to what extent and in what ways results from the two types of data converge, diverge, relate to each other, and/or provide a complete understanding Explain divergence if it occurs		

Note. Adapted from *Designing and Conducting Mixed Method Research* (3rd ed.), by J. W. Creswell & V. L. Plano Clark, 2018, SAGE; CDSS = Clinical decision support system; EMR = Electronic medical record.

Chapter 4 Systems Analysis (Study 2)

4.1 Introduction

The objective of this study was to extract and analyse data from private hospital systems before and after the implementation of an EMR with an integrated CDSS (January 2019–December 2023). The data from the systems are primarily quantitative. However, the nurses' free-text narratives in the new incident management system, Safety Hub, capture some qualitative data that is important to report on. The analysis used data from private hospital systems, including PiMS, Trak Care, PayWiz, Safety Hub and Trendcare, to explore whether an association existed between the adoption of the CDSS and electronic falls assessment via the EMR, and investigate differences in fall rates before and after its implementation.

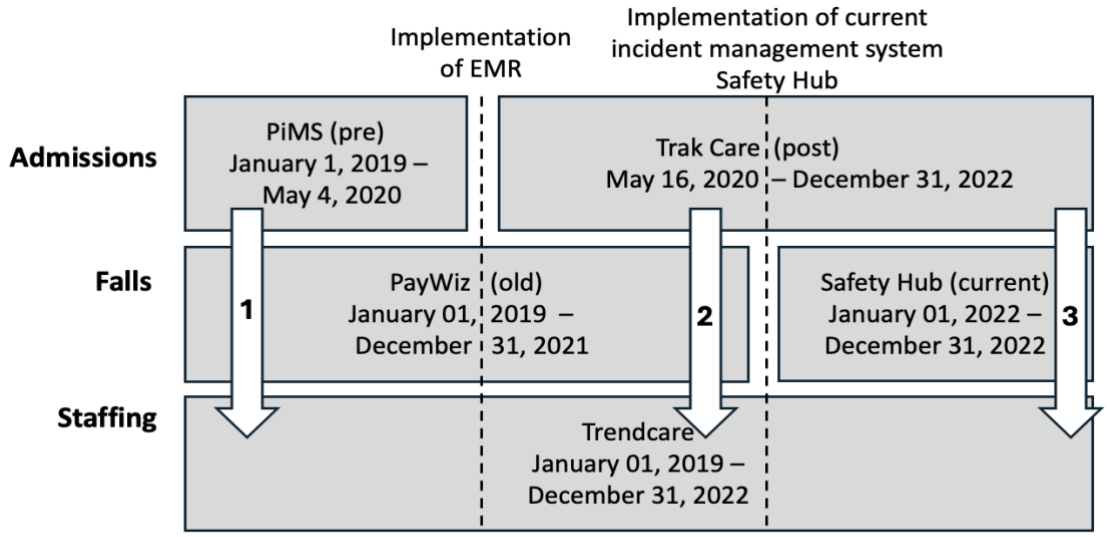
Each system contributed unique data that was essential to the project. PiMS was used between January 1, 2019, and May 4, 2020, and stored, managed, and retrieved patient health information. Trak Care™ is the new EMR implemented on May 16, 2020, and remains in use, managing the patient information, supporting clinical workflows, and providing several CDSS, including the fall assessment, to monitor and manage patient risk. Of note, there is a gap in the reported admission data between May 4 and 16 due to EMR implementation; while admissions may have been entered during this period, the reported date may be incomplete or inaccurate. Paywiz was a unified payments interface; however, in the private hospital involved in this study, it was also used to manage adverse events, including patient falls. It was found to be inefficient and was subsequently replaced with Safety Hub on January 1, 2022. Safety Hub is an application designed to help the private hospital manage its safety, including adverse events (falls). The fifth system used to extract data for this project was Trend Care, which is patient acuity, workload management, and workforce planning software.

It is important to note that the following changes took place across multiple datasets. As requested by the hospital's chief executive officer, ward names are not disclosed to protect the hospital's confidentiality. Each ward has been categorised into one of four specialties: cardiac, general, orthopaedics, and admissions/day stay.

While this comprehensive approach was thorough, it introduced overlapping data across three distinct time periods, as shown in Figure 7.

Recognising the importance of these overlaps was vital for interpreting the findings. These overlaps might reflect changes in data recording practices, shifts in hospital policies, improvements in fall monitoring, or advances in data capture enabled by new technology. During the analysis, the researcher considered these potential inconsistencies or variations in data quality between the systems. The only system that maintained a stable platform throughout this project was Trend Care, the staffing system.

Figure 7. Summary of the overlap in data from the different period.



Time periods

1 = Pre-implementation admission system, previous incident management system and staffing system.
January 1, 2019–May 4, 2020

2 = Post-implementation EMR, previous incident management system and staffing system.
May 16, 2020–December 31, 2022

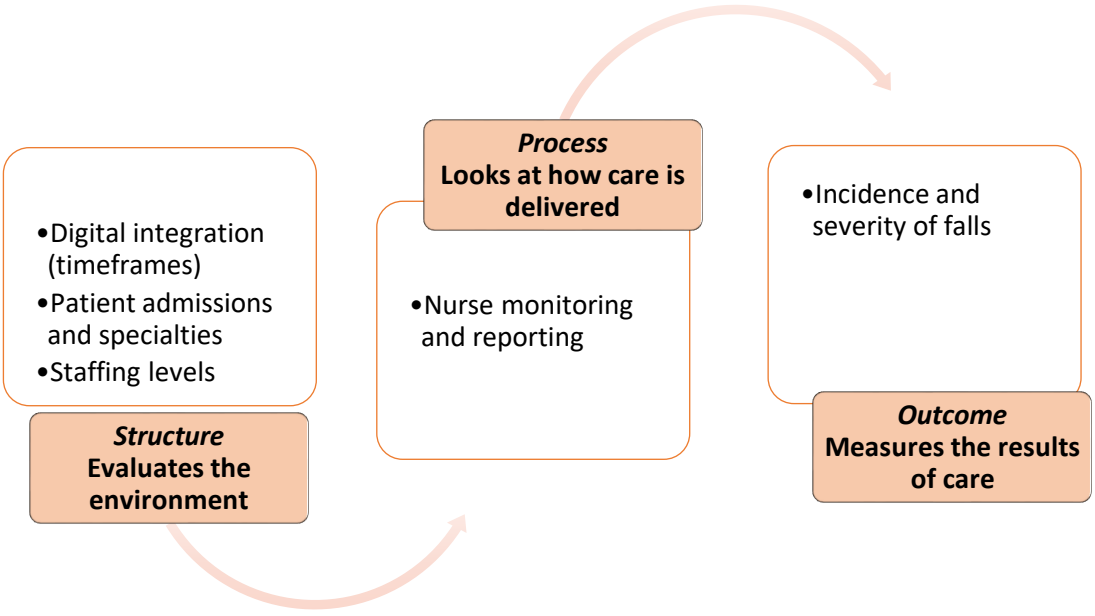
3 = Post-implementation EMR, current incident management system and staffing system
January 1, 2022–December 31, 2022

The researcher chose the Donabedian Framework as the theoretical basis for this study because of its comprehensive structure and insights into healthcare quality. The three components of Donabedian's framework, structure, process, and outcome, offer a strong foundation for analysing and interpreting system findings, making it especially

suitable for this kind of retrospective cohort analysis. The Donabedian Framework was designed in the 20th century, before the introduction of e-health (Tossaint-Schoenmakers et al., 2021). For this review, the Donabedian Framework structure, process, and outcome were adapted to align with this study.

In the systems analysis, the structure component reflects the organisational environment and includes domains of interest (grouping of variables) such as digital integration (timeframes), patient admissions, specialties, and staffing levels. The process component aligns with qualitative insights from nurses' monitoring and reporting. Although not directly measured within the process component, nurse training is also acknowledged in a grey-scale sense, inferred from reporting rather than captured as a domain. The outcome component captures the incidence and severity of falls. Figure 8 illustrates the alignment of these themes within the Donabedian Framework.

Figure 8. Summary of domains using the Donabedian Framework – Systems analysis.



Note. Adapted from "The quality of care: How can it be assessed?" by A. Donabedian, 1988, *JAMA: The Journal of the American Medical Association*, 260(*12*), p. 1743. https://doi.org/10.1001/jama.1988.03410120089033

4.2 Data cleaning

The private hospital data analyst compiled data from five hospital systems, which is summarised in Table 8. During the electronic health system rollout from May 4 to 16, 2022, a gap in admission data was noticed. Although the data analyst confirmed the

hospital was operational during this period, they could not specify how patient admissions were recorded. Without clear evidence, it is reasonable for the researcher to assume that clinical operations continued without interruption, with admissions likely recorded on paper or through a parallel system to maintain continuity of care. It is also possible that these records were not transferred into the analysed dataset, or there was a delay in the digitisation process.

Table 8. Summary of hospital systems.

Data type	System	Time period	Comments
Admissions	PiMS (pre)	January 1, 2019–May 4, 2020	After the initial cleaning, the datasets were combined and then imported into SPSS.
	Trak Care (post)	May 16, 2020–December 31, 2022	No patient records between May 4 and 16, 2022, inclusive, were recorded.
Fall	PayWiz (previous)	January 1, 2019–December 31, 2021	After initial cleaning, the data were imported in two separate files into SPSS.
	Safety Hub (current)	January 1, 2022–December 31, 2022	
Staffing	Trendcare	January 1, 2019–December 31, 2022	After initial cleaning, the data were imported into SPSS.

In collaboration with the primary supervisor, the researcher cleaned the data to ensure its accuracy, consistency, and reliability before analysis. During this process, the researcher discovered that critical elements were missing from the data, including gender in both pre- and post-implementation admission records, a detailed fall description in the previous system, and a patient identifier in the current fall data. Additionally, the previous system only recorded the day of the fall, not the specific time or shift when it happened. In all cases, the hospital analyst noted that he could not extract this information; a list of all the unavailable data fields are shown in Table 9 below.

Table 9. Summary of unavailable data fields.

Data type	Timeframe	Unavailable data fields
Admission data	Pre-implementation	Gender
	Post-implementation	Gender
Falls data	Previous system	Time or shift of fall Detailed falls description Detailed actions following the fall
	Current system	Patient identifier Time or shift of fall

Where variables were absent from the systems or could not be extracted by the hospital analyst, those fields were confirmed unavailable. These omissions meant that certain variables could not be included in the multivariable modelling, and fall-level analyses were limited to the information available. This approach ensured transparency and avoided introducing bias by assumptions about unrecorded or inaccessible data.

As outlined previously, confidentiality was requested, so modifications were made to all the datasets: admissions, falls, and staffing. The specific adjustments are detailed next.

4.2.1 Admission data

The cleaning process identified and managed duplicate admissions, categorising them into three groups: duplicates, splits, and sequential patient admission records. Duplicate patient admission records consisted entirely of duplicate entries. This issue was more common in the post system and is likely due to an extraction process error. Split patient admission records had identical dates and timeframes but different procedural information, mainly identified due to co-funding arrangements, such as a privately funded procedure alongside an insurance-covered procedure. Again, this issue was more prevalent in the EMR. Regarding Donabedian's structure component, duplicate patient records could indicate system-level disorganisation in data management and extraction, highlighting limitations in the integration of digital systems. Simultaneously, the co-funding arrangements could suggest that the funding structure influenced the hospital's administration workflows.

The third area identified in the cleaning process was sequential patient admission records, which occurred when a patient was discharged and immediately readmitted. Usually, this was for a second procedure following a diagnostic test, leading to readmission for further treatment, or for a post-surgical complication requiring additional care, such as postoperative bleeding. In these cases, the patient does not physically leave the hospital; however, due to funding arrangements, they are discharged within the EMR records from one episode of care, followed by readmission for a second episode of care. Regarding Donabedian's process component, sequential patient records highlight complex administrative workflows in which necessary treatment, whatever it is, results in a discharge and readmission within the EMR. These variations emphasise how system structure and organisational processes can affect the quality of data, because it appears that the patient has had two admissions, but this is not the case, and potentially affects patient care, because the private funding covers some provisions of care but not others.

In NZ, ACC funds post-surgical events in most cases. By removing or combining duplicate information, 76 entries (61 + 15) in PiMS, the pre-EMR system, and 20,676 entries (19732 + 886 + 58) in Trak Care, the EMR, were affected. A summary of the admission data cleaning process is shown in Table 10.

Table 10. Summary of the admission data cleaning process.

Data system	**Anomalies**	**Patient admissions (*n*)**	**%**	**Assumption**
PiMS (Pre-EMR)	All records	18,625		
	Duplicate records	0	0	
	Remove duplicates	18,625		
	Split records for admission	-61	0.3	Co-funding resulting in two entries for the same patient
	Single admissions	18,564		
	Sequential records for admissions	-15	0.1	Extended stay resulting in two entries for the same patient, i.e. discharge and immediate readmission
PiMS (Pre-EMR) final single admissions = 18,549				
Trak Care™ (Post)	All records	59,633		
	Duplicate records	-19732	33.1	

	Remove duplicates	39,901		
	Split records for admissions	-886	2.2	Co-funding resulting in two entries for the same patient admission
	Single admissions	39,015		
	Sequential records for admissions	-58	0.1	An extended stay resulting in two entries for the same extended patient admission
Trak Care™ (EMR) final single admissions = 38,957				
Total number of single admissions = 57,506				

Note. EMR = Electronic medical record.

The age data for patient admissions were organised according to Stats NZ (2024) into four categories: 14 years and under, 15–24 years, 25–64 years, and 65 years and older. Similarly, the ethnicity data were categorised by Stats NZ (2024) into six groups: European, Māori, Pasifika peoples, Asian, Middle Eastern/Latin American/African (MELAA), and others. The researcher chose not to explore alternative categorisation methods, as the Stats NZ categories logically fit the needs of this study. No changes were made to the Stats NZ groupings for this analysis. The data is presented descriptively, and this grouping method neither emphasises nor diminishes any demographic trends that could influence the study's findings.

4.2.2 Fall data

The initial fall datasets were collected from two systems: PayWiz, the previous system (*n* = 53), and Safety Hub, the current system (*n* = 76). Starting with 53 falls, the cleaning process for the previous system removed one record that was outside the ward or day stay environment, leaving 52 falls, including the three falls that occurred during admission or day stay. One entry lacked a patient identifier, and another had an NHI that was not found in the admission dataset. No modifications were made to these entries. It is worth noting that the previous system's data did not include descriptions of the falls, making it impossible to verify the initial categorisation regarding the SAC.

Starting with 76 falls, the current system's cleaning process removed two falls that occurred in the theatre and central sterile services department, which were believed to involve staff rather than patients. It also excluded seven falls from 2023, as they fell outside the project timeframe of January 2019 to December 2022. Additionally, four falls that occurred in settings not classified as wards or day stays were excluded, along

with one fall from the cardiac investigation unit, which is also not a ward. This resulted in a total of 62 falls. Unlike the previous system (PayWiz), the current system (Safety Hub) provides both fall descriptions and details of the actions taken.

To ensure consistency between the two sets of fall data, the ward names were reclassified into the same four specialties used in the admission data: general, orthopaedics, cardiac, and admissions/day stay. By standardising this, the researcher minimised classification inconsistencies, ensuring that data comparisons revealed true differences in the patient population rather than differences in naming conventions. This created a structured, consistent framework that simplified organisation and identification. Additionally, the researcher reclassified the reported fall severity rating to align with the SAC rating tool used by the HQSC in NZ (HQSC, 2024), as shown in Table 11. These adjustments could be considered a system-level limitation, underscoring the need for ongoing fall classification training or auditing.

Table 11. Summary of severity assessment code descriptors.

SAC descriptors			
SAC 1: Severe Death or harm causing severe loss of function and/or requiring lifesaving intervention	SAC 2: Major Harm causing major loss of function and/or requiring significant intervention	SAC 3: Moderate Harm causing short-term loss of function and/or requiring moderate additional intervention	SAC4: Minor Harm causing no loss of function and requiring little or no intervention
• Not related to natural course of illness or treatment • Differs from immediate expected outcome of care • Can be physical, psychological, cultural or spiritual	• Not related to natural course of illness or treatment • Differs from immediate expected outcome of care • Can be physical, psychological, cultural or spiritual	• Not related to natural course of illness or treatment • Differs from immediate expected outcome of care • Can be physical, psychological, cultural or spiritual	• Not related to natural course of illness or treatment • Differs from immediate expected outcome of care • Can be physical, psychological, cultural or spiritual

Note. Adapted from *Severity Assessment Code Rating and Process Tool for Healing, Learning and Improving from Harm*, by Health Quality & Safety Commission, 2024. https://www.hqsc.govt.nz/assets/Our-work/System-safety/Adverse-events/Publications-resources/HLIH_poster_SAC_A3_March2024_final_web.pdf.

SAC = Severity assessment code.

The switch from PayWiz to Safety Hub reflects a change in how falls were classified; however, reclassifying falls using the SAC framework provides a clearer understanding

of the severity of harm. The total number of incidents increased from 52 under the previous PayWiz system over 35.5 months to 62 under the current Safety Hub system over 12 months, which is notable considering Safety Hub was used for just over one-third of that period. Additionally, there was a higher proportion of falls classified as SAC 3 (moderate) from PayWiz (*n* = 10) to Safety Hub (*n* = 35). Table 12 presents the reclassification of patient falls.

Table 12. Reclassification of inpatient falls.

Data system	**Previous classification**	***n***	**SAC rating**	**Current classification**	***n***
PayWiz January 1, 2021–December 31, 2021 (35.5 months)	Serious harm	1	2	SAC 2: Major	1
	Minor harm	10	3	SAC 3: Moderate	10
	Other injury No harm	1 40	4 4	SAC 4: Minor	41
	Total	52		Total	52
Safety Hub January 1, 2022–December 31, 2022 (12 months)	Major	3	2	SAC 2: Major	3
	Minimal	35	3	SAC 3: Moderate	35
	Minor	24	4	SAC 4: Minor	24
	Total	62		Total	62

Note. SAC = Severity assessment code.

The fall datasets did not include a patient ID. Subsequently, there was no way to identify ethnicity, so the analysis could not determine fall outcomes for Māori patients. As a result, it was not possible to assess whether Māori experienced different rates, patterns, or severity of falls within this hospital setting.

When a nurse completes the fall assessment, the system calculates a risk score based on criteria including age, mobility, cognitive status, previous falls, and clinical observations. This score prompts the nurse to review and implement the evidence-based, system-generated fall prevention recommendations according to the risk level, such as increased observation, environmental changes, or additional assistance when mobilising. The system also displays a falling man icon on the patient summary view. The icon is colour-coded green for low, amber for medium, and red for high. When the fall prevention recommendations are actioned, the nurse documents this in the patient's notes.

4.2.3 Staffing data

Staffing data was gathered from a single system, Trendcare. No duplicates were identified. However, wards were grouped into specialties to maintain confidentiality. Trendcare calculates the nursing hours required for patient care by measuring and analysing patient acuity, minimum staffing levels, preset nurse–patient ratios, and hours-per-patient-day targets. Nurses estimate the time needed for individual patient care over the coming two shifts, which are then reviewed and approved by the senior nurse. Once approved, these estimates are final, and staffing is organised accordingly. Although the Trendcare system can link with other healthcare systems within this hospital, at the time of this study, it operated as a standalone system.

In this study, staffing is categorised into five groups: <0 indicates overstaffing, while the other four groups represent varying degrees of understaffing: 0–11.9, 12–18.4, 18.5–25.8, and 25.9+, measured in hours.

The analysis was based on live operational data, largely derived from mandatory reporting processes; therefore, data completeness was generally very high. A small number of records contained staffing data but no recorded patients. These records were interpreted as indicating ward closures in which staffing figures had not been updated accordingly. As these entries did not reflect actual operational activity, they were excluded from the analysis.

The staffing data provided for this study offered limited insights, leading the researcher to use logistic regression for comparative analysis, which examined the relationship between staff variance (independent variable) and the odds of a fall (dependent variable).

4.3 Descriptive data analysis

This section offers a descriptive analysis of the study sample and key variables, providing essential context for the subsequent inferential tests. This phase of analysis summarises participant characteristics and outcome measures using frequencies and percentages. Presenting these baseline findings helps set the stage for further analysis. To strengthen the quality and transparent reporting, a STROBE checklist was completed and reviewed by the researchers' supervisors (von Elm et al., 2007).

4.3.1 Admission data

The datasets for this study were extracted from PiMS and a comparable dataset from Trakcare, the current EMR. Understanding the number of patient admissions can help the researcher analyse trends. Information regarding the year a patient was admitted, and the ward speciality, aligns with the structural component of the Donabedian Framework, providing context (structure) about the private hospital, specifically the organisational infrastructure in which care was delivered.

The data were collected over 4 years, with an average of 14,376 patient admissions annually at the private hospital. Table 13 summarises the number of patient admissions by year across the three time periods (T). The annualised patient admissions were highest during T2 (*n* = 14,959), followed by T3 (*n* = 14,646), and lowest during T1 (*n* = 13,912). While admission counts varied across different time periods, T2 had the highest (*n* = 24,309), and T3 had the lowest (*n* = 14,646); however, these figures are not directly comparable. The annualised rates provide a more consistent reflection of admission trends over time.

Table 13. Patient admissions summarised by year across the three time periods.

Year	**T1**	**T2**	**T3**	**Patient admissions**	
	January 1 2019–May 4, 2020 16 months	May 16 2020–December 31, 2021 19.5 months	January 1 2022–December 31, 2022 12 months	*n*	%
2019	15,006	–	–	15,006	26.1
2020	3,543	10,314	–	13,857	24.1
2021	–	13,995	–	13,995	24.3
2022	–	–	14,646	14,646	25.5
Total	18,549	24,309	14,646	57,504	
Annualised admissions	13,912	14,959	14,646		

To protect the private hospital's privacy, the wards were categorised by specialty rather than by name. This method also helped the researcher identify whether falls were more common in specific specialties. Table 14 shows a clear shift in the distribution of patient admissions by specialty over time, with proportional increases in orthopaedics (from 31.2%–36.3%), cardiac (2.4%–3.2%), and admissions/day stay

(13.8%–15.9%), along with a steady decrease in general wards (from 52.6%–44.6%). These trends indicate a move towards more specialised care and shorter-stay procedures.

Table 14. Patient admissions categorised by specialty across the three time periods.

Specialty	**T1**		**T2**		**T3**		**Total**	
	n	%	*n*	%	*n*	%	*n*	%
Cardiac	444	2.4	809	3.3	475	3.2	1,728	3.0
General	9,756	52.6	11,931	49.1	6,526	44.6	28,213	49.1
Orthopaedics	5,783	31.2	7,722	31.8	5,321	36.3	18,826	32.7
Admissions/Day stay	2,566	13.8	3,847	15.8	2,324	15.9	8,737	15.2
Total	18,549		24,309		14,646		57,504	
Number of months	16		19.5		12			

Table 15 presents patient admissions by age groups from Stats NZ (2024) over three periods. According to the HQSC (2020), most falls occur in patients aged 65 years and older. In this study, the 25–64 year age group accounted for the majority of admissions overall, representing 61.1% (*n* = 35,134). However, their numbers decreased significantly from 41.8% (*n* = 14,681) in T2 to 13.3% (*n* = 4,666) in T3, suggesting a possible demographic shift.

Patient admissions for individuals aged 65 and older significantly increased from 30.2% (*n* = 5,567) in T1 to 48.6% (*n* = 8,962) in T3. This indicates an ageing patient population or a strategic emphasis on this age group during T3. Patients under 14 and those aged 15–24 consistently accounted for a small proportion of admissions Table 15 and Figure 9 reveal that patient admissions were most concentrated among the middle-aged (25–64 years) and those 65 and older.

Table 15. Patient admissions categorised by Stats NZ age groups across the three time periods.

Age group	T1		T2		T3		Total	
	n	%	*n*	%	*n*	%	*n*	%
Under 14	331	1.8	279	1.1	234	1.6	844	1.5
15–24	1,160	6.3	1,155	4.8	784	5.4	3,099	5.4
25–64	11,491	61.9	14,681	60.4	4,666	31.9	35,134	61.1
65 and older	5,567	30.0	8,194	33.7	8,962	61.2	18,427	32
Total	18,549		24,309		14,646		57,504	

Figure 9. Patient admissions distribution by age.

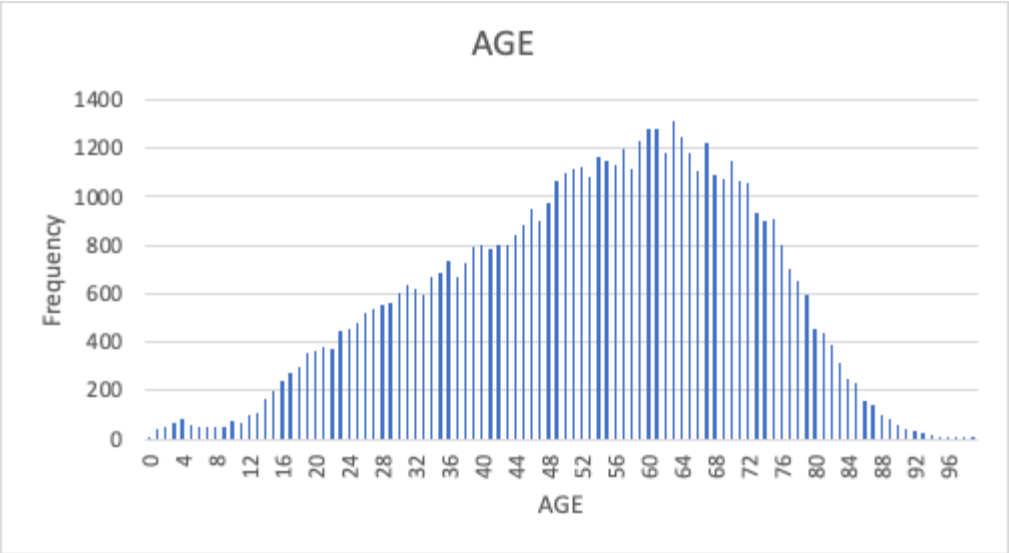


Table 16 displays the patient admissions categorised by Stats NZ (2024) ethnicity groups across three time periods. European patients accounted for the majority of admissions (76.5%; *n* = 44,014). Asian patients were the second-largest group, at 11.7% (*n* = 6,695), followed by Māori at 4.4% (*n* = 2,548), and Pasifika peoples at 4.2% (*n* = 2,401). Collecting Māori statistics helps the hospital recognise the unique cultural needs of Māori patients. This ensures that healthcare services are not only clinically effective but also culturally respectful, aligning with Māori values and practices. This also applies to other ethnic and cultural groups. The overall trend shows an increase in patient admissions from T1, with 32.2% (*n* = 18,549), to T2, at 42.3% (*n* = 24,309), followed by a decrease at T3, with 25.5% (*n* = 14,646). Notably, T3 was the shortest period.

Table 16. Patient admissions categorised by Stats NZ ethnicity group across the three time periods.

Ethnicity group	T1 16 months		T2 19.5 months		T3 12 months		Total patient admissions	Total
	n	%	*n*	%	*n*	%	*n*	%
European	14,366	77.4	18,624	76.6	11,024	75.3	44,014	76.5
Māori	810	4.4	1,063	4.4	675	4.6	2,548	4.4
Pasifika peoples	740	4.0	965	4.0	696	4.7	2,401	4.2
Asian	2,139	11.5	2,780	11.4	1,776	12.1	6,695	11.7
MELAA	253	1.4	304	1.2	229	1.6	786	1.4
Other	241	1.3	573	2.4	–	1.7	1,060	1.8
Total	18,549	32.2	24,309	42.3	14,646	25.5	57,504	

Note. MELAA = Middle Eastern/Latin American/African.

4.3.2 Falls data

Falls data was collected from the previous system, PayWiz, covering January 2019 to December 2021, and from the current safety platform, Safety Hub, covering January 2022 to December 2022. Importantly, the switch of the incident management system was not tied to the EMR rollout. For this study, an inpatient fall is defined as an event in which a patient comes to rest inadvertently on the ground, floor, or another lower level (WHO, 2021a).

The data in Table 17 presents 114 falls across three time periods, with 52 falls in the previous system and 62 in the current system. This increase could suggest improved staff incident reporting. Across all time periods, no SAC 1 (severe) incidents were reported. Slightly more SAC 2 (major) incidents occurred in T3, at 5% (*n* = 3), compared to T2, at 4% (*n* = 1), and no SAC 2 falls were reported in T1. Regarding SAC 3 (moderate) falls, T3 recorded the highest rate, at 56% (*n* = 35), followed by T2 at 28% (*n* = 7), with a significant decrease in T1, at 11% (*n* = 3). T1, however, recorded the most SAC 4 (minor) incidents, at 89% (*n* = 24), closely followed by T2 at 68% (*n* = 17), while T3 had the lowest at 39% (*n* = 24). Throughout all periods, SAC 4 had the highest number of inpatient falls.

Table 17. Patient falls categorised by severity assessment code across the three time periods.

SAC	**Number of patients (Previous system)**				**Number of patients (Current system)**	
Time period	T1		T2		T3	
	January 1, 2019–May 4, 2020 (16 months)		May 16, 2020–December 31, 2021 (19.5 months)		January 1, 2022–December 31, 2022 (12 months)	
SAC 1 (Severe)	0	-	0	-	0	-
SAC 2 (Major)	0	-	1	4%	3	5%
SAC 3 (Moderate)	3	11%	7	28%	35	56%
SAC 4 (Minor)	24	89%	17	68%	24	39%
Total by time period	27		25		62	
Total by system	52				62	
Total number of falls	114					

Note. SAC = Severity assessment code.

The data in Table 18 shows the same number of falls, 114, as in Table 17; however, instead of analysing falls across the three time periods, this data was examined specifically for each year. This study sourced data from hospital falls systems over four years, from January 1, 2019, to December 31, 2022. In 2022, the highest number of falls (*n* = 62) was recorded, followed by 2019 (*n* = 26) and 2021 (*n* = 15), and the fewest falls were reported in 2020 (*n* = 11). It is important to note that the current system, implemented for 12 months during this study, recorded 62 falls, whereas the previous system, over a 35.5-month period, reported 52.

Over the four years, no SAC 1 incidents were recorded. SAC 2 events totalled four, with 2021 (*n* = 1) and 2022 (*n* = 3). The majority of SAC 3 incidents occurred in 2022 (*n* = 35). This was followed by 2020 (*n* = 5), 2019 (*n* = 3), and 2021 (*n* = 2). SAC 4 incidents, which involved the most falls, accounted for the highest number in 2022 (*n* = 24). The numbers were closely followed by 2019 (*n* = 23), 2021 (*n* = 12), and 2020 (*n* = 6), the lowest.

Table 18. Patient falls categorised by severity assessment code and year.

SAC	**Number of patients (Previous system) (35.5 months)**						**Number of patients (Current system) (12 months)**		**Total number by SAC**
Year	2019		2020		2021		2022		
SAC 1 (Severe)	0	–	0	–	0	–	0	–	0
SAC 2 (Major)	0	–	0	–	1	6.7%	3	4.8%	4
SAC 3 (Moderate)	3	11.5%	5	45.5%	2	13.3%	35	56.5%	45
SAC 4 (Minor)	23	88.5%	6	54.5%	12	80%	24	38.7%	65
Total by year	26		11		15		62		
Total by system	52						62		
Total number of falls	114								

Note. SAC = Severity assessment code.

The data in Table 19 shows the same number of falls, 114, as in Table 17 and Table 18 Instead of categorising by severity, the falls are grouped into four specialties: orthopaedics, general, cardiac, and admissions/day stay. Among these, the most falls occurred in orthopaedics (*n* = 69), followed by general (*n* = 27), cardiac (*n* = 15), and the fewest occurred in the admission and day stay unit (*n* = 3).

Within the orthopaedics specialty, most falls were recorded in T3 (*n* = 40), followed by T2 (*n* = 16) and then T1 (*n* = 13). In the general specialty, the highest number of falls occurred in T3 (*n* = 12), followed by T1 (*n* = 8) and then T2 (n = *7*). The cardiac specialty also recorded the most falls in T3 (*n* = 10), followed by T1 (*n* = 4) and T2 (*n* = 1). Admissions and day stay did not record any falls in T3 but did record falls in T1 (*n* = 2) and T2 (*n* = 1).

Table 19. Patient fall categorised by specialty across the three time periods.

Specialty	**Previous system**				**Current system**		**Total number by specialty**
Time period	T1		T2		T3		
	January 1, 2019–May 4, 2020 (16 months)		May 16, 2020–December 31, 2021 (19.5 months)		January 1, 2022–December 31, 2022 (12 months)		
Orthopaedics	13	48.2%	16	64%	40	64.5%	69
General	8	29.6%	7	28%	12	19.4%	27
Cardiac	4	14.8%	1	4%	10	16.1%	15
Admissions/Day stay	2	7.4%	1	4%	–	–	3
Totals by time period	27		25		62		–
Totals by system	52				62		114

4.3.3 Qualitative free text from nurse reporting in the current incident management system

The transition from the previous fall incident management system, Paywiz, to the current incident management system, Safety Hub, marked a notable improvement in the quality and detail of fall incident reports. In the previous system, nurses stated they were limited by predefined categories in the system drop-down menu, such as "*fall*," "*patient fall*," and "*witnessed or unwitnessed,*" which restricted their ability to provide detailed documentation of falls. While this information was useful, it hindered the researcher's ability to gather circumstantial details from nurses about how they managed falls. Conversely, Safety Hub, the current system, introduced a free-text field that allowed nurses to describe both the fall and the actions they took after the fall. This transition enabled more in-depth data, and "*nurses were able to describe the fall and the actions they took afterwards*," providing better insights into how severity ratings aligned with clinical judgment and responses.

The free-text entries in Safety Hub improved fall incident reporting by capturing context missed in the structured fields of the previous system. Nurses documented what patients were doing immediately before the fall, such as "*walking*," "*transferring*," or "*attempting to mobilise to go to the bath*," which provided additional insights into patient behaviour and circumstances prior to the fall. This free-text

feature also allowed nurses to document how they applied their clinical judgment to assess injuries and collaborate with other members of the multidisciplinary team in managing the patient. The data further highlighted environmental factors, offering a better understanding of what may have contributed to the fall.

The free-text entries revealed a range of approaches: one nurse "*rang the emergency button immediately,"* another "*pulled the cord in the bathroom for assistance,"* and a third "*called out for help."* Despite these differences, the urgency and teamwork remained consistent. The recorded interventions also varied but reflected a systematic clinical approach that included "*administering oxygen,"* "*taking bloods,"* and "*recording the patient's observations*" such as "*saturations, blood pressure, and heart rate."* These entries demonstrated how nurses combined quick responses with clinical assessment to ensure the patient's safety.

Discrepancies between severity classifications and clinical descriptions in Safety Hub raised concerns about the reliability of fall data. Two of the falls were classified as major; however, the free-text documentation suggested otherwise. One entry stated, "*The patient sustained no injuries and was helped back to their feet and into the chair*," while the other noted, "*The patient had no injuries but appeared confused, prompting the staff to arrange a watch to ensure the patient's safety."* These inconsistencies raised concerns about the alignment between the entered data and clinical judgment, highlighting the need for an auditing process to monitor free-text entries more closely to ensure accuracy.

Misalignments between the fall classification and description in the Safety Hub uncovered inconsistencies in how injury severity was documented. Although both incidents were initially categorised as minimal, a closer review of the subcategories revealed key differences. In one case, the nurse described being in the bathroom with the patient, who "*felt faint and was assisted to the floor*," and, in this instance, no injuries occurred. However, another incident involved "*the patient tripping over a blanket whilst trying to get out of bed to mobilise*," which resulted in skin tears to the patient's arms. These examples show that the sub-categorisation labels, "*fall non-injury*" versus "*fall with injury*," provide more accurate reflections of clinical reality

than the initial classification, emphasising the need for better alignment between the structure of the system and the narrative documentation.

The nurses demonstrated a consistent focus on patient safety through prompt responsiveness and the use of structured nursing assessments to evaluate patients following falls. Several nurses described assessing patients' conditions using the Glasgow Coma Scale, a neurological assessment tool that rates the level of consciousness after a neurological event, such as a faint. One nurse reported, "*Placing the patient in the supine position and raising their legs*, with *a wheelchair provided to transfer them back to their bed*." These descriptions reflect a systematic approach to managing a patient fall, where nurses combined their clinical judgment and practical nursing interventions to minimise harm.

4.3.4 Reporting completeness and documentation quality

Safety Hub allowed richer documentation

Comparison of the incident management systems indicates that the nature and completeness of fall documentation changed after the implementation of Safety Hub. Whereas PayWiz primarily relied on structured drop-down categories, Safety Hub included mandatory or readily accessible free-text fields that enabled nurses to provide detailed descriptions of fall circumstances, patient activity, environmental factors, clinical assessments and post-fall interventions. Consequently, the amount of contextual information available for each fall report increased substantially in T3. The data was linked by day and ward.

More detailed circumstances were captured

Free text narratives captured information largely unavailable in the previous system, including activities immediately preceding the fall, environmental contributors, post-fall assessments, and multidisciplinary management. This suggests that Safety Hub facilitated more comprehensive incident reporting than the previous system, PayWiz.

Severity coding changed

Table 17 provides useful indirect evidence detailing the distribution of severity classification also altered across time periods. The proportion of falls classified as SAC3 increased from 11% in T1 to 56% in T3, while the proportion classified as SAC4

decreased. Although this may represent a genuine change in injury severity, a review of free-text records identified inconsistencies between narrative descriptions and assigned severity categorisation. This finding suggests that changes in documentation practices and classification processes may have influenced recorded severity patterns.

4.3.5 Inferential data analysis

The analysis then evolved from descriptive to inferential. Descriptive methods define the baseline characteristics, while inferential techniques, such as logistic regression, facilitate the assessment of associations and the calculation of odds ratios. To conduct an inferential analysis across the three time periods, the researcher needed to restrict the data. Admission/Day stay lacked staffing data comparable to that of the other wards, and only three falls were recorded in these wards; therefore, admission/day stay data were excluded from the comparative analysis. Additionally, since the falls data included only the date of the fall event, not the time, it was necessary to aggregate all data by date rather than by date and shift, as initially proposed. In the tables below, the number of ward days is represented by *, and the percentage of falls refers to the number of ward days during which at least one fall event occurred.

As there was no patient identifier in Safety Hub, it was not possible to control for the demographic and clinical shifts evident in the previously presented descriptive data. Logistic regression was the statistical method chosen, a method suitable for analysing binary outcomes, such as the presence or absence of a fall event. The logistic regression also allowed the researcher to examine how variables such as staffing, specialty, time period, and year influenced the odds of a fall. Initially, each variable of interest was examined individually (bivariate) before examining the multiple variable model.

4.3.6 Falls and year

Table 20 outlines the relationship between the calendar year (independent variable) and the odds ratio of a fall (dependent variable), with 2019 as the reference year and 2020, 2021, and 2022 compared against it. Logistic regression analysis indicated that the odds ratio varied each year when compared to 2019. Although 2020 and 2021 had lower odds ratios (OR = 0.50 and 0.61, respectively), these differences were not statistically significant when compared to 2019. Conversely, 2022 showed a significant

increase in odds ratio (OR = 1.96, 95% CI 1.19, 3.23), nearly doubling the odds of a fall relative to 2019. These findings highlight a notable rise in fall risk in 2022, prompting further investigation into potential contributing factors.

Table 20. Relationship between the year variable (independent variable) and the odds of a fall (dependent variable).

	Year	*n**	% falls	OR	95% CI	*p*-value
Year	2019	1,706	1.4	1.00	–	<.001
	2020	1,561	0.7	0.50	(0.24, 1.02)	
	2021	1,617	0.9	0.61	(0.32, 1.19)	
	2022	1,691	2.7	1.96	(1.19, 3.23)	

Note *Units are ward days. CI = Confidence interval; OR = Odds ratio.

4.3.7 Falls and time

Table 21 shows the relationship between the time period (independent variable) and the odds of a fall (dependent variable). The time periods were categorised as follows: January 1, 2019 to May 4, 2020 (1), May 16, 2020 to December 31, 2021 (2), and January 1, 2022 to December 31, 2022 (3), reflecting changes in electronic systems. The statistical analysis revealed an overall *p*-value of <.001, indicating a highly significant relationship between time periods and the odds of a fall. Falls were nearly three times more likely to be reported in the third time period (January 1, 2022 to December 31, 2022). This aligns with the raw data, which indicate a notable increase in recorded falls during the third time period. This could be attributed to the new incident management system, Safety Hub, and the new reporting practices it enables.

Table 21. Relationship between the time variable (independent variable) and the odds of a fall (dependent variable) across the three time periods.

	Grouping category	*n*	% falls	OR	95% CI	*p*-value
Time period	1	2,168	1.2	1.00	–	<.001
	2	2,716	0.9	0.76	(0.44, 1.34)	
	3	1,691	2.7	2.40	(1.47, 3.92)	

Note. *Units are ward days. CI = Confidence interval; OR = Odds ratio.

4.3.8 Falls and staffing

Table 22 presents the relationship between staff hours variance (independent variable) and the odds of a fall (dependent variable). The category <0 (0.9% falls) indicates

overstaffing and serves as the reference category for comparing all other staff variance groups. The categories 0–11.9 (1.2% falls) and 12–18.4 (1.5% falls) show elevated odds of falls compared to the reference, with an OR of 1.26 and 1.63, respectively; however, the differences are not statistically significant. The grouping 18.5–25.8 shows a 2.1% fall rate, the highest across all categories, with an OR of 2.22, more than double the odds compared to the reference. The category 25.9+ (1.1% falls) is similar to the reference group, with an OR of 1.18, also close to baseline, with no evidence of increased risk of falls.

Table 22. Relationship between the staff variable (independent variable) and the odds of a fall (dependent variable).

	Grouping category	***n****	**% falls**	**OR**	**95% CI**	***p*-value**
Staff variance (hours)	<0	422	0.9	1.00	–	.14
	0-11.9	1,508	1.2	1.26	(0.43, 3.75)	
	12.0-18.4	1,500	1.5	1.63	(0.56, 4.73)	
	18.5-25.8	1,528	2.1	2.22	(0.78, 6.31)	
	25.9+	1,607	1.1	1.18	(0.40, 3.52)	

Note. *Units are ward days. CI = Confidence interval; OR = Odds ratio.

4.3.9 Falls and specialty

Table 23 presents the relationship between the specialties (independent variable) and the odds of a fall (dependent variable). The specialists are categorised into groups: cardiac (1.0%, *n* = 1,349), general (1.0%, *n* = 2,628), and orthopaedics (2.2%, *n* = 2,598).

The cardiac specialty served as the reference group. Patients from the general specialty did not show a statistically significant difference in fall risk compared to cardiac patients (OR = 0.99, CI 0.50, 1.94). In contrast, orthopaedic patients had significantly higher odds of a fall (OR = 2.31, CI 1.26, 4.23). The overall *p*-value of <.001 indicates that the association between specialty and the odds of falls is statistically significant.

Table 23. Relationship between the specialty variable (independent variable) and the odds of a fall (dependent variable).

	Grouping category	*n**	% falls	OR	95% CI	*p*-value
Specialty	Cardiac	1,349	1.0	1.00	–	<.001
	General	2,628	1.0	0.99	(0.50, 1.94)	
	Orthopaedics	2,598	2.2	2.31	(1.26, 4.23)	

Note. *Units are ward days. CI = Confidence interval; OR = Odds ratio.

4.3.10 Final multivariable model fall and staffing, specialty and time period

Following the inferential analysis using logistic regression, the researcher developed a final multivariable model (see Table 24). The assumptions of the multivariable logistic regression model were assessed before interpreting the results. As the analysis was exploratory, aimed at identifying associations rather than developing a predictive model, strict adherence to predictive modelling criteria was considered less critical. Logistic regression has relatively few assumptions, with multicollinearity a primary concern.

Potential interactions between explanatory variables were examined, and none were statistically significant. Correlations among model covariates were also assessed. Although some associations were observed, such as between time period and specialty, reflecting minor changes in the patient population over the study period, the correlations were small to moderate in magnitude. These findings suggest only limited multicollinearity and were not considered strong enough to compromise model interpretation.

This analysis examined how staffing, specialty, and time (independent variables) relate to the likelihood of a fall (dependent variable). The multivariable model allowed adjustment for multiple factors simultaneously, helping control for confounding and interaction effects. This approach was essential to improve the robustness and validity of the results, providing a clearer understanding of each variable's individual impact.

To clearly present the results, both the unadjusted logistic regression and the adjusted multivariable outcomes are presented side by side. Presenting them together allows readers to compare how the odds ratios change when confounders are included.

In this study, staffing variance was not statistically significant in either the unadjusted or the adjusted analyses, suggesting that, as measured, this independent variable is not associated with fall risk. However, the odds ratios from the logistic regression (bivariate) differed from those in the multivariable model. The odds ratios for staffing variance decreased, and the *p*-value became even less significant, suggesting some evidence that staffing variance was linked to speciality and/or time period.

In contrast, the specialty of orthopaedics remained significantly associated with a higher odds of a fall even after adjustment (OR 2.08, CI 1.11, 3.89). Similarly, the increased risk in T3 persisted after adjustment (OR 2.48, CI 1.51, 4.07), indicating that both independent variables, specialty and time period, had a strong independent effect on fall risk.

A slight reduction in specialty and an increase in time may, in part, be due to the observed specialty shift (and general demographic shift) over time, which may result in this adjustment. This suggests that it would be important to adjust for the change in patient demographics.

Table 24. Relationship between staffing, specialty and time period (independent variables) and the odds of a fall (dependent variable).

		Unadjusted			**Adjusted**		
		OR	95% CI	*p*-value	OR	95%CI	*p*-value
Staffing variance	<0	1.00	–	.14	1.00	-	.38
	0–11.9	1.26	(0.43, 3.75)		0.96	(0.32, 2.90)	
	12–18.4	1.63	(0.56, 4.73)		1.10	(0.37, 3.29)	
	18.5–25.8	2.22	(0.78, 6.31)		1.54	(0.53, 4.49)	
	25.9+	1.18	(0.40, 3.52)		0.89	(0.30, 2.66)	
Specialty	Cardiac	1.00	–	<.001	1.00	–	.004
	General	0.99	(0.50, 1.94)		0.99	(0.50, 1.95)	
	Orthopaedic	2.31	(1.26, 4.23)		2.08	(1.11, 3.89)	
Time period	1	1.00	–	<.001	1.00	–	<.001
	2	0.76	(0.44, 1.34)		0.77	(0.44, 1.35)	
	3	2.40	(1.47, 3.92)		2.48	(1.51, 4.07)	

Note. CI = Confidence interval; OR = Odds ratio.

4.4 Summary

This chapter highlighted that variability within admissions, falls, and staffing datasets was associated with underlying administrative systems and organisational factors rather than simple data errors. Duplicate, split, and sequential admission records reflected patterns that highlighted the effects of digital integration, specific private hospital funding arrangements, and organisational workflow processes.

The descriptive analysis presented the demographic, clinical, and operational characteristics of the patient population, fall events, and staffing patterns. These findings provided insight into the distribution of falls across specialities, time periods, and staffing levels. The descriptive analysis also showed shifts in patient demographics and specialty mix over time, as well as differences in fall severity and reporting between the previous (PayWiz) and current incident systems (Safety Hub).

The inferential analysis progressed from descriptive observations to statistical modelling using logistic regression. The relationship between calendar year and the odds ratio for a fall showed that fall risk varied across years, with 2022 showing a significant increase in the odds ratio, nearly double that of 2019, the reference year. The time period analysis revealed a highly significant relationship between time periods and the odds of a fall, and showed that falls were nearly three times more likely in T3 (January 1, 2022 to December 31, 2022). Staffing variance showed that understaffing (grouping 18.5–25.8) had the highest odds of falls, although none of the categories reached statistical significance. Overall, specialty and the odds of falling were statistically significant, with orthopaedic patients having more than twice the odds of falling compared with cardiac patients.

The final multivariable model analysed staffing, specialty, and time simultaneously, and unadjusted and adjusted multivariable outcomes were presented to compare the changes in odds ratios when confounders were included. Staffing variance was not statistically significantly associated with the odds of a fall in either the unadjusted or adjusted analyses. In contrast, both independent variables, specialty (orthopaedics) and T3, had a strong independent effect on fall risk.

The next chapter presents qualitative data from semi-structured interviews with eight nurses working in wards or in the hospital's admission and day stay units. The focus is on how nurses describe the influence of the EMR with embedded CDSS on their clinical experiences and decision-making processes related to fall prevention.

Chapter 5 Qualitative Study (Study 3)

5.1 Introduction

The objective of this chapter is to explore nurses' experiences and opinions of the electronic fall-risk assessment CDSS and its influence on fall-related clinical decision-making through semi-structured interviews. The chapter presents qualitative data from semi-structured interviews with eight nurses working in hospital wards, day stay units, or admission units at a private hospital in NZ. The focus is on improving patient safety outcomes and understanding how these factors affect clinical decision-making.

The researcher used a hybrid approach, combining inductive (coding) and deductive (organisation) thematic analysis to interpret the raw data from the nurses' interviews (Fereday & Muir-Cochrane, 2006; Proudfoot, 2023). Initial themes were developed inductively from the data, allowing participants' narratives to guide the emergence of insights (Barrett & Younas, 2024; Proudfoot, 2023). These themes were then organised deductively using the Donabedian Framework: structure, process, and outcome, providing a theoretically grounded perspective for interpreting the findings (Donabedian, 1988).

5.2 Participants

The study involved eight nurses from diverse backgrounds, each offering a wide range of experiences and perspectives. Table 25 summarises the participants' training and experience. The origins of their training varied, with seven trained at different institutions across NZ and one in the UK. Their nursing experience ranged from 12–42 years, with a standard deviation of 9.53 years. From a representation perspective, the study captured a broad spectrum of viewpoints from both highly experienced nurses and those midway through their careers. Experience in the private hospital sector, particularly in surgical wards, ranged from 5–30 years, reflecting a specific understanding of the environment. Familiarity with fall assessments varied from 5–18 years, emphasising participants' expertise in this clinical process. Lastly, experience with using an electronic fall assessment CDSS via an EMR ranged from 1–2 years, suggesting potential unfamiliarity with the recently implemented technology. During

the latter part of the eight interviews, the researcher felt that no new information or insights were revealed, indicating that data saturation had been reached.

Table 25. Summary of participants' training and experience.

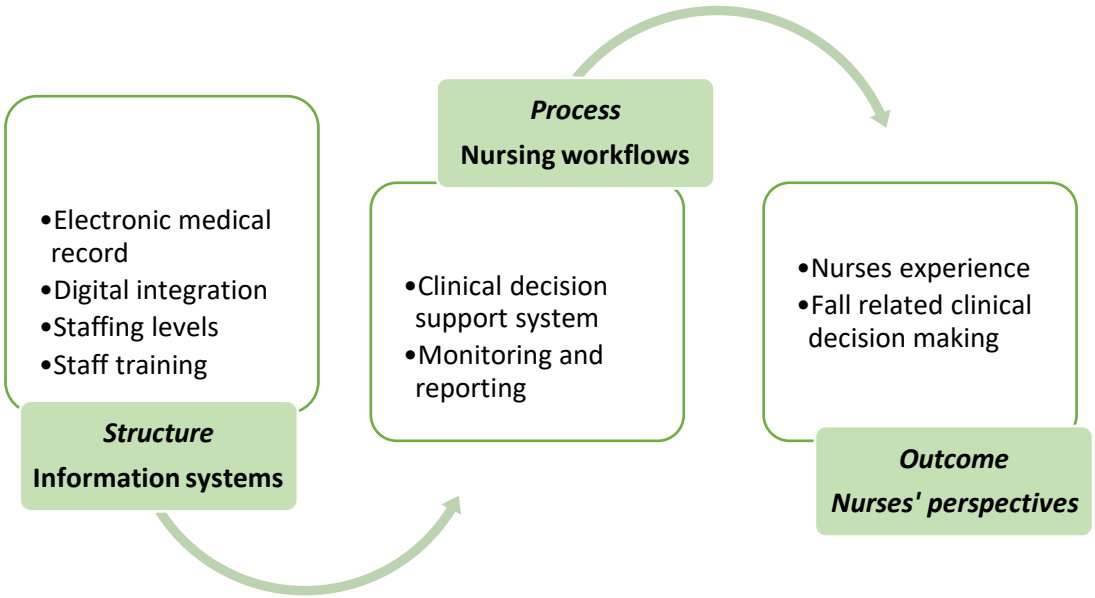
ID	Question 1 Location of training	Question 2 Clinical experience (years)	Question 3 Private hospital experience (years)	Question 4 Fall assessment experience (years)	Question 5 Fall assessment via EMR (years)
1	NZ	42	9	6	2
2	NZ	30	30	10	2
3	NZ	12	7	12	1
4	NZ	19	5	5	2
5	NZ	14	5	14	2
6	NZ	13	6	13	2
7	UK	23	9	9	2
8	NZ	18	9	18	2

Note. EMR = Electronic medical record; NZ = New Zealand; UK = United Kingdom.

5.3 Themes and sub-themes

The deductive analysis identified three themes, which align with the Donabedian Framework: 1. Information systems (Structure) 2. Nursing workflows (Process), and 3. Nurses' perspective (Outcome). The themes included eight subthemes, as shown in Figure 10.

Figure 10. Summary of themes and subthemes for the Qualitative study.



5.3.1 Information systems (Structure)

The theme 'Information systems' comprises four subthemes: EMR, system Integration, staffing levels and staff training, which are presented in more detail below.

Electronic medical record

The new EMR introduced both efficiencies and challenges, depending on nurses' experience with electronic systems. Some participants described initial challenges navigating the current system's interface, noting delays accessing patient details. One nurse stated, "*When we first went live, we struggled to locate things, but we have sorted that out now."* Others found the EMR intuitive after an adjustment period, calmly stating, "*You just go into the EMR patient encounter, and you can look down at all your actions and click on what you want to review."* Conversely, others felt frustrated, noting that the process was unnecessarily complex, "*I mean, it is right there, but you have to go through many steps."* These varied experiences indicate that usability and workflow were influenced not only by system design but also by the support provided during implementation.

The system's hardware also posed challenges for nurses in their clinical setting. While nurses acknowledged that laptops were more compact and easier to manoeuvre than workstations on wheels, they also noted limitations in screen size and layout. One nurse explained, "*The only time it is not user-friendly is when I use it on the laptop*

because, typically, on a regular computer, it is spaced out. It is smaller on the laptop, about half the size of a page." Although nurses noted that laptops provided a limited view, they still preferred laptops to the computer on wheels. One nurse expressed, "*We can manage the laptops much better because it is mobile. The workstations on wheels are bulky, heavy, and take up a lot of space, and there is never that much space in a patient's room anyway*." The nurses' opinions highlighted the importance of selecting the appropriate hardware.

Digital integration

A varied approach across hospital wards disrupted workflow and raised concerns about patient safety. The nurses expressed frustration with internal differences between wards and the use of both paper and digital records, which created confusion and complicated their workflow, making it hard to remember the correct processes. One nurse explained, "*Some information is on the computer in one area, but in another, it is still on paper, which is a nightmare: same hospital, different processes*." The nurses generally agreed that a unified system would improve access and help prevent patient information from being overlooked or lost. Another nurse said, *"One system is needed. I had hoped everything would go electronic; it would be easy, and you would not miss things*."

The inconsistent visibility of the fall assessment icon seemed to cause confusion and undermine nurses' confidence in the documentation process. Some nurses noted that the lack of visible confirmation made it difficult to verify whether the assessment was completed, leading to uncertainty. One nurse noted, *"Not having the icon appear is unhelpful after completing the fall assessment because you question whether you have done it or not."* Others described the need to navigate deeper into the system to confirm completion. Conversely, several nurses clearly explained the presence of an icon on the screen, explaining, *"When you are logged into the EMR, a little icon appears to indicate that you have completed the fall assessment,"* another stated, *"There is a little icon at the top that tells me whether this person is a risk."* These mixed experiences suggest that nurses have varying levels of familiarity with the system, which could impact workflow efficiency and patient safety.

Providing coloured visual cues helped nurses interpret fall risk more accurately and improved their understanding. The system used a green = low, amber = medium, and red = high colour scheme to indicate risk levels, that adjusted based on the results of the completed fall assessment. A nurse explained, "*Once the fall assessment has been done, there is a little symbol at the top of the screen. It is a man falling and changes colour depending on the risk result*." This visual prompt served as an immediate reference, allowing nurses to identify at-risk patients and prioritise their care effectively and quickly.

Staffing levels

Nurses shared a consistent view on staffing levels. Participants described how reduced staffing compromised their ability to deliver timely care, increasing the likelihood of falls. One nurse explained, "*Short staffing is always a high-risk of a fall, less care for the patient. If the nurse has five patients, then with fewer staff on the ward, there is a high-risk that patients will receive less care and less time with the nurse*." Another nurse highlighted delays in responding to call bells, saying, "*When our staffing level is low, we have less time to spend with patients. We are slower answering bells, which can lead to patients needing to go to the toilet and just trying to get out of bed themselves and falling*." Nurses emphasised that adequate staffing was vital for reducing fall risks and providing top-quality patient care.

Staff training

The education on fall-risk assessment during recruitment was inconsistent. While all nurses received an induction pack from the hospital's education team, one nurse described its content as "*A very minor amount of information; it did not cover much*." Some recalled brief and general training, while others noted a checklist-style orientation that covered a wide range of assessments, including falls. One nurse explained*, "You had to get sign off when you first started."* In contrast, another reported having no formal training on falls, stating, *"I have never attended any education around falls."* These disparities suggest gaps in the hospital onboarding system, which may affect the consistency of fall prevention management.

Education on the falls assessment CDSS was delivered in numerous ways, with nurses relying on both formal training and peer support. The participants described

"structured group training", "individual one-on-one sessions" and "the use of an online booklet". One nurse explained, *"The senior nurse educator would come around and would take the staff through the electronic risk assessments."* One participant noted "*That nurses often trained each other"*. However, this process could be challenging, as described, "*Trying to teach someone how to do an admission in the new electronic system is quite hard and time-consuming."* In contrast, others referred to the education as straightforward, "*easy to learn*," "*supported by a preceptor,"* and noted that "*there was always someone to answer questions if you had any questions."* These varied experiences indicate inconsistent training, which could impact the quality-of-care delivery.

5.3.2 Nursing workflows (Process)

Nursing workflows included two subthemes: clinical decision support system and monitoring and reporting, which are presented in more detail next.

Clinical decision support system

Clinical decision-making was embedded in nurses' workflows, with the fall assessments identifying risk and guiding fall management. Nurses described clinical decision-making as "*A process they followed while completing tasks*." The nurse's expertise determined how they engaged with the CDSS, influencing the depth and reliability of decision-making. Experienced nurses described using the fall assessment CDSS as a checklist to ensure thoroughness. One nurse explained, "*I use the fall assessment as a checklist; however, it also serves as a useful reminder, because even when you are experienced, it is easy to overlook things. It is great to have it as a baseline."* This dual function demonstrates how nurses' clinical judgment, combined with digital systems, supports high-quality care.

The nurses viewed the CDSS as a supportive tool that informed their clinical decision-making but did not dictate it. One nurse acknowledged the role of a CDSS in care planning, particularly for high-risk patients. Others viewed it as a supportive rather than a definitive decision-making tool, with one nurse explaining, "*The assessment serves as a guide, a tool to refer to. It reminds you of important patient information, providing a complete picture of their risk level."* Another echoed this sentiment, emphasising its awareness function, saying, "*Yes, but it is just a guide; it makes you*

more aware of the patient's risks before you enter their room. It does support me because it is part of my daily documentation." These perspectives suggested that whilst the CDSS informed care, it was ultimately used to support the broader clinical judgment.

The nurses expressed mixed views on the CDSS's role in supporting their clinical decision-making. While some nurses acknowledged that the CDSS offered them some support, they did not always trust it. One nurse noted, "*It does support me to a degree, but I do not always agree with it*." Others viewed the fall assessment process as a "*Tick-box exercise*," emphasising the importance of trusting their clinical judgment. As one nurse said, "*You cannot just go off a form. There is a real patient at the end of it*." Although some nurses felt the CDSS did not support them, others reflected on the broader role, noting, "*It reminds me of tasks."* Despite mixed opinions on whether the CDSS supported them, the shared commitment was to deliver patient-centred care, regardless of system limitations.

The nurses used the fall assessment CDSS to guide environmental adjustments that enhanced patient safety. After reviewing patient information, the nurse took proactive steps, such as decluttering patient rooms, to reduce fall risk. One nurse explained, "*It is not hard to declutter the patient rooms by removing visitor chairs and putting luggage in cupboards."* For high-risk patients, the nurses described personalising strategies including reducing the bed height, increasing the frequency of observation, and ensuring their belongings and the call bell were within reach. These actions, while aligned with the hospital's broader norms for patient care, were also influenced by the outcomes generated through the CDSS.

Uncertainty in the CDSS-generated fall-prevention actions undermined nurses' confidence in falls management. Some nurses were unsure whether the CDSS offered preventative actions, with one nurse stating, "*No, not that I recall,"* and another confidently confirmed they were not available, saying, "*No, they were not in this system*." Among participants who recalled the generated fall-prevention actions, implementation was affected by unclear instructions. One nurse explained, "*It did provide them, but then did not give specific details."* Of interest, no participants mentioned the hospital's fall policy; however, they demonstrated a clear

understanding of the various safety strategies and their importance based on fall risk levels. This suggests that clinical judgment often compensates for system limitations, and the lack of clarity could compromise patient care and safety.

Monitoring and reporting

Monitoring the patient involved understanding and anticipating potential risks by assessing and determining the patient's current health status, discussing pre-existing health issues with the patient, planning, and developing a care plan, implementing it, and continually assessing and re-evaluating the patient throughout their shift. During admission, nurses gathered patient information, including baseline observations, echocardiograms, and risk assessments, to assess risk and ensure patient safety. One nurse explained, "*You observe and check the patient's risk, including fall*," emphasising the importance of the fall-risk assessment. Another nurse emphasised the importance of "*Just working your way through the assessment systematically."* These practices reflect a structured model of care in which the nurse's constant monitoring and documentation support patient safety.

Despite both systems containing the same information, the nurses found paper records to be more straightforward and easier to access for immediate reference. While both formats contained the same patient information, many nurses found the paper version more intuitive for quick reference. One remarked, "*I cannot remember if I have a prompt on my screen, nor can I recall what I have completed, so if I write it down as well, then I know this is what I have done."* Another nurse described a two-step process to ensure she did not forget anything because, "*If I jot it down on paper as well as in the computer, I know that is what I have done."* The paper records were valued for their physical presence at the bedside because they were easy to access without navigating the electronic system. One nurse noted, "*It is usually a pre-packaged set of notes that start in admissions and work their way up to the wards. It is right at the bedside."* These practices suggested to the student that workflow integration is critical to effective monitoring and reporting practices.

Challenges with digital notetaking altered how nurses documented/reported these risks, potentially impacting workflow efficiency and, ultimately, patient safety. Some nurses found it difficult to record notes in the EMR, often delaying their

documentation until the end of their shift. One nurse explained, "*I feel like I used to jot down some notes during the shift, as opposed to now, when it seems like I am doing them all at the end of the shift."* This change in practice suggests that the EMR may inadvertently alter how nurses document, potentially delaying record-keeping and impacting timely decision-making. Despite the issues with the EMR, some nurses preferred it over paper because of its clarity and legible handwriting. As one nurse noted, "*A lot of the time you cannot read people's handwriting; I think it is easier with the electronic system*."

However, some nurses also described that the ability to update and view notes from any computer streamlined daily workflows and reduced delays. One nurse explained, "*You do not have to chase the notes because someone else is writing in them. The doctor can be on one computer doing their notes, and I can be on another at the same time."* Another highlighted, *"You do not have to look for notes, and everything is legible on a computer."* These different perspectives highlighted the importance of balancing timely care, accessibility, and accuracy in reporting patient care through a digital system.

5.3.3 Nurses' perspective (Outcomes)

Nurses' perspective comprised two subthemes: nurses' experience and fall-related clinical decision-making, which are presented in more detail next.

Nurses' experience

The nurses described the fall assessment CDSS as identifying key risk factors and generating a score that categorised the patient's fall risk as low, medium, or high. This classification was linked to the recommended fall-prevention actions embedded in the CDSS. One nurse explained, "*You select from the list in the electronic system, which generates interventions that should be implemented*." Despite recognising this functionality, several nurses questioned the accuracy of the risk scores. One nurse stated, "*This is not the patient, it is not right, the patient can do this."* In response to these concerns, this nurse admitted to manually reviewing and adjusting her inputs, explaining, *"I would look through it again, and again and check what I have ticked*." These responses suggested that nurses relied on their clinical judgment rather than a formal process within the CDSS to support clinical decision-making.

Nurses reported limited engagement with the preventive actions generated by the CDSS. Although the nurses acknowledged these actions as available, they admitted to not engaging them. One nurse stated, "*Yes, they are potentially available, but I have never clicked on them."* This highlighted broader concerns about the system's accuracy and its practical usefulness in guiding clinical decision-making. Overall, during the interviews, the nurses did not outrightly reject the current system but recognised the need for improvement, stating they would like it to "*Reflect the patients' risks and support them rather than complicating things."* These insights suggested tension between the system design and supporting nurses' fall-related clinical decision-making.

Nurses reported that neither the paper nor the electronic fall assessment fully captured the complexities of patient risk, requiring them to rely on clinical judgment to complement the system. Misclassification of risk was described across both formats. One nurse stated, "*I sometimes encounter a medium patient risk score that I felt was not quite accurate."* While another noted that the CDSS *"Risk assessment was not accurate, especially for elderly patients*." Although initial resistance to the electronic system was evident, many nurses recognised that technological change in healthcare was inevitable.

Experiences with ease of use varied. Some nurses viewed the paper fall assessment positively, describing it as *"Easy to use and very quick to do."* Its tangible format allowed nurses to view the information at a glance, providing a sense of satisfaction. The electronic fall assessment was also viewed positively by many nurses, with one describing it as "*Pretty good and effective in doing its job,"* and rating it seven out of ten. However, others found the electronic system "*Challenging at times due to the multiple screens required to access,"* rating it four out of ten. Overall, the nurses expressed cautious optimism about gradually adopting the electronic system.

The nurses reported that the transition from paper to an EMR affected their psychological well-being and their ability to make decisions, perform tasks, and provide patient care. The implementation process was described as "*not smooth*." The nurses frequently sought help and support during implementation but received

inadequate assistance, which undermined their confidence. One nurse reflected, "*You work your way into self-doubt*."

System reliability also influenced nurses' experience. Hardware failures and system crashes caused frustration and disrupted care. One nurse said, "*The only concern I have with electronics is how the system crashes,"* while another noted that, "*Sometimes available or they are not working."* Perceived accessibility of the EMR varied, with some nurses describing it as unreliable and hard to access. One nurse expressed concern, saying, "*It is just a wing and a prayer, the RNs' experience. No, it was not accessible*." In contrast, others valued having the patient information readily available, with one noting, "*It was right there. You did not have to open anything up to look at it*."

The nurses highlighted gaps in feedback and collaboration. While post-fall communication with colleagues and incident reporting were generally well managed, formal feedback was lacking. One nurse stated, *"I have never received any post-fall feedback in nine years".* Collaboration during implementation was reported to be inconsistent across the wards, with one nurse reporting, *"we were doing observations in the EMR on one ward, but no one else was, so they were not being looked at."* Nurses also emphasised the importance of engaging with patients. One nurse said, *"when referring to the paper fall assessment, you felt more engaged with the patient."* Others raised concerns that EMR use affected patient perception, stating, "*We did get comments from patients about the nurse facing the computer, saying she did not know what she was doing and was spending too long on the computer."*

Finally, the nurses expressed differing opinions on how often fall assessments should be completed. Although hospital policy required a fall assessment on the day of admission and daily or as needed thereafter, practices varied. Some nurses reported, "*the fall assessment is routine for every patient, we do it each shift*," supported by a colleague who confirmed, "*every shift, and if there were any changes*." However, another nurse disagreed, saying, "*it was daily*." These inconsistencies suggest a lack of shared understanding of policy implementation.

Fall-related clinical decision making

The EMR facilitated multidisciplinary coordination and supported nurses to deliver patient-centred care following a fall. Nurses valued shared access to clinical information in the EMR, which allowed the team to view the patient's entire clinical notes and care plans. One nurse said, *"You can go in and see everyone's clinical notes and the doctor's plans."* This improved communication and assisted in making fall-related clinical decisions across disciplines.

The nurses discussed a collaborative response such as "*calling on colleagues for assistance*," *"getting someone to help assess the patient*," and "*handing over details of the fall during the next shift."* One nurse outlined her approach as, "*call for help, ensure the patient was rousable, and check their blood pressure. If possible, put them back into bed and do some recordings. Let the surgeon and anaesthetist know. Ask the patient how they are feeling."* The nurses also recognised that, following a fall, the hospital policy indicates that the fall assessment be reviewed and updated accordingly, reinforcing the system's role in ongoing risk management.

5.4 Conclusion

The chapter explored nurses' experiences with the CDSS fall assessment within the EMR and how it influenced their clinical decision-making. While the CDSS offered benefits such as multidisciplinary access, clear documentation, and more efficient record-keeping, nurses relied on their clinical judgment to address concerns about accuracy, usability, and contextual relevance. The CDSS was viewed not as a definitive decision support tool but as a resource that complemented their clinical judgment and informed routine care.

In the next chapter, the convergent analysis brings together the quantitative and qualitative findings to provide an integrated interpretation of the study's results. This approach enables the researcher to understand the effects of implementing EMR with CDSS on falls, nurses' clinical experiences, and decision-making related to fall prevention.

Chapter 6 Integration of data

6.1 Introduction

Donabedian emphasised that systems are merely enabling mechanisms; it is the ethical dimensions of individuals that are essential to a system's success. (Berwick & Fox, 2016). While EMRs offer useful design principles for guiding procurement, configuration, change management, and everyday use, this statement highlights the need to balance technological considerations with human and ethical factors. In previous chapters, the lens of Donabedian's (1988) structure, process, and outcome framework provided a robust theoretical model for evaluating factors influencing the implementation of an EMR with CDSS to assess patient fall risk and nurses' clinical decision-making regarding fall-related outcomes. This chapter presents a revised Donabedian Framework (structure, process, and outcome), which integrates the study's findings and consolidates them into new, integrated themes. The revised framework adapts the traditional model to the specific context of EMR and CDSS implementation.

6.2 Design

This chapter will discuss the combined findings from the three studies, the systematic review, the systems analysis, and the qualitative study that explored nurses' perceptions. A convergent design was used, in which qualitative and quantitative data were collected and analysed simultaneously, then integrated for interpretation (Creswell & Plano Clark, 2018). This design enabled systematic review findings, numerical trends from the systems analysis, and nurses' perceptions to be synthesised into a single unified perspective (Fetters et al., 2013).

6.3 Merging of data

Data integration followed the multi-stage mixed-methods framework, incorporating findings from the systematic review, systems analysis, and qualitative study. The convergent design is particularly suited to the evaluation and implementation of programmes or interventions (Fetters et al., 2013), which, in this thesis, was the implementation of an EMR with a CDSS. The merging of the qualitative and

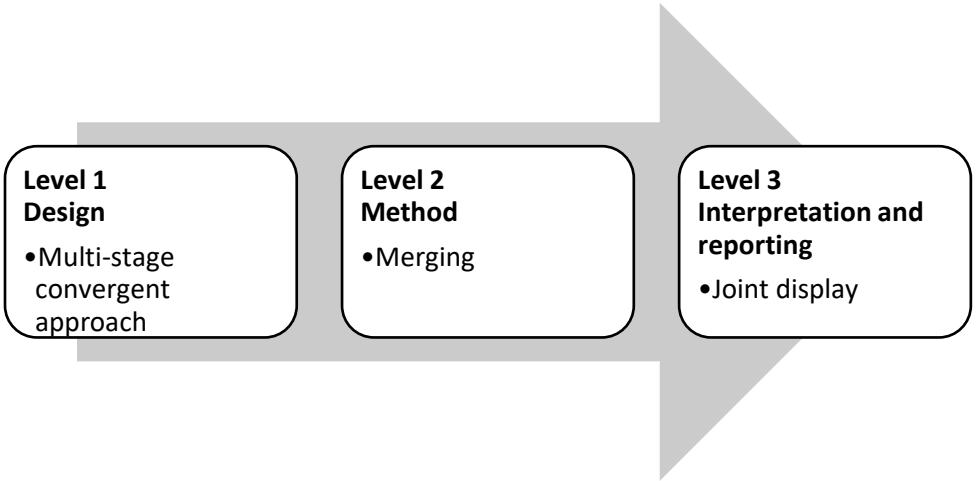
quantitative data occurred through direct comparison of findings from the systematic review, systems analysis, and qualitative study. The process highlighted similarities and differences between data sources, and the insights were then cross-checked to confirm or question the emerging interpretations.

To support integration, joint displays were guided by the Donabedian Framework. These displays enabled the researcher to identify insights beyond those gained from the separate studies (Fetters et al., 2013). A colour-coding system was used to visually distinguish data sources, being blue for the systematic review, orange for the systems analysis, and green for the qualitative study. This assisted in highlighting alignments and gaps between data sources.

6.4 Interpretation and reporting

Interpretation and reporting of the findings were guided by the Donabedian Framework and presented using its three components: structure, process, and outcome. These components provided a foundation for presenting the integrated findings. Through an iterative comparison process across the three data sources, the researcher developed an understanding of which led to the reviewed application of the Donabedian Framework in the context of EMR with CDSS implementation. Figure 11 illustrates the levels of integration used in this thesis.

Figure 11. Levels of Integration used in this thesis.



Note. Adapted from "Achieving integration in mixed methods designs: Principles and practices," by M. D. Fetters, L. A. Curry, & J. W. Creswell, 2013, *Health Services Research*, *48*(6), p. 2134. https://doi.org/10.1111/1475-6773.12117

6.5 Structure

Structure represents the organisational foundations that shape care delivery and includes the three integrated themes: system design and usability, staffing and workforce capacity, and staff training, presented in more detail next.

6.5.1 System design and usability

The systematic review identified current system features, such as improved fall documentation and risk assessment tools, including nursing documentation, fall-monitoring modules, and daily nurse alerts (Cho et al., 2021; Dowding et al., 2012; Walker-Czyz, 2016; Ye et al., 2020). These features also supported personalised care and facilitated real-time communication among team members (Dykes et al., 2010). Nurses shared their clinical experiences, noting initial difficulties navigating the system's complex interface and multiple steps, which made it hard to find patient information. Nevertheless, they found the system increasingly user-friendly over time and appreciated the visible icon that helped identify at-risk patients. Hardware challenges were also reported, laptops, though portable, had small screens, and mobile workstations were bulky and difficult to handle, highlighting the need for better hardware. Similarly, in the review, Cho et al. (2021) reported that initial reactions were neutral or slightly negative, with negative responses diminishing as experience with the system grew.

This study's three data sources all discussed digital integration, each offering a distinct perspective on its role and effects in clinical practice. The systematic review explicitly mentioned digital integration (Carroll et al., 2022; Cho et al., 2021; Dowding et al., 2012; Dykes et al., 2010; Furukawa et al., 2011; Walker-Czyz, 2016), highlighting its varied scope—from extensive EMR implementations to specialised workflow tools such as fall assessments and risk prediction. These systems could be integrated all at once or through a planned, step-by-step process (Dowding et al., 2012; Dykes et al., 2010; Furukawa et al., 2011; Walker-Czyz, 2016). Additionally, digital integration supports functionalities such as alerts and reminders within these systems (Carroll et al., 2022; Cho et al., 2021). Unlike the systematic review, which emphasised a support function for digital integration, the systems analysis revealed practical limitations, including duplicate patient admission records in the new EMR and a gap in admission

data during the implementation period from May 4–16, highlighting the complexity of achieving seamless integration (see Table 8).

In contrast, in the interviews, the nurses referred to a varied approach and inconsistent practices across hospital wards following implementation, causing confusion about which processes were carried out in the previous system and which in the new system, triggering concerns about patient safety. The nurses noted that different processes increased the risk of missing key steps during care.

6.5.2 Staffing and workforce capacity

All three studies in this thesis reported on staffing. In the systematic review, both Furukawa et al. (2011) and Cho et al. (2021) highlighted the vital role of staffing levels in implementing EMR and in nurse-sensitive outcomes. Furukawa et al. (2011) developed a conceptual framework that demonstrated its impact on staffing needs. Cho et al. (2021) noted that nursing staffing levels across the 12 units were modified during the study due to a Korean Government policy on comprehensive nursing services within the national health insurance system. Both studies emphasised the importance of providing quality healthcare (Cho et al., 2021; Furukawa et al., 2011). Nurses also reported that staff shortages hindered their ability to provide timely care, including delayed responses to call bells and patients attempting unsupervised mobility, which increased fall risk. Although the statistical analysis did not find a significant association between staffing changes and falls, some adjusted odds ratios in the multivariable model suggested a possible link, consistent with the existing literature and nurses' perceptions of staffing levels.

6.5.3 Staff training

The systematic review highlighted varying degrees of staff training. Nurses discussed staff training, although it was not quantified in the systems analysis. Several studies show that the increasing complexity of EMRs, combined with insufficient training and poor coordination, led to staffing inefficiencies and increased risks (Dowding et al., 2012; Furukawa et al., 2011; Walker-Czyz, 2016). The review also stresses the need to train nurses on new electronic tools during EHR implementation to reduce adverse events (Dowding et al. 2012; Furukawa et al. 2011; Walker-Czyz, 2016). Nurses agreed that training was vital but reported inconsistencies in fall-risk assessment during

recruitment. Although information was provided, it was often minimal or checklist-style. Training on the new CDSS falls assessment in the EMR was delivered but inconsistently, through group sessions, one-on-one instruction, and online booklets. Nurses frequently relied on peer support, which some found challenging, especially when teaching occurred during patient care, such as admissions. Others described the education as straightforward, "*easy to learn*," "*supported by a preceptor*," and noted that "*there was always someone to answer questions*." These diverse experiences reveal inconsistent training that could impact quality-of-care.

Table 26 details the summary of the findings with regard to structure from the previous chapters.

Table 26. Summary of findings – Structure.

Structure: Evaluates the environment **Summary of findings**		
Systematic review	Systems analysis	Qualitative study
• Initial reactions were neutral or slightly negative, but nurses were more accepting of the new tool over time. • Improvements in fall documentation and risk assessment, including features such as nursing documentation tools, fall-monitoring modules, and daily alerts. • Digital integration can occur at various levels and integrating technology into clinical practice provides support functionalities within the system, such as risk predictions that nurses receive and, in turn, provide proactive patient care. • Literature reinforces the importance of adequate staffing for delivering quality healthcare. • Staff training is a critical part of implementing a new system or tool. • The ability of nurses to provide individualised care and to support real-time communication among the team. • The systematic review also stressed the need to train nurses on new electronic tools during EHR implementation to reduce adverse events.	• Systems analysis revealed practical limitations, resulting in a mismatch between the system structure and organisational processes, which affected data quality. • Staffing variance was not statistically significant in either the unadjusted or the adjusted analyses, suggesting that, as measured, this independent variable was not associated with fall risk.	• Difficulty navigating the new system's user interface, which involved many steps, was perceived as unnecessarily complex • Some nurses appreciated the visible icon, which helped identify at-risk patients. • Laptops with limited screen size were compact and easy to manoeuvre, whereas workstations on wheels were bulky and heavy, highlighting the importance of selecting the appropriate hardware. • In time, the new EMR became intuitive. • The use of hybrid systems (paper and electronic) across wards caused confusion. • Staff shortages limited the nurses' capacity to deliver timely care. • Training is essential; however, inconsistencies affected the consistency of fall-prevention management.

Table 27 details the synthesised findings from the structure component.

Table 27. Synthesised findings – Structure.

Structure: Encompasses the organisational foundations that shape care delivery		
Themes	**Integrated themes**	**Similarities and differences**
EMR (2 data sources)	System design and usability	Limited literature (see Cho et al, 2021); initial reactions were neutral or slightly negative, with negative responses decreasing as nurses gained more experience.
		Difficulty navigating the current system's user interface, which involved many steps, was perceived as unnecessarily complex.
		Some nurses appreciated the visible icon, which helped to identify at-risk patients.
		Laptops with limited screen size were compact and easy to manoeuvre, whereas workstations on wheels were bulky and heavy, highlighting the importance of selecting the appropriate hardware.
		Improvements in fall documentation and risk assessment, including features such as nursing documentation tools, fall-monitoring modules, as well as daily alerts.
		Nurses reported that in time the new EMR was intuitive.
Digital integration (3 data sources)		Digital integration can occur at various levels and integrating technology into clinical practice provides support functionalities within the system, such as nurses receiving risk predictions and therefore provide proactive patient care.
		The systems analysis revealed practical limitations, duplicate records, and missing data. Sequential patient admission: mismatch with system structure and organisational process, affected quality of data.
		Nurses reported the use of hybrid systems (paper and electronic) across wards caused confusion.
Staffing levels (3 data sources)	Staffing and workforce capacity	Literature reinforced the importance of adequate staffing for delivering quality healthcare.
		Staffing variance was not statistically significant in either the unadjusted or the adjusted analyses, suggesting that, as measured, this independent variable was not associated with fall risk.
		Nurses reported staff shortages limited their capacity to deliver timely care.
Staff training (2 data sources)	Staff training	The literature emphasised staff training as a critical part of implementing a new system or tool.
		The ability of nurses to provide individualised care and to support real-time communication among the team.
		The systematic review also stresses the need to train nurses on new electronic tools during EHR implementation to reduce adverse events.
		Training is essential however, inconsistencies affected the consistency of fall-prevention management.

Colour-coding key:

Systematic review	Systems analysis	Qualitative study

6.6 Process

Process represents the way in which electronic systems interact with clinical workflows and includes two integrated themes: the role and function of the CDSS and monitoring and reporting, which are presented in more detail next.

6.6.1 Role and function of the clinical decision support system

The systematic review and qualitative study agreed that the CDSS is a tool to support clinical decision-making rather than replace clinical judgment. The systematic review described the CDSS as a tool that offered nurses automated action recommendations in their daily routines, triggered patient safety alerts, assisted nurses in customising interventions based on individual risk assessments, and delivered decision support and communication at the bedside (Carroll et al., 2022; Cho et al., 2021; Dowding et al., 2012; Dykes et al., 2010; Walker-Czyz, 2016; Ye et al., 2020; Yokota et al., 2018). While nurses described the CDSS as "*a process they followed while completing tasks*," "*a guide*," or "*a checklist*" to remind them of important patient information, it did not dictate care. Nurses highlighted that their expertise and judgment remained essential in directing clinical decision-making and care.

The systematic review and the qualitative study both associated CDSS with enhanced patient safety; the systematic review reported that predictive tools and EHR-based systems identified risks early, enabling individualised interventions and the integration of EBP standards into care (Carroll et al., 2022; Walker-Czyz, 2016; Ye et al., 2020). Nurses reported challenges with digital notetaking, which altered how they documented, potentially affecting workflow efficiency and, ultimately, patient safety. Conversely, the nurses used the fall assessment CDSS to guide environmental adjustments that enhanced patient safety, such as decluttering patient rooms, relocating patients closer to the nurses' station, and implementing interventions for higher-risk patients.

The systematic review portrayed the CDSS as effective and evidence-based, associated with improved outcomes (Dowding et al., 2012), whilst others noted challenges with implementation, which led to dissatisfaction and workarounds (Furukawa et al., 2011). In contrast, nurses expressed variable views of the current system, with some trusting

it as a helpful guide and others seeing it as a tick-box exercise, preferring to rely on their own clinical judgment.

The systematic review and the qualitative study both confirmed that the CDSS enhanced communication. The systematic review emphasised CDSS tools, such as the FPTK (Dykes et al., 2010), that supported bedside communication and structured care planning. Similarly, nurses confirmed the CDSS raised awareness of patient risk before entering the room, thereby aiding communication and planning.

6.6.2 Monitoring and reporting processes

Monitoring and reporting were evident in both the systematic review and systems analysis. The systematic review identified monitoring and reporting of falls as crucial for quality and safety activities, while acknowledging variation in levels of automation and organisational integration across studies (Dowding et al., 2012; Dykes et al., 2010; Furukawa et al., 2011; Walker-Czyz, 2016; Yokota et al., 2018). Furukawa et al. (2011) highlighted the importance of the NDNQI, which uses standardised specifications and provides quarterly benchmarking reports to support quality improvement. Other studies accessed patient data at the unit level, some using an electronic dashboard for real-time reporting (Dowding et al., 2012; Dykes et al., 2010; Walker-Czyz, 2016; Yokota et al., 2018).

The systematic review also described a range of additional monitoring and reporting approaches, including embedding fall-risk scores into the EMR to enhance team awareness (Carroll et al., 2022), implementing educational programmes and chart reviews to address underreporting (Cho et al., 2021), and using predictive systems for real-time risk communication (Ye et al., 2020). Across the studies, monitoring and reporting systems were widely recognised as important, with variation in implementation and integration within clinical environments.

The systems analysis examined local hospital processes using descriptive and inferential methods for admissions (Tables 12–15), falls (Tables 16–18), and staffing data (Tables 21). This analysis was converted into descriptive summaries that enabled comparisons across systems. Differences were observed in fall severity classifications and reporting between Paywiz (previous system) and Safety Hub (current system), indicating variation in how falls were documented across reporting platforms.

The introduction of the free-text field in Safety Hub was associated with more detailed fall incidents. Documentation, compared with the structured fields available in the previous system, captured free-text entries that contextualised information not routinely recorded in the structured formats, including environmental factors present at the time of the fall. These narrative descriptors also documented nurses' clinical assessment of injury, their use of clinical judgment, and communication with colleagues following a fall. The free-text data illustrated a range of nursing responses to inpatient falls, providing additional insight into clinical practice beyond categorical data alone.

At the same time, inconsistencies were noted between severity, classification, and clinical descriptions within Safety Hub. Two incidents were classified as major falls, although the accompanying text described injuries that appeared less severe. These discrepancies highlight variability within the dataset and raise questions about consistency between structured severity categories and the narrative documentation.

Variation was also identified within admission records, reflecting differences in how admissions were recorded across systems. Duplicate admissions were identified and categorised into three groups: duplicate, split and sequential admissions and were addressed during the data cleaning process. These patterns indicate that the organisation's processes were not taken into consideration when the current system was implemented, leading to workarounds to process patient admissions.

Table 28 details the summary of the findings with regard to process from the previous chapters.

Table 28. Summary of findings – Process.

Process: Looks at how care is delivered **Summary of findings**		
Systematic review	Systems analysis	Qualitative study
• CDSS as a tool offers nurses automated action recommendations in their daily routines, triggers patient safety alerts, assists nurses in customising interventions based on individual risk assessments, and delivers decision support and communication at the bedside. • EBP standards of care. • The literature reports that CDSS are effective and evidence-based, associated with improved outcomes. • The literature emphasises that CDSS tools support bedside communication and structured care planning. • The literature acknowledges that monitoring and reporting are crucial for quality and safety, but the levels of automation and their integration into organisations vary.	• The descriptive analysis identified differences in fall severity and reporting between Paywiz (previous) and Safety Hub (current). The free-text entries in Safety Hub™ improved fall incident reporting by capturing context missed in the structured fields of the previous system. This free-text function also allowed nurses to input how they used their clinical judgment to assess injuries and collaborate with other members of the multidisciplinary team to manage the patient. The data further highlighted environmental factors, giving a better understanding of what may have contributed to the fall. The free-text entries in Safety Hub improved fall incident reporting by capturing context missed in the structured fields of the previous system and highlighted a range of approaches to how the nurses responded to inpatient falls. • Discrepancies between severity classifications and clinical descriptions in Safety Hub raised concerns about the reliability of fall data. Two of the falls were classified as major; however, the free-text documentation suggested otherwise. • Variations in admission records highlighted the effects of digital integration on the hospital's workflow. Identifying duplicate admissions, which were categorised into three groups: duplicates, split, and sequential patient admissions records, were managed during the data cleaning process.	• CDSS used as a checklist for thoroughness, a helpful reminder, a baseline, a guide, and a reference tool. Also highlights key patient information, offering a comprehensive view of their risk level. • Nurses used CDSS information to inform environmental changes and interventions for high-risk patients. • Nurses expressed variable views of the current system, with some trusting it as a helpful guide and others seeing it as a tick-box exercise, preferring to rely on their own clinical judgment. • CDSS raises awareness of patient risk before entering the room, thereby aiding communication and planning.

Table 29 details the synthesised findings of the process component.

Table 29. Synthesised findings – Process.

Process: **Represents the way in which electronic systems interact with clinical workflows**			
Systematic review		Systems analysis	Qualitative study
Themes	**Integrated themes**	**Similarities and differences**	
CDSS (2 data sources)	Role and function of the CDSS	The CDSS was a tool that offered nurses automated action recommendations in their daily routines, triggers patient safety alerts, assists nurses in customising interventions based on individual risk assessments, and delivers decision support and communication at the bedside.	
		The CDSS was a checklist for thoroughness, a helpful reminder, a baseline, a guide, and a reference tool. It also highlights key patient information, offering a comprehensive view of their risk level.	
		EBP standards of care.	
		Nurses used CDSS information to inform environmental changes and interventions for high-risk patients.	
	Communication and Care Coordination	Literature reports the CDSS as effective and evidence-based, associated with improved outcomes.	
		Nurses expressed variable views of the current system, with some trusting it as a helpful guide and others seeing it as a tick-box exercise, preferring to rely on their own clinical judgment.	
		Emphasises that CDSS tools, such as the FPTK, support bedside communication and structured care planning.	
		CDSS raise awareness of patient risk before entering the room, thereby aiding communication and planning	
Monitoring and reporting (2 data sources)	Monitoring and reporting	The systems analysis identified differences in fall severity and reporting between Paywiz (previous) and Safety Hub (current). The free-text entries in Safety Hub improved fall incident reporting by capturing context missed in the structured fields of the previous system. This free-text function also allowed nurses to enter how they used their clinical judgment to assess injuries and collaborate with other members of the multidisciplinary team to manage the patient. The data further highlighted environmental factors, giving a better understanding of what may have contributed to the fall. The free-text entries in Safety Hub improved fall incident reporting by capturing context missed in the structured fields of the previous system and highlighted a range of approaches to how the nurses responded to inpatient falls.	
		Discrepancies between severity classifications and clinical descriptions in Safety Hub raised concerns about the reliability of fall data. Two of the falls were classified as major; however, the free-text documentation suggested otherwise.	
		Variations in admission records highlighted the effects of digital integration on the hospital's workflow process. Identifying duplicate admissions, which were categorised into three groups: duplicates, split and sequential patient admissions records, was managed during the data cleaning process.	
		The literature acknowledges that monitoring and reporting are crucial for quality and safety, but the levels of automation and their integration into organisations vary.	

Colour-coding key:

Systematic review	Systems analysis	Qualitative study

6.7 Outcome

The outcome component represents patient safety, system impact, and human factors, and includes the integrated themes: effectiveness of electronic systems on incidence and severity of falls, and nurses' satisfaction and compliance, which are presented in more detail next.

6.7.1 Effectiveness of electronic systems on incidence and severity of falls

Across the three studies, which included a systematic review, systems analysis, and qualitative study, there were both similarities and notable differences. All the studies acknowledge that falls continued to occur, even with fall-prevention strategies in place.

The systematic review highlighted severity, noting that approximately 10% of inpatient falls lead to injury, with unassisted falls causing more serious injuries (Carroll et al., 2022). The systems analysis recorded 114 falls in the private hospital during the study period, with the largest number in 2022 (T3). Following the introduction of the new incident management system, Safety Hub, 62 falls were reported in just 12 months, compared with 52 falls over 35.5 months under the previous system, Paywiz (Tables 16 and 17). This pattern suggests the increase in recorded incidents could reflect improved staff incident reporting rather than a true rise in fall incidence.

Across the four years, fall severity remained low. No SAC 1 (severe) incidents were reported; SAC 2 (major) events were rare, totalling only four. SAC 4 (minor) events were the most common across all three time periods, with a notable increase in 2022, while 2020 recorded the fewest SAC 4 falls (Tables 16 and 17). The rise in SAC 3 and 4 events in 2022 aligns with the broader conclusion that electronic systems tend to enhance reporting completeness rather than reduce falls.

Further analysis identified variation in fall occurrence across clinical specialties and time periods. Orthopaedics remained significantly associated with higher odds of a fall even after adjustment (OR 2.08, CI 1.11, 3.89). Similarly, falls recorded during time period 3 (2022) continued to show increased odds after adjustment (OR 2.48, CI 1.51, 4.07) (Table 23). These findings indicate that both specialty and time period had independent effects on fall risk.

The nurses described the transition from the previous fall incident management system, Paywiz, to the current incident management system, Safety Hub, as an improvement in the quality and detail of fall incident reports. The nurses' free-text entries in Paywiz demonstrated how they combined rapid responses with clinical assessment to care for the patient. Despite the presence of a CDSS, nurses reported relying primarily on their clinical judgment when making decisions related to fall prevention and their response.

The nurses' free-text narratives also revealed inconsistencies between the severity they assigned and the clinical description of the event. Two incidents were initially classified as minimal; further review of their subcategories revealed important differences. In one case, the nurse reported being in the bathroom with the patient, who "*felt faint and was assisted to the floor*," with no injuries resulting. Conversely, another incident involved "*the patient tripping over a blanket while trying to get out of bed to mobilise*," leading to skin tears on the patient's arms. These examples show that the labels *"fall non-injury*" and "*fall with injury*" more accurately reflect clinical reality than the original classification, highlighting the need for better alignment between the system structures and narrative documentation.

The systematic review confirmed that falls remain common despite the use of electronic systems (Carroll et al., 2022; Cho et al., 2021; Walker-Czyz, 2016). Carroll et al. (2022) reported a fall rate of 0.92% across 35,709 inpatient encounters and estimated that 700,000 to 1 million falls occur annually in USA hospitals. Cho et al. (2021) identified 707 (1.66%) falls and 134 (0.32%) fall-related injuries across 42,476 admissions, reinforcing the importance of monitoring both frequency and severity. Walker-Czyz (2016) reported a reduction in fall rates following EHR implementation, with the EHR model accounting for 15% of the variance, indicating a moderate but important impact. Overall, these findings suggest that while electronic health systems can improve reporting and may reduce some fall events, their overall effect is inconsistent and falls continue to occur.

6.7.2 Nurses' satisfaction and compliance

Across two studies, the findings offered both theoretical insights and nurses' perceptions of lived experiences. They demonstrate that nurses' satisfaction can

influence the effectiveness of an electronic health system and, consequently, impact outcomes. Several studies in the systematic review reported that involving nurses in system design and refinement improves usability and integration into care. For example, Walker-Czyz (2016) used focus groups before EHR implementation to collect nurses' views on supporting nursing practice standards, incorporating their suggestions, and refined the tool based on ongoing feedback. Similarly, Dykes et al. (2010) used qualitative inquiry in the first phase of their study to identify barriers and enablers to fall-risk communication, with nurses' feedback on missing alerts directly informing the design of the FPTK. Yokota et al. (2018) highlighted that the use of the fall-risk assessment tool was discretionary for nurses, suggesting that behavioural changes in nurses' patient care related to falls reduced the likelihood of falls. In contrast, nurses reported that implementing the new EMR was challenging and disruptive. The process was described as "*messy*" and "*sometimes frightening*." Limited support during implementation repeatedly left nurses seeking help, eroding their confidence and, for some, leading to self-doubt. Nurses in this study were end users, not contributors to design and refinement.

The systematic review evaluated accuracy primarily from a system performance perspective, focusing on how well predictive models identified fall risk (Carroll et al., 2022; Cho et al., 2021; Ye et al., 2020). These systems evaluate algorithmic performance but do not assess how well their outputs align with actual bedside care. In contrast, nurses noted that although the CDSS categorised risk levels and recommended fall-prevention actions, they questioned its accuracy and instead relied on their clinical judgment to determine care. Several nurses expressed concern that the score did not always reflect the patient's condition, prompting one nurse to manually review and modify her inputs to address this perceived inaccuracy. These responses indicate that nurses primarily relied on their clinical judgment rather than the CDSS's formal recommendations when making decisions.

The systematic review noted that nurses' feedback was used to refine tools (Dykes et al., 2010; Walker-Czyz, 2016). Poor implementation led to workarounds, dissatisfaction, and reduced efficiency (Furukawa et al., 2011). Carroll et al. (2022) acknowledged that nurses were uniquely positioned to intervene in fall risk and discussed how automating fall-risk assessment affected their workflow and cognitive

load. However, the study did not explicitly examine the psychological or emotional impact of electronic systems on nurses, unlike the nurses' interviews.

Nurses reported that the transition from paper to an EMR affected their psychological well-being and their ability to make decisions, perform tasks, and provide patient care. Some described the transition as "*frankly quite rubbish*," and "*really not a nice experience at all*." Perceived EMR accessibility influenced nurses' overall satisfaction and their ability to manage patient data effectively. Some nurses felt unsupported by the system, describing it as "*unreliable and hard to access*." One nurse expressed concern, saying, "*It is just a wing and a prayer*." The experience was not negative for all nurses, as some valued the convenience of having records readily available. This range of satisfaction demonstrated that the system's design and usability could directly impact the quality of care.

Table 30 summarises the findings regarding outcome from the previous chapters.

Table 30. Summary of findings – Outcome.

Outcome: Measures the results of care **Summary of findings**		
Systematic review	Systems analysis	Qualitative study
• The literature emphasises severity, noting that approximately 10% of inpatient falls result in injury, with unassisted falls associated with more severe injuries • These studies indicate that although an electronic health system can affect fall reporting and potentially reduce some incidents, their overall impact remains inconsistent and falls still happen at clinically significant rates. • Several studies reported that when nurses are involved in design and refinement, systems are more usable and better integrated into care. • The literature evaluates accuracy primarily from a system performance perspective, focusing on how well predictive models identify fall risk. • The literature acknowledges that nurses' feedback was used to refine tools	• Falls data recorded 114 falls across three time periods, with 52 falls in the previous system (35.5 months) and 62(12 months) in the current system, and the severity remained low. No SAC 1 (severe) incidents were reported, and only three SAC 2 (major) incidents were reported. SAC 4 (minor) events remained the most common category across both time periods and calendar years. This reinforces the literature's conclusion that electronic health systems influence reporting more than they eliminate falls. • The specialty of Orthopaedics remained significantly associated with a higher odds of a fall even after adjustment (OR 2.08, CI 1.11, 3.89). Similarly, the increased risk in time period three persisted after adjustment (OR 2.48, CI 1.51, 4.07), indicating that both independent variables, specialty and time period, had a strong independent effect on fall risk. • Increased number of falls reported over a shorter period of time. This could suggest improved staff incident reporting in the new EMR.	• Nurses described the transition from the previous fall incident management system, Paywiz, to the current incident management system, Safety Hub, as a notable improvement in the quality and detail of fall incident reports. • Nurses mainly relied on their clinical judgment rather than a formal process within the CDSS to support their clinical decision-making. • Nurses dismissed the CDSS's preventative measures and questioned their accuracy. Whilst the nurses acknowledged that the fall-preventive actions were available, they admitted to not engaging them. These insights suggested tension between the system design and clinical relevance. • Nurses were end users, not contributors to design and refinement. • These responses indicate that nurses primarily relied on their clinical judgment rather than the CDSS's formal recommendations when making decisions. • The nurses reported that the transition from paper to an EMR impacted their psychological well-being and ability to make decisions, perform tasks, and provide patient care. • Nurses mainly relied on their clinical judgment rather than a formal process within the CDSS to support their clinical decision-making

Table 31 details the synthesised outcome findings. The outcome component represents patient safety, system impact and human factors, and includes the integrated themes: effectiveness of electronic systems on incidence and severity of falls and nurses' satisfaction and compliance.

Table 31. Synthesised findings – Outcome.

Outcomes: Represents patient safety, system impact and human factors		
Themes	**Integrated themes**	**Similarities and differences**
Incidence and severity of falls (3 data sources)	Effectiveness of electronic systems on incidence and severity of falls	The literature emphasised severity, noting that approximately 10% of inpatient falls result in injury, with unassisted falls associated with more severe injuries.
		Falls data recorded 114 falls across three time periods, with 52 falls in the previous system (35.5 months) and 62 (12 months) in the current system, and the severity remained low. No SAC 1 (severe) incidents were reported, and only three SAC 2 (major) incidents were reported. SAC 4 (minor) events remained the most common category across both time periods and calendar years.
		The specialty of orthopaedics remained significantly associated with a higher odds ratio of a fall even after adjustment (OR 2.08, CI 1.11, 3.89). Similarly, the increased risk in time period 3 persisted after adjustment (OR 2.48, CI 1.51, 4.07), indicating that both independent variables, specialty and time period, had a strong independent effect on fall risk.
		Nurses mainly relied on their clinical judgment rather than a formal process within the CDSS to support their clinical decision-making.
		These studies indicated that although electronic health systems can affect fall reporting and potentially reduce some incidents, their overall impact remains inconsistent, and falls still happen at clinically significant rates.
		Increased number of fall reported over a shorter period of time. This could suggest improved staff incident reporting in the new EMR.
		Nurses dismissed the CDSS's preventative measures and questioned their accuracy. Whilst nurses acknowledged that the fall-preventive actions were available, they admitted to not engaging them. These insights suggested tension between the system design and clinical relevance.
Nurses' experience and opinions (2 data sources)	Nurses' satisfaction and compliance	Several studies reported that when nurses are involved in design and refinement, systems are more usable and better integrated into care.
		The nurses in this study were end users, not contributors to design and refinement.
		The nurses described the transition from the previous fall incident management system, Paywiz, to the current incident management system, Safety Hub, as a notable improvement in the quality and detail of fall incident reports.
		The literature evaluated accuracy primarily from a system performance perspective, focusing on how well predictive models identify fall risk.
		These responses indicate that nurses primarily relied on their clinical judgment rather than the CDSS's formal recommendations when making decisions.
		The literature acknowledged that nurses' feedback was used to refine tools.
		The nurses reported that the transition from paper to an EMR impacted their psychological well-being and ability to make decisions, perform tasks, and provide patient care.

Colour coding key:

Systematic review	Systems analysis	Qualitative study

6.8 Summary

This chapter integrated findings from the three studies: systematic review, systems analysis, and qualitative study, using a convergent mixed-method design to understand the effects of implementing an EMR with an embedded CDSS for fall prevention.

Structure findings showed that system design and usability, staffing, workforce capacity, training, and communication are foundational to EMR/CDSS implementation. The systematic review identified that EMRs/CDSS introduced new functionalities, such as structured nursing documentation, alerts, and tools that support individualised care and real-time team communication. However, systems analysis revealed challenges with the digital system implementation, including duplicate admission records and gaps in the admission data, demonstrating the complexity in the transition from a patient management system to an EMR with CDSS. The nurses' perceptions further highlighted inconsistent practices across wards during the system implementation, creating confusion with workflows and raising concerns about patient safety. Staffing and workforce capacity emerged across all data sources as critical to fall prevention, with nurses reporting staff shortages, limited timely care and system analysis, and increased fall risk conceptually aligned with trends observed in the systems analysis and systematic review. Training was identified as essential but was delivered inconsistently, with nurses reporting varied experiences that affected their confidence, efficiency, and care delivery.

Process findings focused on how EMRs and CDSS interacted with the clinical workflow. The systematic review noted that the CDSS is used as a support tool rather than a replacement for clinical judgment. The systematic review also reported that CDSS provided automated recommendations, alerts and evidence-based support to the nurses' decision-making. Nurses similarly described the CDSS as a guide or checklist that supported, but did not replace, care decisions. Communication and care coordination were enhanced through structured tools and increased awareness of patient risk. However, some nurses perceived the system as a tick-box exercise and relied more on personal judgment. Monitoring and reporting processes varied; the systematic review identified a range of approaches, from national benchmarking systems to the use of ward dashboards. The system analysis used admission, fall, and

staff data to demonstrate how reporting processes shaped fall documentation and the effects of the digital system implementation on workflow.

Outcome captured patient safety, system impact, and human factors. All data sources agreed that falls continued to occur despite access to an EMR with a CDSS. The systematic review emphasised fall severity, noting that a proportion of inpatient falls resulted in injury, particularly when unassisted. The systems review identified 114 falls, with an increase in reported falls following the implementation of the current system. The majority of the falls reported in the current system were SAC 4, categorised as no harm or a near miss. The nurses described improvements in the quality and detail of fall reporting with the current system and demonstrated how clinical assessment and rapid response supported patient safety following falls. However, nurses also identified inconsistencies between how the system classified a fall and reality, highlighting a misalignment between the system's structure and clinical reality. Nurses' satisfaction emerged as a significant human factor influencing system effectiveness. The systematic review reported that involving nurses in system design and refinement improved usability and integration. In contrast, the nurses in this study were end users rather than contributors, describing the implementation as disruptive and challenging. Emotional responses included anxiety, reduced confidence, and reliance on workarounds, although some nurses valued improved access to the patient notes over time. Overall, the integrated findings demonstrated that EMR with CDSS implementation influences fall prevention through complex interactions among system design, clinical processes, and human integration.

Table 32 details a summary of the study's integrated findings.

Table 32. Summary of integrated findings.

Component	Integrated theme	Summary of integrated findings
Structure	System design and usability	• Limited literature (see Cho et al., 2021); initial reactions were neutral or slightly negative, with negative responses decreasing as nurses gained more experience. • Difficulty in navigating the current system's user interface, which involved many steps, was perceived as unnecessarily complex. • Some nurses appreciated the visible icon, which helped identify patients at risk. • Laptops, with limited screen size, were compact and easy to manoeuvre, whereas workstations on wheels were bulky and heavy, highlighting the importance of selecting the appropriate hardware. • Improved workflows: improvements in fall documentation and risk assessment, including features such as nursing documentation tools, fall-monitoring modules, and daily alerts. • Nurses reported in time the new electronic medical record was intuitive. • Digital integration can occur at various levels and integrating technology into clinical practice, provides support functionalities within the system such as nurses receiving risk predictions and therefore provide proactive patient care • The systems analysis revealed practical limitations, duplicate records and missing data. • Sequential patient admission: mismatch with system structure and organisational process, affected quality of data. • Nurses reported the use of hybrid systems (paper and electronic across wards caused confusion.
	Staffing and workforce capacity	• Literature reinforced the importance of adequate staffing for delivering quality healthcare. • Staffing variance was not statistically significant in either the unadjusted or the adjusted analyses, suggesting that, as measured, this independent variable was not associated with fall risk. • Nurses reported staff shortages limited their capacity to deliver timely care.
	Staff training	• The literature emphasises staff training as a critical part of implementing a new system or tool. • The ability for nurses to provide individualised care and supported real-time communications among the team. • The systematic review also stresses the need to train nurses on new electronic tools during EHR implementation to reduce adverse events. • Training is essential; however, inconsistencies affected the consistency of fall prevention management.

Component	Integrated theme	Summary of integrated findings
Process	Role and function of the CDSS	• CDSS as a tool that offers nurses automated action recommendations in their daily routines, triggers patient safety alerts, assists nurses in customising interventions based on individual risk assessments, and delivers decision support and communication at the bedside. • CDSS as a checklist for thoroughness, a helpful reminder, a baseline, a guide, and a reference tool, it also highlights key patient information, offering a comprehensive view of their risk level • EBP standards of care • Nurses used CDSS information to inform environmental changes and interventions for higher-risk patients. • Literature reports the CDSS as effective and evidence-based, associated with improved outcomes • Nurses express variable views of the current system, with some trusting it as a helpful guide and others seeing it as a tick-box exercise, preferring to rely on their own clinical judgment. • Emphasises that CDSS tools, such as the FPTK, support bedside communication and structured care planning. • CDSS raises awareness of patient risk before entering the room, thereby aiding communication and planning
	Monitoring and reporting	• Literature acknowledges that monitoring and reporting are crucial for quality and safety, but the levels of automation and their integration into organisations differed. • The systems descriptive analysis identified differences in fall severity and reporting between Paywiz (previous) and Safety Hub (current). The free-text entries in Safety Hub improved fall incident reporting by capturing context missed in the structured fields of the previous system. This free-text function also allowed nurses to input how they used their clinical judgment to assess injuries and collaborate with other members of the multidisciplinary team to manage the patient. The data further highlighted environmental factors, giving a better understanding of what may have contributed to the fall. The free-text entries in Safety Hub improved fall incident reporting by capturing context missed in the structured fields of the previous system and highlighted a range of approaches to how the nurses responded to inpatient falls. • Discrepancies between severity classifications and clinical descriptions in Safety Hub raised concerns about the reliability of fall data. Two of the falls were classified as major; however, the free-text documentation suggested otherwise. • Variations in admission records highlighted the effects of digital integration on hospital workflow process. Identifying duplicate admissions which were categorised into three groups: duplicates, split and sequential patient admissions records and managed during the data cleaning

Component	Integrated theme	Summary of integrated findings
Outcomes	Effectiveness of electronic systems on incidence and severity of falls	• The literature emphasises severity, noting that approximately 10% of inpatient falls result in injury, with unassisted falls associated with more severe injuries • Falls data recorded 114 falls across three time periods, with 52 falls in the previous system (35.5 months) and 62(12 months) in the current system, and the severity remained low. No SAC 1 (severe) incidents were reported, and only three SAC 2 (major) incidents were reported. SAC 4 (minor) events remained the most common category across both time periods and calendar years. • The specialty of Orthopaedics remained significantly associated with a higher odds of a fall even after adjustment (OR 2.08, CI 1.11-3.89). Similarly, the increased risk in time period three persisted after adjustment (OR 2.48, CI 1.51-4.07), indicating that both independent variables, specialty and time period, had a strong independent effect on fall risk. • Nurses mainly relied on their clinical judgment rather than a formal process within the CDSS to support their clinical decision-making. • These studies indicate that although electronic health systems can affect fall reporting and potentially reduce some incidents, their overall impact remains inconsistent and falls still happen at clinically significant rates. • Increased number of fall reported over a shorter period of time. This could suggest improved staff incident reporting in the new EMR. • Nurses dismissed the CDSS's preventative measures and questioned their accuracy. Whilst the nurses acknowledged that the fall-preventive actions were available, they admitted to not engaging them. These insights suggested tension between the system design and clinical relevance.
	Nurses' satisfaction and compliance	• The nurses described the transition from the previous fall incident management system, Paywiz, to the current incident management system, Safety Hub, as a notable improvement in the quality and detail of fall incident reports. • Several studies reported that when nurses are involved in design and refinement, systems are more usable and better integrated into care. • The nurses in this study were end users, not contributors to design and refinement. • The literature evaluates accuracy primarily from a system performance perspective, focusing on how well predictive models identify fall risk. • These responses indicate that nurses primarily relied on their clinical judgment rather than the CDSS's formal recommendations when making decisions. • The literature acknowledges that nurses' feedback was used to refine tools • The nurses reported that the transition from paper to an EMR impacted their psychological well-being and ability to make decisions, perform tasks, and provide patient care.

Note. CDSS =Clinical decision support system; CI = Confidence interval; EBP = Evidence-based practice; EHR = Electronic health record; EMR = Electronic medical record; FPTK = Fall Prevention Tool Kit; OR = Odds ratio; SAC = Severity assessment code.

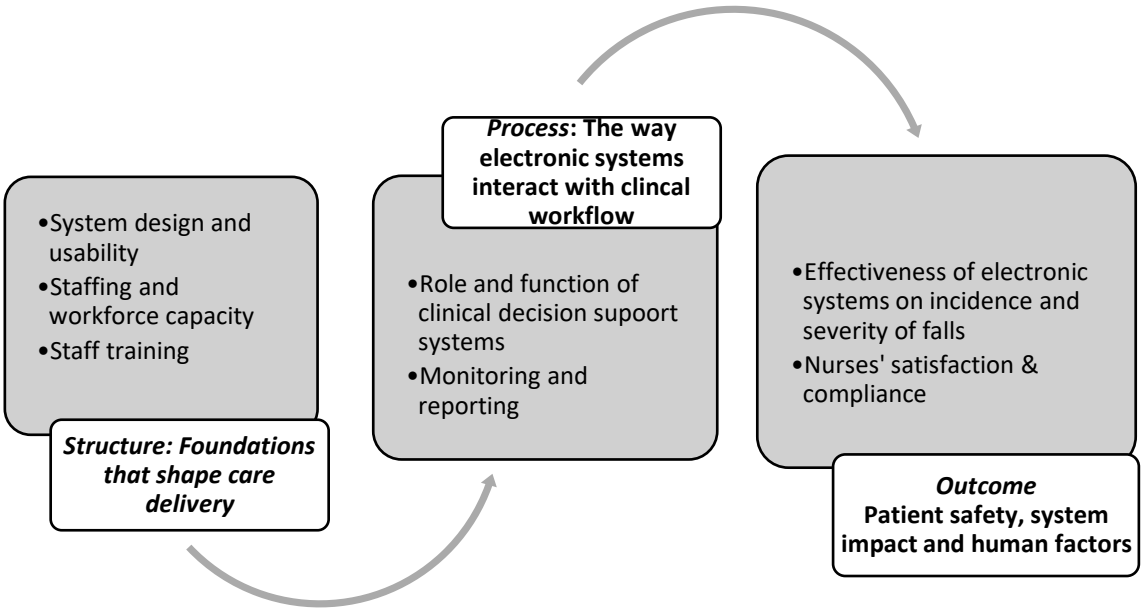
Chapter 7 Discussion

7.1 Introduction

This chapter will synthesise and interpret the thesis findings and explain their significance by connecting them to the existing literature, theories, and real-world applications. It goes beyond stating the results to argue for their importance, identify their contributions to knowledge, acknowledge their limitations, and make recommendations for future research.

While the Donabedian Framework was originally developed within traditional healthcare delivery systems, this study applies it in a contemporary digital health context, extending the operational interpretation of structure, process, and outcome to include socio-technical and organisational dimensions. Figure 12 details the adapted framework.

Figure 12. Electronic medical record/Clinical decision support system revised integrated model.



Note. Adapted from "The quality of care: How can it be assessed?" by A. Donabedian, 1988, *JAMA: The Journal of the American Medical Association*, *260*(12), p. 1743. https://doi.org/10.1001/jama.1988.03410120089033

7.2 Structure

This section critically discusses the findings on the structural component and includes the integrated themes, system design and usability, staffing and workforce capacity, and staff training.

7.2.1 System design and usability

This study highlighted system design and usability as key structural factors affecting nurses' interactions with the new EMR and CDSS, influencing care processes and patient safety outcomes. Although the implementation of improved CDSS functionality was intended to support fall prevention, the results showed that technology adoption alone was not enough to enhance safety outcomes if system design did not align well with nursing workflow.

From a structural perspective, features such as a visible fall-risk icon supported nurses' ability to identify patients at risk. However, overall perceptions of the systems during early implementation remained neutral due to usability issues. In particular, the requirement to take multiple steps to access patient information disrupted established workflows and increased workload at a time when nurses were still developing trust in the system. These findings are significant given that nurses are reported to spend between 28.3% to 40% of each shift using electronic systems (McBride et al., 2023; Roumeliotis et al., 2018), yet such systems are often designed and implemented with limited consideration of clinical workflow, context, or environment (Kellogg et al., 2017).

In line with the Donabedian Framework, these structural limitations influenced care processes. The complex interface fragmented access to patient information, increased the need for workarounds, and disrupted nursing workflows. As a result, nurses developed workaround behaviours to manage inefficiencies, aligning with evidence that usability issues in electronic systems can lead to adaptations that may compromise safety (Kellogg et al., 2017). Although the system became more user-friendly over time, early design shortcomings introduced workflow inconsistencies that risk becoming normalised, with potential implications for data quality and long-term system use (Fraczkowski et al., 2020; Olakotan et al., 2025).

These process disruptions had clear implications for outcomes, particularly patient safety and data integrity. Poorly designed, fragmented interfaces have been shown to increase task-switching, fragment information across electronic health systems, and undermine workflow continuity, thereby increasing the risk of error (Cahill et al., 2025; Olakotan et al., 2025). In contrast, systems that incorporate customisation, streamlined data entry, and alignment with clinical workflow are associated with improved usability and safer practice (Cahill et al., 2025; Schwappach et al., 2025). Nurses' preference for laptops over bulky wheeled workstations further reinforces that hardware selection, as a structural component, directly influences workflow efficiency and bedside documentation practices (Ozkaynak et al., 2025).

From a human factor perspective, the workaround behaviours reported in this study indicate a misalignment between system design and established workflows, increasing risk and reducing efficiency (Carayon & Hoonakker, 2019). Importantly, these findings suggest that patient safety risks associated with EMR and CDSS implementation may be embedded within system design itself, rather than arising from nurses' behaviour and/or insufficient training.

This study contributes to an underrepresented area of the NZ literature by exploring how electronic health systems affect nurses' work, decision-making, and experiences during implementation. Consistent with the Donabedian Framework, the findings demonstrate how structural characteristics of electronic health systems shape care processes and ultimately influence outcomes (Donabedian, 1988). Difficulties with EMR and CDSS adoption were therefore not solely transitional or training-related but reflected broader issues of usability and organisational readiness.

These findings support the use of user-centred design approaches such as the Technology Acceptance Model, which emphasises understanding of end users' cognitive needs, capabilities, and work environments during system development (Ratwani et al., 2015; Tsarfati & Cojocaru, 2022). When combined with organisational readiness assessments, such approaches can facilitate the integration of CDSS functionality into everyday workflows, supporting improved data quality and fall-related clinical decision-making. Overall, this study adds to the growing evidence

supporting co-design and usability standards as essential structural prerequisites for implementing HIT.

7.2.2 Staffing and workforce capacity

Across all three studies in this thesis, staffing levels emerged as an important structural factor influencing patient safety. The literature demonstrates that adequate nurse staffing is essential for safe, high-quality care, with extensive evidence linking nurse-to-patient ratios to patient outcomes, including falls (Aiken et al., 2018; Griffiths et al., 2018; Kim et al., 2018). Within the Donabedian Framework, staffing represents a core structural element that shapes care processes and, in turn, patient safety outcomes (Donabedian, 1988). Consistent with this literature, nurses in study 3 reported staff shortages limited their ability to provide timely care and supervision, particularly for patients at risk of falling. These findings reinforced concerns that reduced staffing can create conditions that compromise patient safety (Twigg et al., 2016).

In contrast, study 2, the systems analysis revealed staffing variance was not a statistically significant predictor of fall risk. Rather than contradicting existing evidence, these findings highlight important data and contextual limitations, including the absence of key variables such as patient acuity, age, and comorbidities, and how staffing levels interacted with these factors. Without accounting for such contextual influences, the relationship between staffing levels and falls cannot be reliably interpreted. This supports existing literature indicating that falls are influenced by multiple factors, including patient characteristics, environmental conditions, and care processes rather than staffing alone (Oliver et al., 2010).

From a complexity perspective, healthcare outcomes emerge from dynamic interactions among system structures, staff behaviours, workflows, and clinical judgment rather than from single variables operating independently (Greenhalgh & Papoutsi, 2018; Plsek & Greenhalgh, 2001). The significance of these findings lies in the implications for healthcare policy and practice management. While staffing ratios are a key safety measure, this study shows that increasing staff levels alone may not be enough to lower fall rates unless accompanied by process improvements, such as targeted training and effective use of decision support tools.

7.2.3 Staff training

Training emerged as an important influence on how nurses engaged with the EMR and its embedded CDSS, with variability in training quality directly influencing confidence, competence, and system use. This aligns with evidence showing that the quality of implementation training affects how electronic health systems and CDSS tools are used and the extent to which they support safe clinical practice (Chen et al., 2023; Wilks, 2025). The wider literature also highlights that comprehensive and ongoing training supports staff competence and confidence when adopting new technologies (Quinn et al., 2019). The findings from this study align with the qualitative study, where nurses described the variability in the training they received, which contributed to their confusion and undermined their confidence. The systematic review also stresses the need to train nurses on new electronic tools during EHR implementation to reduce adverse events (Dowding et al., 2012; Furukawa et al., 2011; Walker-Czyz, 2016).

Nurses in study 3 identified limitations in training models that prioritised system functionality over integration with clinical workflows. This also highlights inherent limitations in CDSS design, as systems well aligned with clinical workflows tend to require less training for effective use. Such training, often conducted in classrooms or computer labs by trainers who may lack clinical backgrounds, can create a disconnect between what is taught and the realities of daily patient care (Olley & Hozynka, 2023). This misalignment can lead to uncertainty and lower confidence among nurses when applying system functions in practice, as reported in study 3. Evidence from alternative training methods suggests potential solutions. For example, Smailes et al. (2019) found that shifting from classroom-based training to e-learning helped experienced nurses advance more quickly and provided less experienced users with more time, thereby improving learner satisfaction and training efficiency. Additionally, ongoing training, including annual updates and continuous competency assessments, is a key care process that supports system use and skill maintenance over time (Quinn et al., 2019). These findings demonstrate that single, functionality-focused training sessions are inadequate for fostering clinically integrated use of electronic health systems.

The findings highlighted the need for the private hospital to invest in structured, ongoing training to support the scale of the investment. Simulation-based training, task simulation, and computer-generated scenarios have been shown to fill gaps in

clinical learning (Koukourikos et al., 2021) and are already used in the private hospital for emergency training. Mentoring and coaching models further support learning, with digital nurse champions providing peer support and reducing stress among nurses who regularly access this resource (Burgess & Honey, 2022). However, such training and support activities need time away from clinical duties, which can add extra pressure on workloads and highlight the importance of adequate staffing to maintain these process-level supports. In contrast, nurses in this study reported relying heavily on informal peer support, which, while common, was problematic and revealed gaps in structured training and support mechanisms, especially considering existing workloads.

These findings carry important implications for practice and policy without sustained, high-quality training, even well-designed systems may fail to deliver intended improvements in safety and outcomes. The result reinforces that digital implementation is not just a technical challenge but a socio-technical process that requires ongoing engagement, feedback, and continuous adjustments.

7.2.4 Structural Summary

The findings at the structural level demonstrate that system design, staffing, and training are interconnected factors that collectively influence care processes and patient outcomes. Despite supportive features (such as visible fall risk icons), usability limitations, disrupted workflow and increased workload, especially considering that nurses spend a significant portion of their shift (28.3-40%) using electronic systems that are poorly aligned with clinical workflow and context (Kellogg et al., 2017; McBride et al., 2023; Roumeliotis et al., 2018). In line with existing research, staff levels limited the nurses' ability to deliver timely care and supervision. These findings underscore concerns that reduced staffing may create conditions that jeopardise patient safety (Twigg et al., 2016).

Staff training was a vital structural factor affecting nurses' confidence, competence, and efficient use of the EMR and CDSS. Consistent with existing research, variability in training quality impaired system use, whereas comprehensive, ongoing, and workflow-integrated training enhanced confidence and competence (Chen et al., 2023; Quinn et al., 2019; Wilks, 2025). From a complexity viewpoint, these findings showed that

patient safety outcomes emerge from interactions among multiple system components rather than a single intervention (Greenhalgh & Papoutsi, 2018; Plsek & Greenhalgh, 2001). Hence, lasting improvements in fall prevention require coordinated efforts across system design, staffing, and related areas training.

7.3 Process

This section reviews the findings on the process component and includes the integrated themes, the role and function of CDSS, and the monitoring and reporting processes.

7.3.1 Role and function of the clinical decision support system

The CDSS integrated into the EMR supported nurses by providing evidence-based fall-prevention recommendations and patient safety alerts tailored to each patient's risk assessment. Nurses reported that the CDSS functioned as both a checklist and a reference tool, intended to complement rather than replace their clinical judgment. This aligns with evidence suggesting that CDSS can improve adherence to evidence-based care standards and enhance patient safety when embedded in workflows by offering real-time risk assessments and prevention advice (Mebrahtu et al., 2021; Sutton et al., 2020). Nurses also noted the CDSS improved their situational awareness and supported decision-making related to the patient environment, especially for higher-risk individuals. These findings indicate that while a CDSS can enhance cognitive clinical decision-making and act in a support role, its effectiveness largely depends on how well it is integrated into organisational workflows.

The CDSS also improved system-level coordination by strengthening communication and shared understanding of patient risk. Nurses reported using the CDSS to guide environmental adjustments and interventions for higher-risk patients, noting that having this information before entering the room was helpful. This approach enabled clearer, proactive care planning and underscored the importance of communication and teamwork for patient safety (Falade et al., 2024). These functions align with findings from the systematic review, which indicate CDSS tools can enhance bedside communication, foster team collaboration, and standardise care processes (Dykes et al., 2010; Walker-Czyz, 2016). Additionally, the broader literature shows that when

integrated with EMRs, CDSS can support evidence-based care planning and coordinated efforts across multidisciplinary teams (Laka et al., 2022).

The thesis findings reveal the effectiveness of CDSS is shaped by sociotechnological factors rather than solely by system design. While CDSS support clinical judgment and team coordination, the literature warns that risks such as alert fatigue can diminish its effectiveness if alerts are too frequent or poorly handled (Amaral & Cuthbertson, 2024). There is also concern that overreliance on automated prompts might lead to the abdication of responsibility, especially as CDSS evolve into AI-driven predictive models (Rajendrakumar, 2025). The FITT framework provides valuable insights into successful adoption, emphasising the need for alignment between user needs, task requirements, and system features, as noted by Zhai et al. (2022).

The findings also emphasise that CDSS effectiveness depends not only on technical ability but on how well the system integrates with nursing workflows (Mebrahtu et al., 2021). These tools are increasingly applied in risk management, diagnostics, and medication management (Sutton et al., 2020). New theories propose a shift towards AI-powered decision support systems that utilise predictive analytics and integrated intelligence data to enable more proactive care planning (Rajendrakumar, 2025). Notably, how well process-level functions are realised relies on the structural design of the CDSS, with well-aligned systems being more capable of supporting decision making.

7.3.2 Monitoring and reporting

The systems analysis study transformed numerical data into descriptive summaries that facilitated comparisons, supporting the examination of falls as an adverse event alongside the systematic review and wider literature. Monitoring and reporting adverse events are important for healthcare organisations because it provides valuable insights into the quality of care and potential areas for improvement (Vikan et al., 2023). The systems analysis reported 114 falls over 4 years and noted a large increase in reported falls after the implementation of the new incident management system. This is in line with the broader literature, which reports electronic systems have been found to improve productivity, documentation, and the quality of care, but have also been associated with productivity loss, erroneous data, and poor system usability

(Kruse et al., 2018; Priestman et al., 2018). These mixed findings about outcomes are also accompanied by user dissatisfaction. To understand and, ultimately, counteract adverse outcomes and dissatisfaction, more research is needed on the contemporary implementation of electronic systems (Morten et al., 2025).

Incident reporting is widely recognised as a mechanism for monitoring adverse events in healthcare settings (Scott et al., 2024). However, incident reporting is valuable not just for addressing individual events but also for detecting patterns and trends within populations over time, since isolated adverse events may be context-specific rather than indicative of systemic issues (Scott et al., 2024; Stavropoulou et al., 2015). The systematic review in this study showed that hospitals use a range of monitoring approaches to support fall prevention and detection, including embedding fall-risk scores into the EMR to enhance team awareness (Carroll et al., 2022), implementing educational programmes and chart reviews to address underreporting (Cho et al., 2021), and adopting predictive systems that communicate real-time risk (Ye et al., 2020). Across these reviewed studies, monitoring and reporting adverse events to promote patient safety is seen as a long-term endeavour, where success is measured by strengthening the organisation’s safety culture rather than by making frequent changes to work processes in response to individual adverse events (Niv & Tal, 2023).

7.3.3 Process summary

The process-level findings showed that although the EMR with embedded CDSS supported clinical decision-making, monitoring, and reporting, its effectiveness depended on structural factors like the system's design. The CDSS within the EMR supported nurses with individualised patient safety alerts, reinforcing existing evidence that CDSS can enhance adherence to evidence-based care standards and patient safety when integrated into workflows (Mebrahtu et al., 2021; Sutton et al 2020).

Monitoring and reporting are vital for healthcare organisations because they provide valuable insights into the quality of care and areas for improvement (Vikan et al., 2023). After implementing electronic systems, findings and the literature report enhance productivity, documentation, and care quality, but they have also been linked to productivity loss, incorrect data, and poor system usability (Kruse et al., 2018; Priestman et al., 2018).

7.4 Outcomes

This section reviews the findings related to the outcome component, including the integrated themes, effectiveness of electronic systems on the incidence and severity of falls, as well as nurse satisfaction and compliance.

7.4.1 Effectiveness of electronic systems on the incidence and severity of falls

Falls remain a safety concern in hospitals, with literature indicating approximately 10% of inpatient falls result in injury and unassisted falls tend to have more serious outcomes (Carroll et al., 2022; Vikan et al., 2023). Since the introduction of the new incident management system, Safety Hub, 62 falls were reported in just 12 months, compared with 52 falls over 35.5 months with the previous system, Paywiz. This increase may reflect better staff reporting rather than an actual rise in falls. The literature shows that improving reporting systems and raising awareness of adverse events often lead to a higher reported incidence of such events (Ferorelli et al., 2020; Jung et al., 2023). It is important to note that management needs to be aware that an 'improved' incident management system and increased awareness can result in more reported incidents, but this may not indicate increased risk.

Dykes et al. (2020) showed reductions in falls when a patient-centred fall-prevention toolkit was implemented with strong workflow integration. My findings differ because the EMR/CDSS in this study improved documentation and communication but did not reduce fall rates. This aligns with Morris et al. (2022), who found that risk-assessment tools alone do not reliably reduce falls. Kim et al. (2022) also showed limited predictive validity of common fall-risk tools. Collectively, these findings indicate that although digital systems can improve the consistency and quality of fall-risk documentation, improvements in clinical outcomes are unlikely to occur unless implementation is accompanied by broader practice changes, effective workflow integration, and interventions that influence workforce behaviour.

The severity of reported falls remained low, with no SAC 1 (severe) incidents and only three SAC 2 (major) events. SAC 4 (minor) events were the most frequently recorded across both systems and time periods. However, the systems analysis identified misclassification in the new system, with several falls coded as minor despite narrative descriptions indicating higher severity. This suggests the potential for over-reporting of

low-severity events or inaccurate categorisation of fall severity. These findings reinforce that electronic health systems influence reporting practices more than they reduce falls, and they highlight the need for ongoing staff training, routine monitoring, and structured feedback processes to ensure accurate and reliable incident reporting (Quinn et al., 2019).

The association between specialty and fall risk, especially in orthopaedics (OR 2.08, CI 1.11-3.89), highlights that patient-specific and contextual factors remain key predictors of falls. The higher risk observed in T3 (OR 2.48, CI 1.51-4.07) may be attributable to changes in the patient population and care environment rather than to the time period alone. During this time, there was a greater proportion of older patients, which is a known fall risk factor. This aligns with multifactor fall prevention models, which emphasise patient characteristics, environment, and care processes over single interventions (Mulkey et al., 2023). During the study period from January 2019 to December 2022, patients aged 65 and older accounted for 32% of all hospital admissions; however, the falls data did not include the age of patients who had fallen, so this characteristic could not be examined.

For hospitals, these findings emphasise the need to extend interventions beyond the implementation of EMRs and CDSS, as this technology alone cannot address complex, multifactorial safety issues such as inpatient falls (Abell et al., 2023; Rahmadani et al., 2025). From a hospital management perspective, a rise in reported falls after implementing EMR and CDSS might initially seem negative; however, evidence suggests these increases may reflect improved accessibility and usability of reporting rather than an actual rise in incident rates (Pak et al., 2025; Scott et al., 2024). This study contributes to the body of knowledge by demonstrating that technology adoption alone does not eliminate falls.

7.4.2 Nurses' satisfaction and compliance

Nurses perceived the transition from the previous to the current incident management systems as a notable improvement in the quality and detail of fall incident reports. This supports evidence that when human interaction and systems align, electronic systems can enhance data accuracy and usability (Carayon & Hoonakker, 2019). For the hospital, these findings emphasise how the EMR can facilitate ongoing quality

improvements, but this must be complemented with training, co-design, and multidisciplinary involvement.

Several studies in the systematic review showed that involving nurses in the design and refinement of electronic systems improves usability and supports better integration in care processes. In contrast, the qualitative study revealed that nurses acted as end users rather than contributors to the development of the private hospital system, limiting the extent to which the system aligned with their workflow. It is recognised that nurses play a crucial role in the design of electronic health systems, serving as primary users who enhance workflow efficiency and safety (Smyth et al., 2024).

The design of health information technology is a multidisciplinary field that incorporates clinical expertise alongside technical and design knowledge, helping ensure that system design is human-centred (Van Velsen et al., 2022). When nurses are involved in the design and refinement processes, systems are more likely to reflect the realities of patient care and support their clinical decision-making and potentially patient outcomes (Van Velsen et al., 2022). Therefore, health facilities should establish policies and procedures that assist nurses in recognising usability issues, thereby aiding system improvements and strengthening the foundational aspects of EMR, potentially minimising negative impacts on nursing practice (Smyth et al., 2024). To further inform this, Smyth et al. (2024) advocate for ethnographic research to better understand how EMR design influences nurse productivity, well-being, job satisfaction, and patient safety concerns.

An important consideration when interpreting Study 2 findings is that the implementation of Safety Hub may have altered reporting behaviour rather than patient fall incidence. The number of recorded falls increased substantially in T3, and the analyses indicated significantly higher odds of reporting a fall during this period. However, descriptive analysis and review of free-text incident narratives suggest that the reporting environment changed simultaneously.

Unlike PayWiz, Safety Hub enabled nurses to provide detailed narrative descriptions of fall circumstances, assessments, and interventions. These additional reporting capabilities likely improved documentation completeness and may have increased

staff willingness or ability to record events that were previously undocumented or recorded with less detail. Consequently, some proportion of the increase in T3 may reflect improved ascertainment rather than a true increase in falls.

Further support for this interpretation comes from inconsistencies identified between severity classifications and free-text descriptions. These findings indicate that incident classification remained dependent on user judgement and system processes, highlighting the complexity of interpreting temporal changes in recorded incident rates following implementation of a new reporting platform.

7.4.3 Outcome summary

These findings suggest that electronic health systems enhance the quality and completeness of fall reporting, improve nurses' satisfaction with documentation processes, and support system usability; however, they do not inherently reduce inpatient falls. Although significantly more falls were recorded after Safety Hub implementation, a qualitative review of the free-text incident reports indicated substantial improvements in documentation detail and reporting completeness. Consequently, the increase in recorded falls should be interpreted cautiously, as it may reflect improved ascertainment and reporting rather than a true increase in patient fall incidence. The findings therefore suggest that the electronic systems influenced reporting practices more strongly than fall outcomes.

The results differ from those of Dykes et al. (2020), who demonstrated reductions in falls through a patient-centred fall-prevention toolkit closely integrated into clinical workflows and supported by comprehensive implementation processes. Instead, the findings align more closely with evidence that risk-assessment and documentation tools alone do not reliably reduce falls unless accompanied by broader behavioural, organisational, and workflow changes (Kim et al., 2022; Morris et al., 2022). The higher fall risk observed among orthopaedic patients and during T3 further suggests that patient characteristics, clinical context, and care environment remain important determinants of falls, consistent with multifactorial fall-prevention models (Mulkey et al., 2023).

Effective system design should therefore extend beyond technological implementation to include a multidisciplinary, human-centred approach that integrates clinical expertise with technical and design knowledge (Van Velsen et al., 2022). Involving nurses in system design, implementation, and refinement increases the likelihood that electronic systems will reflect real-world clinical practice, support decision-making, and contribute to meaningful quality improvement initiatives (Smyth et al., 2024).

7.5 Strengths and limitations

This study used a convergent mixed-methods approach comprising three studies: a systematic review, a systems analysis and a qualitative study. While this approach provided a thorough overview, it is important to acknowledge the associated strengths and limitations.

7.5.1 Systematic review (Study 1)

This study identified eight articles. Although there is no fixed minimum number of studies for a systematic review, a small sample can limit the certainty and generalisability of the findings, reduce the ability to assess heterogeneity, and increase vulnerability to small-study effects and publication bias. (Brignardello-Petersen & Guyatt, 2025). Despite the use of a comprehensive and systematic search strategy, when few studies meet the inclusion criteria, conclusions may be tentative and should be interpreted with caution, as they are derived from a limited body of evidence (Owens, 2021). Nonetheless, these findings contribute to current knowledge and help identify a research gap on the effects of electronic health systems on facility management and nurses' perspectives.

Restricting the search to English-language studies can introduce language and publication bias, potentially excluding relevant research published in other languages (Pieper & Puljak, 2020). The chosen date range, from January 1, 2010, to June 22, 2025, may have missed earlier foundational studies or the latest developments in electronic health systems (Stokes et al., 2022). Additionally, focusing only on nurses' perceptions limited the scope and excluded insights from other healthcare professionals. Although four databases (CINAHL, MEDLINE, Scopus, and PsycINFO) were searched, relevant studies indexed in other databases or published as grey literature, such as government reports, policy documents, dissertations, and

organisational evaluations, may not have been captured, limiting the completeness of the evidence base (Adams et al., 2016). Excluding grey literature can be seen as a limitation, indicating that while the review offers valuable insights, the findings may not fully capture the extent of existing evidence and should, with this in mind, be interpreted accordingly. (Mahood et al., 2014).

7.5.2 Systems analysis (Study 2)

A key strength of this study was access to routinely collected operational data spanning four years, allowing for analysis of fall reporting patterns before and after the implementation of a new EMR with embedded CDSS. The use of real-world administration and clinical data is valued for assessing healthcare interventions and quality improvement initiatives, as it mirrors routine practice and tracks trends over time (Clarke et al., 2019).

During the study, the analyst was unable to extract certain data, which raised uncertainty about whether this was due to system limitations, such as incomplete admission data (PiMS and Track Care) and incomplete incident management systems (PayWiz and Safety Hub), or a lack of technical skill or capacity of the analyst, since the analyst was the sole data specialist within the private hospital. This limitation, regardless of its cause, reduced the depth of the statistical analysis because patient-level risk factors could not be integrated into inferential models. It also potentially affects the quality of hospital reporting and monitoring if the analyst cannot extract these key pieces of information. A known limitation of studies is the difficulty accessing or reliably extracting clinically relevant variables due to constraints imposed by system design and original data capture purposes (Emerson et al., 2024). This may also limit the generalisability of the findings to other healthcare settings with more advanced electronic health systems, as differences in system maturity, data integration, and completeness can influence both analytic capability and the quality of management reporting derived from these systems (Lewis et al., 2023; Sauer et al., 2022), despite the robustness of the results and the demonstrated influence of electronic systems on reporting quality.

Falls were nearly three times more likely to be documented during T3. However, interpretation of this finding should be cautious because implementation of Safety

Hub was accompanied by substantial changes in incident documentation processes. The new systems enabled richer free-text reporting and may have increased the completeness of incident capture. Consequently, the observed increase in recorded falls may reflect improved detection and reporting, a true increase in fall incidence, or a combination of both factors.

Another limitation was the absence of patient ID in the fall incident datasets, and subsequently, no way of identifying ethnicity. It was not possible to determine whether this gap reflected a system-level omission, such as ethnicity not being captured, or whether the analyst was unable to extract the relevant fields due to technical constraints. This uncertainty limited the researchers' capacity to analyse fall outcomes among Māori patients and hindered the development of equity-focused statistical modelling consistent with Te Tiriti o Waitangi principles. The Ministry of Health's Te Tiriti o Waitangi framework recognises Treaty obligations as a foundation for achieving Māori health aspirations and equity for Māori (Ministry of Health, 2024).

The retrospective design also restricts control over data quality and completeness. Key confounders, such as gender, time of day, shift when the fall occurred, and patient identifiers related to reported falls, were not fully accounted for, which reduces the study's ability to thoroughly adjust for individual patient risk factors. This is significant given the documented changes in patient demographics over the years studied, especially known risk factors such as age and gender. This was partly mitigated by including specialty in the inferential models.

While nurses' 'free text' responses regarding fall reporting were examined descriptively, offering valuable insights into post-implementation fall reporting processes, comparable information for the pre-implementation period was not available for comparison.

Additionally, since the research was carried out in a single hospital, its findings may not be generalisable to other settings with different workflows or electronic health systems.

7.5.3 Qualitative study (Study 3)

Although this study only involved interviews with eight nurses, their extensive experience provided valuable insights into implementing the new EMR and using CDSS for fall-risk assessment. While the small sample size may limit broader applicability, the detailed accounts from participants provided rich qualitative data that might be difficult to obtain from a larger group. It is also important to consider that those who opted to participate may have been particularly motivated, perhaps due to personal experience, which could lead to self-selection bias. Despite this, their detailed feedback enhanced the study's credibility and provided a strong basis for understanding how EMR implementation affected nurses.

The qualitative component of this study relied exclusively on face-to-face interviews with nurses, excluding perspectives from other stakeholders, such as doctors or IT personnel, which may have provided a more holistic understanding of the impact of implementing the system. The hybrid inductive/deductive approach, while methodologically sound, carries the risk of researcher bias in theme selection and interpretation. Additionally, the retrospective nature of the interviews raises the possibility of biased recall, as nurses may reconstruct their experiences with hindsight.

Finally, the findings may have limited transferability to healthcare settings that use different electronic systems, organisational structures, or patient populations. As this study was conducted within a single New Zealand private hospital, the specific findings relating to the EMR, CDSS, workflows, and reporting practices should not be assumed to apply directly to other organisations. However, the underlying mechanisms identified in this thesis, particularly the influence of system usability, workflow integration, reporting processes, training, and user engagement on clinical practice, are likely to be relevant across a wide range of healthcare settings. What may differ is how these mechanisms are expressed and experienced within different organisational contexts.

Private hospitals typically operate in more controlled, predictable environments, with planned admissions, lower patient acuity, and comparatively stable workflows. In contrast, public hospitals often manage higher patient volumes, higher acuity, more complex care pathways, and greater organisational pressures. These contextual

differences may influence how electronic systems are implemented, adopted, and used in practice, as well as their impact on patient safety outcomes. Therefore, the transferability of this research lies less in the specific fall rates or system configurations observed and more in the broader conclusion that the effectiveness of EMRs and CDSS depends on the interaction among technology, users, organisational processes, and the clinical environment in which they are implemented.

7.5.4 Researcher reflexivity

The researcher's background as a healthcare manager and nurse provided valuable contextual insights during the qualitative part of the study; this positionality also necessitated ongoing reflexivity throughout the research process. Reflexivity involves critically examining how a researcher's opinions, professional experiences and worldview may influence decision-making and interpretations (Olaghere, 2022). During data collection and analysis, the researcher engaged in deliberate reflexive practice, such as supervisory reflexive conversations to critically examine the interpretations and challenge assumptions, reflexive journalling of supervisor meetings to practice ongoing self-examination and reflexive interview techniques using open ended and neutral questions, to ensure that her prior knowledge informed but did not direct or bias the inquiry (Olmos-Vega et al., 2023).

To mitigate the risk of undue influence arising from the researcher's prior managerial role at the research site, explicit safeguards were built into the study design. Participants were excluded if they had a prior supervisory or managerial relationship with the researcher, a criterion that was clearly outlined in the participant information sheet. This strategy was implemented to prevent power imbalances that could pressure participants to disclose information or prevent the authenticity of their responses. Importantly, while the researcher's familiarity with the EMR with CDSS enabled her to recognise subtle contextual nuances during interviews, this knowledge did not influence participants' responses or the direction of analysis. Rather, it facilitated a more accurate interpretation of participants' meaning while remaining grounded in their accounts.

7.6 Recommendations

This section provides recommendations that encompass implications for practice, research, policy, and knowledge.

7.6.1 Practice

Executives should adopt a co-design approach with nurses for new modules or system updates, ensuring that end users' cognitive needs, abilities, limitations, and work environment constraints are incorporated throughout the design process. An organisational readiness assessment should support this approach to confirm that both the workforce and the system are prepared for effective and sustainable change.

With the implementation of a new EMR featuring an integrated CDSS, a mandatory comprehensive training programme should be introduced to address the variability in system use, documentation practices, and data quality identified after system deployment. The hospital should require ongoing training for all nursing staff, including scenario-based exercises, to ensure consistent and confident use of the new EMR and CDSS for fall prevention. Considering the inconsistencies observed in fall severity classification and narrative documentation, targeted education should aim to standardise fall documentation, including a clear definition of a fall. This should distinguish between assisted and unassisted falls, be reinforced through training materials, and include guidance on accurate coding and sub-coding in accordance with the SAC levels.

To support effective implementation, healthcare organisations should establish dedicated integration teams comprising multidisciplinary representatives from IT, nursing, and management to facilitate smooth integration and enable the quick resolution of emerging issues. At the same time, existing clinical workflows should be systematically reviewed and aligned with the structure and functionality of the electronic system to minimise friction between organisational processes and technology requirements. Additionally, incident reporting processes should be streamlined by integrating the incident management system directly with the EMR, improving usability, reducing reporting time, and seamlessly incorporating incident documentation into nursing workflows.

This study showed that implementing an EMR system and an associated CDSS, specifically for fall-risk assessment, had noticeable effects on nurses' psychological well-being, as well as their fall-related clinical decision-making and workflow. Gaining a clearer understanding of which parts of the system influenced nurses, how, and why these changes happened can help develop targeted interventions to better support nurses during the implementation and ongoing use of digital systems.

In resource-constrained private hospitals, co-design can be implemented through existing structures rather than establishing new committees. For example, each ward could nominate a "nurse champion" to participate in system update discussions and act as a liaison between frontline staff, management, and the digital team. Nurse champions could gather feedback from colleagues, identify workflow issues, and test new EMR or CDSS functions before wider implementation. This approach minimises costs while ensuring frontline nursing perspectives are incorporated into system development and refinement.

Similarly, ongoing training need not rely on dedicated study days or external educators. Scenario-based micro-training could be integrated into existing ward huddles, safety briefings, and shift handovers. For example, a five-minute discussion could review a recent fall, demonstrate the correct use of the fall-risk assessment tool, clarify SAC coding requirements, or compare examples of high and low quality documentation. These brief, regular learning activities would reinforce consistent documentation practices, build confidence in using the EMR and CDSS, and minimise disruption to clinical workloads. Hospitals could also use nurse champions to deliver these sessions and provide peer support, creating a sustainable, cost-effective approach to education and continuous improvement.

7.6.2 Research

Future research should adopt a human-centred evaluation that shifts the focus from predictive accuracy to exploring how technologies such as the new EMR influence usability, workflow integration, and nurse satisfaction, as these factors are key to improving the quality-of-care patients receive. A longitudinal study of the entire private hospital setting is also advised to track changes over time and investigate factors that help the effective use of the EMR, including how organisational aspects,

technology design, and user behaviour connect, to better understand the mechanisms through which these elements can improve healthcare quality and safety.

Furthermore, more research on fall prevention is necessary, as this thesis mainly examined risk assessment. Exploring whether different interventions are needed or if nurses actually apply them could provide valuable insights for creating more personalised fall-prevention strategies.

Future research should replicate this study across a wider range of hospitals using electronic health systems to enable a higher volume of admissions, improved system interoperability, and a more diverse and representative sample of nurses. Further evaluation of technology is also recommended to investigate how different electronic health system vendors and system architectures, such as cloud-based versus on-premises platforms and integrated versus modular designs, influence fall-risk documentation practices and clinical workflows. Lastly, future studies should include an equity and cultural safety perspective to assess how EMRs capture and respond to the needs of diverse patient populations, including Māori, Pasifika, and Asian patients, ensuring that digital systems provide culturally respectful care and equitable health outcomes. This work should be guided by robust data sovereignty principles, particularly Indigenous data sovereignty, to ensure that the collection, use, storage, and reporting of health data support community ownership, authority, and trust, and align with Māori rights to governance over Māori health and wellbeing data (Te Mana Raraunga, 2023).

Future research should adopt a whole-hospital approach to studying electronic health systems, broadening the focus to include other members of the multidisciplinary team, such as medical and allied health staff, who also use the EMR and CDSS. It should also consider cultural and spiritual support staff involved in patient care, such as pastoral carers, kaumātua, and specialised practitioners, who play an essential role in supporting holistic well-being within the NZ health system, even though they may not directly use the EMR and CDSS. Examining how these systems influence practices, workflows, and decision-making across different professional groups could provide a comprehensive understanding of their impact and help develop more inclusive implementation strategies.

7.6.3 Policy

At the policy level, it is important to set realistic expectations that CDSS may not immediately reduce falls. In practice, strategies such as proactive communication with staff and leadership might initially lead to an apparent rise in reported falls, which could reflect improved detection and reporting rather than an actual increase in incidents. Clarifying this early helps prevent misinterpretation of fall data. Policies should explicitly state the expected impact of CDSS on fall outcomes. Although it might seem logical that CDSS implementation will directly decrease falls, improved usability could initially result in more falls being reported, not fewer.

National standards should be established to guide the implementation of electronic health systems, including CDSS, with mandatory interoperability and usability benchmarks for digital health systems across NZ. These standards should require systems to be designed by multidisciplinary teams, including clinical, technical, and design experts, and configured to support existing clinical workflows and optimise data quality while reducing documentation burden and disruption to existing processes staff. At the same time, mandatory training requirements should be enforced, with minimum competency standards needed before deploying any new electronic system in healthcare facilities, complemented by periodic refresher training to maintain long-term proficiency. Managers and policymakers should also remain vigilant about the potential unintended effects of EMR implementation on patient safety, recognising that as systems mature, informal workarounds can emerge when systems do not fit with workflows, which could compromise the intended safety and data quality enhancements.

Investment in digital infrastructure should be prioritised by allocating dedicated funding within hospital budgets to support robust hardware and software solutions that enable system integration and usability. Governance frameworks for data utilisation should be strengthened by establishing clear policies that ensure reporting data generated through electronic systems is analysed and actively used to inform continuous quality improvement initiatives.

This study provides valuable insights for nurses, executive management, policymakers, and other healthcare organisations by enhancing understanding of the association

between the implementation of an EMR with CDSS and patient outcomes, as well as nurses' satisfaction and fall-related clinical decision-making. It also provides knowledge of how these systems affect nurses' satisfaction and influence fall-related clinical decision-making, thereby informing more effective, evidence-based approaches to digital health implementation.

7.6.4 Knowledge

These findings challenge the common belief in healthcare that staffing levels directly determine patient safety outcomes. Given the limitations of the available data, an association between staffing variance and fall risk could not be established. This study advances existing knowledge and calls for a more detailed understanding of the factors influencing patient safety. Furthermore, the findings highlight how design flaws and structural mismatches within an EMR affect data quality and workflow integration, shifting attention away from staffing metrics alone and toward the role of HIT design. In doing so, this study contributes to the growing body of evidence supporting the use of co-design and usability standards in health IT as mechanisms for improving clinical practice and patient safety outcomes.

By illustrating how CDSS operate in practice, this study contributes to the growing understanding of healthcare integration by demonstrating that CDSS effectiveness is not solely a technical issue, but also involves complex interactions among system design, compatibility, and usability. The findings show how CDSS can improve situational awareness and structured clinical planning, while also emphasising that effective communication in healthcare requires more than automation alone; it depends on active user engagement and clearly defined, widely understood organisational processes. Furthermore, the study advances knowledge of systems analysis by demonstrating how raw data can be transformed into actionable insights, thereby informing how health IT can improve quality and safety.

This study contributes to knowledge by demonstrating that technology adoption alone does not eliminate falls, thereby challenging assumptions that electronic systems directly translate into improved safety outcomes. The findings strengthen existing knowledge by demonstrating that electronic systems primarily improve the consistency and quality of fall reporting rather than reducing fall rates.

By recognising the link between system usability and nurses' psychological well-being, these findings enhance our understanding of the human factors essential for successful EMR/CDSS implementation and their influence on healthcare quality and safety. Going forward, the growing integration of artificial intelligence into CDSS will further emphasise these issues, introducing new challenges related to algorithmic transparency, data privacy, and data sovereignty. As AI-enabled systems become more embedded in clinical workflows, ensuring ethical governance and secure, sovereign data practices will be crucial. These emerging dynamics highlight the importance of future policy development that addresses not only human-technology interaction but also the wider socio-technical implications of AI-driven decision support.

7.7 Conclusion

This thesis shows that implementing an EMR with an integrated CDSS is more than a technical upgrade. It is a significant organisational intervention with the potential to reshape clinical practice, workflows, communication, and the lived experiences of nurses who use it. The three Donabedian components: structure, process and outcome consistently indicated that technology alone does not enhance patient safety. Its effectiveness depends on design, usability, organisational preparedness, and human input, which determine whether the electronic health system is a helpful resource or a barrier in clinical care.

The findings challenge the longstanding belief in healthcare that staffing levels alone determine patient safety outcomes. By showing that staffing variability was not linked to fall risk, this research challenges a traditional narrative and shifts the focus to the structural, technological, and cognitive factors that influence clinical decision-making. It redefines fall prevention as a systemic issue rather than a staffing concern, encouraging leaders to move beyond staffing ratios and consider the quality of the work environments in which nurses operate.

Across all Donabedian components within the thesis, a pattern emerged. When digital systems are poorly aligned with workflows, when definitions and documentation processes lack clarity, and when usability is compromised, nurses resort to workarounds. Over time, these workarounds become part of routine practice, gradually undermining data quality, situational awareness, and, ultimately, patient

safety. This thesis therefore highlights the urgent need for co-design, not as a desirable option but as a foundational requirement for any digital health system implementation. Nurses should be viewed not just as passive users of technology but as active collaborators whose understanding, limitations, and skills influence the system's design from the beginning.

The research emphasises the need for comprehensive, ongoing training that goes beyond basic system navigation. It aims to develop a shared understanding, standardised documentation, and confident clinical application of digital tools such as CDSS. Scenario-based training, clear definitions of falls, and uniform SAC coding are not just operational details; they are vital mechanisms that enable digital systems to support, rather than hinder, clinical judgment.

At the policy level, the findings highlight the need for national standards that mandate interoperability, usability, and training. Without these safeguards, hospitals may adopt systems that unintentionally threaten safety, disrupt workflows, or fail to fulfil the needs of the patient population. There is a need for governance structures that ensure data from these systems is not only collected but also actively analysed and used to drive continuous improvement.

Finally, this thesis deepens understanding by examining the psychological and social dimensions of digital transformation. Nurses' trust in the CDSS, their perceived cognitive load, workflow integration, and emotional responses to system design all influence how technology is used in practice. Simply adopting technology does not directly decrease falls; however, it does enhance reporting and visibility. Fall prevention continues to rely mainly on human effort, involving clinical judgment and active patient engagement.

A summary of this thesis will be made available to the participating private hospital so the suggestions can be reviewed and, if necessary, amendments made to their current EMR and CDSS fall assessment.

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Appendix A. Summary of data from the selected articles.

Author (Year) Country	Design	Participants	Data collection	Findings	Implications for practice	JBI score		
Dykes et al. (2010) USA	Randomised control trial	Patients in four urban hospitals Nurses caring for the patient at the time of a fall Unit managers and hospital quality personnel		Through a cluster-randomised study conducted from January 1, 2009, to June 30, 2009, comparing patient fall rates across four hospitals		There were fewer patients with falls in intervention units (n = 67) than in control units (n = 87). The intervention units had a significantly lower adjusted fall rate (3.15 per 1,000 patient-days) than the control units (4.18 per 1,000 patient-days), with a rate difference of 1.03 per 1,000 patient-days. Patients aged 65 or older benefited most from the Fall Prevention Tool Kit (FPTK), with an adjusted rate difference of 2.08 per 1,000 patient-days.	The study indicated that an HIT intervention targeting underlying risk areas, specifically the FPTK, can prevent patient falls.	8/13
Title: Falls prevention in acute care hospital: A randomised trial Aim: Investigate whether a fall-prevention toolkit using health information technology reduces patient falls in hospitals								

Author (Year) Country	Design	Participants	Data collection	Findings	Implications for practice	JBI score		
Furukawa et al. (2011) USA	Cohort study	3,038 medical/surgical units in 509 hospitals. These hospitals were part of the National Database of Nursing Quality Indicators (NDNQI).		Data on nurse staffing and patient outcomes came from the 2004–2008 NDNQI. Data on EMR implementation came from the 2004–2008 Healthcare Information and Management Systems Society (HIMSS) analytics database.		Nurse sensitive patient outcomes improved significantly over this time period. Total falls declined by 7.9%, while injurious falls declined by 13.1%. Total nurse hours per patient day increased by 8% from 2004–2008. Total nursing hours were 2.1%–3.5% lower with all EMR stages in year 1 of implementation.	The study suggests that as more advanced EMR systems are implemented, managers and policymakers should be aware of the potential negative associations with patient safety. The findings call for re-examining EMR practices across hospitals and for a more careful examination of EMR-human-computer interaction issues that can lead to higher risks.	8/11
Title: Electronic medical records, nurse staffing, and nurse-sensitive patient outcomes: Evidence from the national database of nursing quality indicators Aim: Examine the association between electronic medical records implementation and nurse staffing levels, skill mix, and patient outcomes in USA hospitals								

Author (Year) Country	Design	Participants	Data collection	Findings	Implications for practice	JBI score		
Dowding et al. (2012) USA	Interrupted time series (ITS)	29 hospitals in northern and southern California		Data on process and outcome measures were obtained from the Collaborative Alliance for Nursing Outcomes, which has been collecting unit-level outcomes data on nursing staff, care processes, and nursing-sensitive outcomes (falls) since 1996.		The implementation of an integrated EHR was not associated with a reduction in patient fall rates. The impact on fall rates was unclear, with no significant variation observed over time. Implementation of an EHR was associated with increased documentation of fall risk, but this did not translate into a reduction in fall rates.	The study suggested that future research should explore the factors that shape EHRs' impact on nursing care processes and outcomes. It also noted that organisational factors, such as collaboration, teamwork, and supportive leadership, are important in determining the successful implementation and use of HIT.	5/9
Title: The impact of an electronic health record on nurse sensitive patient outcomes: An interrupted time series analysis Aim: Evaluate the impact of an EHR (Health Connect) on nursing-sensitive patient care processes and outcomes, including falls								

Author (Year) Country	Design	Participants	Data collection	Findings	Implications for practice	JBI score		
Walker-Czyz (2016) USA	Cohort study	Registered nurses employed in a 431-bed hospital, with 10 medical surgical unit and two critical care units		The data were collected monthly for 46 months, and an ITS model was used to analyse the data 1 year prior to EHR. Existing data from the organisation's human resource and performance improvement departments was used.		The data revealed that total fall rates were positively impacted after the implementation of an integrated EHR. Preintervention, there was no significant relationship between months and fall rate ($b = 0.48$, $p > .05$). Postintervention, there was a significant decline in fall rate. Each month, fall rates (falls per 1,000 patient days) decreased by 0.5 falls per 10-month period.	Healthcare systems should consider that nurses can positively impact patient care quality.	7/9
Title: The impact of an integrated electronic health record adoption on nursing care quality Aim: Measure the impact of an integrated EHR innovation adoption on the quality of nursing care delivered								

Author (Year) Country	Design	Participants	Data collection	Findings	Implications for practice	JBI score		
Yokota et al. (2018) Japan	Cohort study	25,039 patients in 24 general wards of a single institute		Data were collected from patients using data stored in the EMR. The study also used Intensity of Nursing Care Needs (INCN) data, which is used to record patients' daily nursing care, medical treatment, and activities of daily living, and matched it with data for age and sex.		The probability of falls decreased after implementing the fall risk screening tool. However, using the tool did not reduce the actual occurrence of falls.	The study suggests the need to improve not only fall risk assessment but also fall prevention interventions.	7/9
Title: Evaluating the effectiveness of a fall risk screening tool implemented in an electronic medical record system Aim: Evaluate whether implementing and using the fall risk screening tool in an EMR system contributed to a reduction in the occurrence of falls								

Author (Year) Country	Design	Participants	Data collection	Findings	Implications for practice	JBI score		
Ye et al. (2020) USA	Cohort study	265,225 older patients (aged 65 years or older)		Data were collected from EHR records of Maine from 2016–2018.		The study developed and validated an EHR-based fall risk tool using machine learning to identify elders at higher risk of falls. This model achieved a validated C-statistic of 0.807, with 50% of the identified high-risk true positives confirmed to fall within the first 94 days of next year. The model also captured 58.01% and 54.93% of falls that occurred within the first 30 and 30–60 days of the next year, respectively.	By using EHR data, this risk assessment tool improved its discriminative ability and can be immediately deployed in the health system to provide automatic early warnings to older adults with increased fall risk and to identify their personalised risk factors, facilitating customised fall interventions.	8/11
Title: Identification of elders at higher risk for fall with statewide electronic health records and a machine learning algorithm Aim: Construct and validate an EHR-based fall risk predictive tool to identify elders at a higher risk of falls								

Author (Year) Country	Design	Participants	Data collection	Findings	Implications for practice	JBI score		
Cho et al. (2021) Korean	Interrupted time series (ITS)	Patients: 18 years or older admitted to 12 medical surgical units between 01.05.2017 and 30.04.2019 Nurses: All nurses in the 12 medical-surgical units		During the study, data on patient demographics and medications, nursing activities, STRATIFY data, and administrative information were collected from the EHR system, and fall data were collected from the hospital's quality assurance department.		The mean fall rate increased from 1.95–2.11 in control units and decreased from 1.92–1.79 in intervention units. A separate ITS analysis revealed that the immediate reduction was 29.73% in the intervention group (z = -.06, p = .039) and 16.58% in the control group (z = -1.28, p = .20), but there was no ongoing effect. The injury rate did not differ significantly between the two groups (0.42 vs 0.31, z = 1.50, p = .134).	The early-stage evaluation suggests that implementing an analytic tool to predict fall risk can increase awareness of fall risk, leading to positive changes in nurses' interventions over time. The study also indicates that nurses were amenable to using the tool in practice and that meaningful changes were achieved to prevent patient falls.	8/9
Title: Clinical impact of an analytic tool for predicting the fall risk in inpatients Aim: Determine the impact of an electronic analytic tool for predicting fall risk on patient outcomes and nurses' responses								

Author (Year) Country	Design	Participants	Data collection	Findings	Implications for practice	JBI score		
Carroll et al. (2022) USA	Observational study	Patients 18 years or older, admitted to an inpatient unit at Northwestern or Prentice hospitals between 11.09.2019 and 18.06.2020.		Observational study to evaluate the accuracy of the Johns Hopkins Fall Risk Assessment Tool (JHFRAT) and the risk of fall (ROF) model to predict inpatient falls at the hospital.		The total fall rate was 0.92%. Of the 329 patients who fell, 60.8% were high risk according to the ROF model (fall rate = 1.82%) and 75.4% were high risk according to the JHFRAT (fall rate = 1.39%). The ROF model had better specificity than JHFRAT (69.7% vs 49.2%), but similar C-statistic (0.717 vs 0.702) and lower sensitivity (60.8% vs 79.3%). The performance of the ROF model was similar to that of the JHFRAT in predicting inpatient falls.	The study provides evidence to support transitioning from the JHFRAT to a more automated process using the cognitive computing ROF model.	6/10
Title: Comparison of two different models to predict fall risk in hospitalized patients Aim: Validate the reliability of an EMR-based computerised predictive ROF model for inpatient falls								

Note. EHR = Electronic health record; EMR = Electronic medical record; FPTK = Fall Prevention Tool Kit; HIMSS = Healthcare Information and Management Systems Society; HIT = Health information technology; INCN = Intensity of Nursing Care Needs; ITS = Interrupted time series; JBI = Joanna Briggs Institute; JHFRAT = Johns Hopkins Fall-Risk Assessment Tool; NDNQI = National Database of Nursing Quality Indicators; ROF = Risk of fall; STRATIFY = St. Thomas' Risk Assessment Tool in Falling Elderly Inpatients; USA United States of America

Appendix B Ethics approval letter - Study 2

Auckland University of Technology Ethics Committee (AUTEC)

Auckland University of Technology
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6 December 2022

Eamon Merrick
Faculty of Health and Environmental Sciences

Dear Eamon

Re Ethics Application: **22/339 A mixed method study of the impact of a Clinical Decision Support System (CDSS) on the incidence of falls and related clinical decision-making in a private hospital in New Zealand**

Thank you for providing evidence as requested, which satisfies the points raised by the Auckland University of Technology Ethics Committee (AUTEC).

Your ethics application has been approved for three years until 5 December 2025.

Standard Conditions of Approval

1. The research is to be undertaken in accordance with the Auckland University of Technology Code of Conduct for Research and as approved by AUTEC in this application.
2. A progress report is due annually on the anniversary of the approval date, using the EA2 form.
3. A final report is due at the expiration of the approval period, or, upon completion of project, using the EA3 form.
4. Any amendments to the project must be approved by AUTEC prior to being implemented. Amendments can be requested using the EA2 form.
5. Any serious or unexpected adverse events must be reported to AUTEC Secretariat as a matter of priority.
6. Any unforeseen events that might affect continued ethical acceptability of the project should also be reported to the AUTEC Secretariat as a matter of priority.
7. It is your responsibility to ensure that the spelling and grammar of documents being provided to participants or external organisations is of a high standard and that all the dates on the documents are updated.
8. AUTEC grants ethical approval only. You are responsible for obtaining management approval for access for your research from any institution or organisation at which your research is being conducted and you need to meet all ethical, legal, public health, and locality obligations or requirements for the jurisdictions in which the research is being undertaken.

Please quote the application number and title on all future correspondence related to this project.

For any enquiries, please contact ethics@aut.ac.nz. The forms mentioned above are available online through http://www.aut.ac.nz/research/researchethics

(This is a computer-generated letter for which no signature is required)

The AUTEC Secretariat
Auckland University of Technology Ethics Committee

Cc: Kft9095@autuni.ac.nz; nada.signal@aut.ac.nz; nick.garrett@aut.ac.nz

Project Description	
Project title	A mixed method study of the impact of a Clinical Decision Support System (CDSS) on the incidence of falls and related clinical decision making in a private hospital in New Zealand.
Researcher/s	Paula Anne Murray
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School / Department	AUT, School of Clinical Services, Nursing
ID	Project ID
Project description	There is a high incidence of falls in hospital, despite the implementation of fall prevention strategies. Patients are sustaining life-threatening injuries, and these injuries are costing the health service billions of dollars. At the forefront of healthcare delivery, are the nurses, whose role places them in the best position to prevent patients from falling. A fall risk assessment tool, combined with the nurses' clinical decision making, has been used as a preventative strategy. Recently, there has been growth in Clinical Decision Support Systems (CDSS), which is digital technology in healthcare to improve patient safety and the quality of care by supporting nurses to make better decisions. However, insufficient evidence supports the claim that patient safety has improved or that nurses are making better clinical decisions because of the CDSS. Despite the lack of evidence, the use of CDSS continues to grow in hospitals. Since falls are preventable largely by nurses' actions, it is fundamental to explore whether the CDSS does support the efforts of nurses in preventing falls. The proposed study will investigate the association between CDSS, the incidence of falls, and the nurses fall related clinical decision making using the Donabedian (2003) framework (structure, process, and outcome), and an explanatory sequential research mixed method design.

	Phase one of this study will apply a retrospective analysis of administrative data using variables including patient demographic details, admission details and adverse event information on falls only, for all patients admitted to the NZ Private Hospital as an inpatient between February 2019 - February 2023. A CDSS was introduced in February 2022. De-identified patient demographic data including age, ethnicity, postcode of usual residence, primary diagnosis (ICD 10 code), co-existing conditions, length of stay (LOS), and date of admission and date of discharge will be extracted from the inpatient management systems PiMS and Trakcare. Falls data will be extracted from the online workplace health and safety platforms used to record adverse events PayWiz and Safety Hub and ward details and nursing hours will be retrieved from the workforce planning management system Trendcare. The patient data which has been de-identified by the NZ Private Hospital will be assembled into a single data set. It will be analysed as pre and post CDSS implementation. As this is a mixed methods study, a separate ethics application (EA1) and data management plan will be submitted for phase 2. The results of this study will support nurses, executive management, policy makers and other hospitals within the health sector to better understand the association between implementing a falls assessment tool delivered via a CDSS and the incidence of falls in a private hospital in NZ. While research has been carried out internationally, no single study exists in NZ within the private hospital setting. Therefore, the need for a study is critical since the potential of CDSS in improving patient safety and streamlining the patient care process has yet to be fully realised.
Project start & end dates	Pending ethics
Funding information including reference number	None
Ethics	
Budget	NZD 3,000
Contracts / agreements	Supervision agreements, authorship, and data sharing agreement

Related policies & guidelines	The link below details all the policies and guidelines to consider during the writing of a research data management plan to meet AUT requirements. Guidelines for AUT researchers More specifically the following documents were referenced: HRC Research Ethics Guidelines- April 2021_1.pdf Health Information Privacy Code 2020 website version.pdf AUT Code of Conduct for Research.pdf AUT Research Data Storage Guideline Feb2022.pdf Data Management Plan Guide.docx Nga Tikanga Paihere Guidelines December 2020.pdf anonymisation-code.pdf TMR Māori Data Sovereignty & Principles Oct 2018.pdf

Data management	
Data collection methods	Once the AUT ethics application is approved a locality application will be submitted to the NZ Private Hospital. Once local approval has been obtained, the Chief Information Officer who is responsible for the Information Systems department, will allocate a data analyst who will assist with extracting the required data from the various electronic health systems. Prior to the implementation of the Trakcare (Feb 2022) the patient admission details and demographics details with be extracted from the Patient management system (PiMS). Following the implementation of Trakcare, the same data set will be extracted with the additional of the falls assessment, the fall assessment outcome and the name of the ward. Nurse staffing details will be extracted from the workforce planning management system Trendcare and the adverse events (falls only) will be extracted from the old technology platform used to record adverse events PayWiz and the newly implemented safety platform used to record adverse events Safety Hub. Patient demographics were collected as part of the NZ Private Hospital admission process. Nurse staffing was

<table>
<tr><td></td><td>collected as part of resource management within the NZ Private Hospital wards. Adverse event data as collected as guided by the national adverse events reporting policy. This policy is intended to assist the NZ Private Hospital, develop and operate their own adverse event, review and learning systems, to improve the quality, and experience of patients.</td></tr>
<tr><td>Types of data</td><td>The study population will include all patients admitted to the NZ Private Hospital between Feb 2019 and Feb 2023. The CDSS was implemented in this hospital in February 2022; thus this timeframe will provide two cohorts of pre and post data. The average number of patients admitted to the private hospital is approximately 9,500 patients a year.</td></tr>
<tr><td>File formats</td><td>Once the data has been extracted from PiMS, Trakcare, Trendcare, PayWiz, and Safety Hub with the assistance of the NZ Private Hospital data analyst, the data will be imported to Microsoft excel in Comma Separated Value format and will be merged into a single data set. The data analyst at the NZ Private Hospital will de-identify the unique patient identifier (National Health Identifier (NHI) number), with an encrypted unique Patient Reference Number (PRN).</td></tr>
<tr><td>File organisation</td><td>The raw data with de-identified NHI number file will be saved as a master copy with a file name ‘Master copy ddmmyy. v1.0’. During the data cleaning process, the consecutive data sets will be renamed with a file name ‘Master Copy ddmmyy. v1.1’. The version number will continue to change until the final version for analysis. The final version for analysis will be saved under the file name ‘Master copy Final ddmmyy. v1.0’. Every change during the analysis will be reflected on the date and version numbers. The changes completed on every version will be documented in a version history table detailed below
<table>
<tr><th>Version Number</th><th>Completed by</th><th>Notes</th><th>Last amended</th></tr>
<tr><td></td><td></td><td></td><td></td></tr>
</table>
A versions control table will also be used every time the researcher makes any changes or amendments. Information will be collected under the following headings: File name, description of the content, created by, created on, last modified, version and notes.</td></tr>
<tr><td>Documentation</td><td>The data will be extracted from the five pre-existing data sources relevant to this study (PiMS, Trakcare, Trendcare, PayWiz, and Safety Hub) by the data specialist employed at the NZ private hospital. The table below describes each data</td></tr>
</table>

source and provides a description and details which data will be obtained.

Data Source	Description	Data
PiMS	Patient management system prior to the implementation of the EMR Trakcare (Feb 2022).	Encrypted by NZ Private Hospital data analyst National Health Identifier (NHI), age, ethnicity, postal code of usual residence, primary diagnosis, co-existing conditions, length of stay, admission, and discharge date.
Trakcare	EMR.	Encrypted NHI by NZ Private Hospital data analyst, age, ethnicity, postal code of usual residence, primary diagnosis, co-existing conditions, length of stay, admission, and discharge date, morse fall assessment (MFA), MFA outcome, name of ward.
Trendcare	Workforce planning and workload management system.	Ward-Nursing Hours variance.
PayWiz	Is a technology platform that was used by the private hospital to record adverse events.	Adverse event (falls only), adverse event SAC.
Safety Hub	Is an online workplace health and safety platforms that is used to record adverse events.	Adverse event (falls only), adverse event SAC.

Confidentiality	The NHI number is the only patient identifier included in the data collection. However, the NHI number will be de-identified by the NZ Private Hospital data analyst and a unique Patient Reference Number allocated prior to the research data being available to the researcher.
Quality control	All data sets will be reviewed for completeness and field accuracy by the data analyst at the NZ Private Hospital prior to making the data available to the researcher. The researcher will not have input or access to the data during

	this period. Following transfer of the comma separated value files the named researcher supported by her supervisors will undertake a further analysis for missing data, data entry, extraction errors, and analysis for outliers. Where outliers are identified modification will be undertaken only after consultation with a supervisor & biostatistician (Dr. Garrett). If significant anomalies are identified by the researcher and the supervision team, then the team will seek consultation with the NZ Private Hospital data analyst.
Cultural data	Ethnicity data will be collected for this study. A subgroup analysis for the Māori and Pacific ethnicity will be undertaken. Based on estimates of Māori and Pacific patient numbers in private hospital admissions we anticipate that less than 3% of patients will represent Māori and Pacific. If this is the case subgroup analysis is likely to be underpowered, therefore this analysis would be descriptive in nature and undertaken in consultation with the Māori health advisor for the NZ Private Hospital and the primary researchers supervisors.

Storage	
Storage and backup	The data will be stored in a secure manner in accordance with the National Ethical standards for Health and Disability research and quality improvement as well as the NZ Private Hospital standards. All data will be stored on a secure password protected server at AUT in compliance with AUT research data storage guideline AUT Research Data Storage Guideline Feb2022.pdf . The access to these files will only be available to Mrs Paula Anne Murray, Associate Professors Eamon Merrick, Nick Garrett and Mandie Foster. Professor Nada Signal.
Non-digital data collections	Not applicable
Preservation	Data will be retained in an encrypted and password protect file on an AUT server for a period of no less than ten years following publication. All data stored will be securely destroyed at 10 years post completion of this project. This is in accordance with the principle 9 in the *Privacy Act* (2020) section 22.

Publishing and sharing	
Publishing	External communication about this project will not include raw data or analysis other than the anonymous and aggregated reporting of results and methodology. All publications and conference papers that result from this research will be shared with and credited to the NZ Private Hospital. The researchers will ensure that 'no individual, facility, and/or support provider' will be identifiable. At six and twelve months (or at the request of NZ Private Hospital) the researchers will provide a written report and/or presentation of methods and results of the study. Data will be available to external researchers for the purposes of auditing and meta-analysis following request and subject the requesting party's ethical approval in consultation with Auckland University of Technology Ethics Committee.
Access and sharing	The data with encrypted patient reference number will be available to Mrs Paula Anne Murray, Associate Professors Eamon Merrick, Nick Garrett and Mandie Foster. Professor Nada Signal.
Licensing	Check Creative Commons for licence options Share your work - Creative Commons
Ownership/IP	Paula Anne Murray
Restrictions	None noted.

Appendix D Data sharing agreement - Study 2

DATA SHARING AGREEMENT

This agreement is made between the Discloser and the Recipient (as those parties are identified in Schedule 1). The Discloser[s] and the Recipient[s] may be also referred to as the Parties and singularly as a "Party".

Background

A. The Discloser is the custodian of Data defined below and the Data includes Personal Information.

B. The Recipient wishes to access and use the Data for the Purpose defined below, and acknowledges the importance of safeguarding Personal Information.

C. In consideration of and subject to compliance with the obligations on the part of the Recipient in this agreement, the Discloser is granting the Recipient a right to use and access the Data only for the Purpose.

The Parties agree as follows:

Definitions

In this agreement, capitalised terms have the meaning given to them in context and/or as defined below:

Access Request means a request by an Individual for access to, or correction of, their personal information in accordance with Privacy Law.

Additional Security Requirements means those additional security requirements to prevent unauthorised access or disclosure of the Data required by Discloser set out in Schedule 1 (if any).

Affected Party is defined in clause 0.

Agreement means this data sharing agreement, including Schedule 1 and Schedule 2 and any schedules that may be added from time to time.

Authorised Users means those individuals employed by or working with the Recipient identified Schedule 1, if any, who are authorised to access, use and Process the Data in accordance with the terms of this Agreement.

Business Day means any day of the week other than a Saturday, Sunday, public holiday in Auckland, New Zealand, or any day in the period commencing with 25 December in any year and ending with 15 January in the following year.

Data means the data shared between the Parties pursuant to this Agreement as described in Schedule 1.

Data Breach means:

(a) actual, attempted or suspected unauthorised, unlawful or accidental access to, disclosure or Processing of, loss, destruction, alteration or damage of any Data; or

(b) an action that prevents the Recipient from accessing the Data on either a temporary or permanent basis.

Delivery Means means the approved method of delivery of the Data set out in Schedule 1.

Discloser means the Party disclosing Data under this Agreement as identified as such in Schedule 1.

Effective Date means the date this agreement has been signed by both Parties.

End Date means the intended date of expiry of this Agreement noted in Schedule 1.

Individual has the meaning given to it under Privacy Law.

Information Security Program is defined in clause 4.3.

Notified Party is defined in clause 0.

Personal Information has the meaning given to that term in the New Zealand Privacy Act 2020.

Privacy Laws means any applicable statute, regulation, bylaw, rule, order, or subordinate legislation in force from time to time and includes, without limitation, the New Zealand Privacy Act and the Health Information Privacy Code.

Process means any operation or set of operations which is performed on Data or on sets of Data, whether or not by automated means, such as collection, recording, organisation, structuring, storage, adaptation or alteration, retrieval, consultation, use, disclosure by transmission, dissemination or otherwise making available, alignment or combination, restriction, erasure or destruction.

Purpose means the purpose for which the Recipient may access and use the Data defined in Schedule 1.

Recipient means the Party receiving Data under this Agreement and identified as such in Schedule 1.

Regulator means any regulator and/or person entitled under Privacy Law to investigate the Processing of Personal Information, and includes the New Zealand Privacy Commissioner.

Special Terms means any special terms and conditions of this agreement set out in Part B Schedule 1 that either amend or additional to other terms in this agreement.

Term is defined in clause 7.1.

1.2 **Interpretation**

In this agreement, except where the context otherwise requires:

(a) words importing the singular number include the plural and vice versa and words importing gender include all genders;

(b) the meaning of general words is not limited by specific examples introduced by 'including', 'for example' or similar expressions;

(c) another grammatical form of a defined word has a corresponding meaning;

(d) headings are for ease of reference and do not affect interpretation;

(e) references to clauses and other sub clauses are to those parts of this agreement;

(f) a reference to any Law includes regulations made under it and consolidation, amendments, re-enactments or replacement of any of them.

2. Purpose of Accessing Data

2.1 The Recipient may only access, use and Process the Data for the Purpose.

2.3 If the Recipient, including any of its Authorised Users, becomes aware of any attempted or actual use of the Data for any other purpose or use, other than the Purpose, the Recipient must immediately notify the Discloser and follow the steps set out in clause 6 Data Breach.

3. Use of Data and Authorised Users

3.1 Use and Disclosure

Subject to both Parties having obtained all necessary regulatory and organisational approvals prior, the Discloser shall, using the Delivery Means, deliver the Data on the Effective Date to the Recipient and thereafter the Recipient:

(a) may Process the Data in accordance with this agreement and only as required to fulfil for the Purpose;

(b) will allow Authorised Users only to Process the Data and will procure that each Authorised User (current or future) is made aware of and is bound by the terms of this agreement;

(c) will maintain a record of Authorised Users;

(d) will not without the prior written consent of the Discloser, allow any other person other than an Authorised User to access, use or Process the Data.

3.2 Compliance with Privacy Laws

Each Party shall comply with all applicable Privacy Laws and its respective publicly available privacy policies (as may be amended from time to time) in relation to its access to, possession, use and disclosure of the Data.

3.3 Confidentiality

The Recipient will hold the Data in strict confidence and impose confidentiality obligations on personnel who will be provided access to the Data, including to protect all Data consistent with the requirements of this Agreement and Privacy Law.

3.4 Data Integrity

The Recipient will:

(a) take all reasonably practicable measures to ensure that the Data remains secure, accurate, intact and complete;

(b) ensure that any publication based on the Data Set does not directly or indirectly disclose Personal Information relating to any Study Participant;

(c) not link, or combine the Data with any other data or information;

(d) not disclose, share or transfer the Data (or any part of it), or attempt to do so, to any person, including a member of the Discloser's organisation who is not an Authorised User;

(e) may not transfer or save the Data or any part of it to any device, application or storage facility that is not authorised by the Recipient or the Discloser;

(f) promptly comply with all reasonable directions issued by the Discloser in relation to Data.

3.5 Discloser Warranties

The Discloser:

(a) warrants as at the Effective Date and to the best of its knowledge and belief that the all necessary consents and approvals have been obtained to enable the Data to be shared and Processed by the Recipient for the Purpose;

(b) provides no other warranties in relation to the Data save as set out in clause 3.5(a) above.

3.6 Publication

Subject to clause 3.4(b), the Recipient will not publish the Data (in whole or part) without the prior written consent of the Discloser.

4. Security and Confidentiality of Data

4.1 Standard of Care

Each Party shall exercise at least the same degree of care as it uses with its own data and confidential information, but in no event less than reasonable care, to protect the Data from misuse and unauthorised access or disclosure.

4.2 Safeguards around Data

Each Party must ensure that all Data is protected by such security safeguards as are reasonable in the circumstances to take against loss, unauthorised access, use, modification and disclosure or other misuse, including:

(a) maintaining adequate physical controls and password protections for any server, system or device on which the Data is accessed and/or stored;

(b) ensuring that the Data is not stored on any mobile device (for example, a laptop or smartphone) or transmitted electronically, unless encrypted;

(c) taking any other measures reasonably necessary to prevent any access, use or disclosure of the Data other than as permitted under this Agreement.

4.3 Information Security Safeguards and Additional Security Requirements

The Recipient will meet as a minimum:

(a) the information security safeguards described in Schedule 2; and

(b) such Additional Security Requirements as are listed in Schedule 1,

to protect the Data against Data Breaches and unauthorised Processing. In the event of a conflict between any security provision in this clause, the information security safeguards in Schedule 2 and any Additional Security Requirements in Schedule 1, the latter will prevail.

4.4 Intellectual Property

The Discloser shall retain all intellectual property rights recognised by the laws of New Zealand in relation to Data notwithstanding any rights exercised by the Recipient in relation to the Processing of it.

5. Subcontractors

5.1 Subcontractors

The Recipient may not disclose Data to any subcontractors or agents without the Discloser's prior written consent.

6. Data Breach

6.1 Notification of Data Breach

If either Party becomes aware of a Data Breach (the **Affected Party**), that Party shall, without undue delay, notify the other Party of the Data Breach (**Notified Party**), providing sufficient information to enable the Notified Party to meet any obligations to report a Data Breach under Privacy Laws.

6.2 Cooperation

The Affected Party will promptly cooperate with the other Party to take all such reasonable steps as are directed by the Notified Party to assist in the investigation, mitigation and remediation of each Data Breach.

6.3 Public statement

The Parties acknowledge and agree that, in the event of a Data Breach attributable to the Affected Party, the Notified Party may wish to make a public statement in relation to that Data Breach. The Parties will discuss in good faith the contents of any such statement, but the Notified Party may, in its sole discretion, determine the contents of that statement.

6.4 Cooperation and Mitigation

The Parties shall in good faith cooperate with each other in relation to the response to and remediation of any Data Breach, and agree to use reasonable steps to:

(a) address any applicable reporting requirements relating to the Data Breach; and

(b) mitigate any effects of such Data Breach.

7. Term and Termination

7.1 Term

This agreement will commence on the Effective Date and continue until the End Date, unless otherwise terminated in accordance with this clause 0 (the **Term**).

7.2 Termination for Convenience

Either Party may at any time terminate its status as a Party to this Agreement on not less than two calendar months' notice served on the other Party.

7.3 Termination Rights

Either Party may terminate this Agreement in the event the other Party:

(a) breaches this Agreement and the breach is not capable of remedy;

(b) breaches this Agreement and does not remedy the breach within fifteen Business (15) days after service of a notice by the non-breaching Party or such other reasonable period as may be specified;

(c) suffers an event of insolvency;

by serving a notice of breach on the breaching Party in accordance with the provisions of clause 8 (Notices).

7.4 Consequences of Termination

(a) Where a Party exercises the right to terminate this Agreement, such termination will not affect the obligations impose on Parties under clauses 2, 0, 0, 0 and 0 of this Agreement with respect to Data disclosed or transferred prior to the termination of this Agreement.

(a) Early termination will be without prejudice to the rights and remedies of either Party in respect of any antecedent breach of this Agreement by the other Party.

(c) Upon any termination, cancellation or expiry of this Agreement:

i. the Recipient shall immediately cease and have no right to use or Process Data or any portion thereof;

ii. the Recipient will delete or destroy, or will procure the deletion or destruction of, the Data (and all copies of it) within 14 days of termination and provide reasonable evidence of the same to the Discloser.

7.4 Ability to Suspend Access

Notwithstanding any other right or action the Discloser may have under this agreement, the Discloser may suspend access to and Processing of the Data by the Recipient, in the event of a breach of this agreement until the Recipient has corrected the breach to the reasonable satisfaction of the Discloser.

8. Notices

8.1 Method of Notice

The Parties shall give all notices and communications between the Parties in writing by personal delivery, prepaid post, or email to the Party's address specified in this agreement, or to the address that a Party has notified to be that Party's address for the purposes of this section.

8.2 Receipt of Notice

A notice given under this agreement will be effective:

(a) if sent by personal or courier delivery, at the time and date that the notice is handed to a representative of the recipient; or

(b) if sent by email, on the day of transmission if received before 5.00pm on a Business Day, and otherwise on the next Business Day, unless a notice of non-delivery is received by the sender.

9. General Provisions

9.1 Assignment

Neither Party may assign this agreement or any of its rights or obligations under this Agreement.

9.2 Severability

If any part of this Agreement is declared unenforceable or invalid, the remainder will continue to be valid and enforceable.

9.3 Variation

This Agreement may be amended only by an amendment in writing signed by both Parties.

9.4 Waiver

Neither Party's failure or neglect to enforce any of rights under this Agreement will be deemed to be a waiver of that Party's rights. A waiver or extension is only effective if it is in writing and signed by the Party granting it.

9.5 Further actions

Each Party shall take all action and execute all further documents necessary to give full effect to this Agreement.

9.6 Counterparts

This Agreement may be executed in counterparts, each of which is to be deemed an original, but all of which together are to constitute a single agreement.

9.7 Governing Law

This Agreement will be governed by and construed in accordance with the laws in force in New Zealand. The Parties agree to submit to the exclusive jurisdiction of the Courts of New Zealand.

9.8 Several Liability where multiple parties

If either the Discloser or the Recipient are comprised of more than one legal person, then the obligations owed by and liability of those persons is several only, and not joint and several.

9.9 Precedence of Special Terms

If there is any conflict between the Special Terms (if any) and any other term or condition written in this Agreement, the provisions of the Special Terms shall prevail.

10. Fees

10.1 Relevance

This clause is only applicable if there are Fees payable under this agreement.

10.2 Fees

(a) In consideration of the ability to use, access and Process the Data during the term of this agreement, the Recipient will pay the Fees to the Discloser, without deduction or set-off and exclusive of Goods and Services Tax (GST).

(b) The Discloser shall send a valid, proper GST invoice to the Recipient for the Fees and the Recipient shall settle the invoice in full on the 20th day of the month following issue of the invoice, or other period as the Discloser may specify to the Recipient.

11. Information Access Requests

11.1 Each Individual has rights of access and correction

The Recipient agrees that each Individual has a right to access, and to seek correction of, their personal information held by the Recipient that is included in the transferred information.

11.2 How to handle a request for access

Schedule 1– Agreement Definitions & Special Terms

Part A - Agreement Definitions

<table>
<tr><th>ITEM No</th><th>DEFINITION USED IN THIS AGREEMENT</th><th>DESCRIPTION</th></tr>
<tr><td>1</td><td>Discloser</td><td>NZ Private Hospital</td></tr>
<tr><td rowspan="3">2</td><td rowspan="3">Recipient</td><td>Dr Eamon Merrick (Primary Supervisor)
Senior Lecturer- Nursing
School of Clinical Sciences
Auckland University of Technology</td></tr>
<tr><td>[AND]*</td></tr>
<tr><td>Paula Anne Murray
Doctor of Health Sciences Candidate, AUT
Chief Executive Office
Kakariki Hospital</td></tr>
<tr><td>3</td><td>Data</td><td>The data will be extracted from the five pre-existing data sources relevant to this study (PiMS ™, Trakcare™, Trendcare™, Pay Wizz™, and Safety Hub™) by the data analyst employed at the NZ Private Hospital. Prior to the implementation of the Trakcare™ (February 2022) the patient admission details and demographics details will be extracted from the Patient management system (PiMS™). Following the implementation of Trakcare™, the same data set will be extracted with the additional of the falls assessment, the fall assessment outcome and the name of the ward. Nurse staffing details will be extracted from the workforce planning management system Trendcare™ and the adverse events (falls only) will be extracted from the old technology platform used to record adverse events PayWiz™ and the newly implemented safety platform used to records adverse events Safety Hub™.

The data below is required for all patients admitted to the NZ Private Hospital as an inpatient between Feb 2019 and Feb 2023.
<table>
<tr><th>Required Variable</th><th>Available from (Data Source)</th></tr>
<tr><td>NHI number (deidentified with patient reference number before releasing the data to the researcher)</td><td>PiMS™ & Trakcare™</td></tr>
<tr><td>Age</td><td>PiMS™ & Trakcare™</td></tr>
<tr><td>Ethnicity</td><td>PiMS™ & Trakcare™</td></tr>
<tr><td>Post code of usual residence</td><td>PiMS™ & Trakcare™</td></tr>
<tr><td>Primary diagnosis (ICD10 code)</td><td>PiMS™ & Trakcare™</td></tr>
<tr><td>Co-exisiting conditions</td><td>PiMS™ & Trakcare™</td></tr>
<tr><td>Length of stay</td><td>PiMS™ & Trakcare™</td></tr>
</table></td></tr>
</table>

If an Individual requests access to their transferred information, then subject to clauses 11.4 and 11.5, the Recipient will confirm whether or not it holds any transferred information about them and, if it does, will provide them with access to the information and advise them that they may request correction of their information.

11.3 How to handle a request for correction

Where an Individual requests correction of their transferred information, the Recipient will take reasonable steps to ensure that the information is accurate taking into account the Purpose. If the Recipient is not willing to correct the information as requested, the Recipient will take reasonable steps to ensure a statement of the requested correction is attached to the information, so as to ensure it will always be read with the information. Where the Recipient corrects any transferred information or attaches a statement of correction, the Recipient must take reasonable steps to inform any person to whom the Recipient has disclosed the relevant transferred information.

11.4 Timeframes for responding to requests for access or correction

The Recipient must respond to an Individual's request for access to or correction of their transferred information as soon as reasonably practicable and no later than 30 days after receiving the request. The Recipient must provide reasonable assistance to the Individual in relation to each request.

11.5 Refusing a request

In relation to any request from an Individual under this clause 11, the Recipient may refuse access, extend the timeframe for complying with the request, and/or charge the Individual for complying with the request, to the extent that this would be permitted if the request was made under the Privacy Act and the Recipient was subject to the Privacy Act.

12. Legal Compliance

12.1 The Recipient will comply with its own laws

The Recipient will ensure that its Processing of the Data is consistent with the "Local Data Laws" specified in Schedule 1 and the Governing Law specified in clause 9.7. However, where a requirement of the Local Data Law is less protective than the other requirements of this agreement, to the extent permitted by law the Recipient will comply with the requirement that is the most protective of the transferred information and the interests of the relevant Individuals.

12.2 The Recipient must notify the Discloser about any use or disclosure compelled by law

If the Recipient is required by a court or government agency under any law to disclose or use the Data or any part of it in a way that would not otherwise be permitted by this agreement, then to the extent law allows the Recipient must notify the Discloser to give it the opportunity to contest that legal requirement (for example, by taking the matter to court).

12.3 The Recipient is not aware of any local laws that would undermine this agreement

The Recipient confirms that at the time of entering into this agreement it has made reasonable efforts to identify whether it is covered by any law that could reasonably be expected to have a substantial adverse effect on the protections intended by this agreement, and is not aware of any such law. The Recipient will use reasonable efforts to ensure that, if any such law applies to it in the future, it will promptly notify the Discloser.

		Data of Admission (inpatients only)	PiMS™ & Trakcare™
		Date of Discharge	PiMS™ & Trakcare™
		Morse fall assessment	Trakcare™
		Morse fall assessment outcome	Trakcare™
		Ward name	Trakcare™ & Trendcare™
		Ward-Nursing hours variance	Trendcare™
		Adverse events (falls only)	PayWiz™ & Safety Hub™
		Adverse events (falls only) SAC rating	PayWiz™ & Safety Hub™
4	**Authorised Users**	1. Paula Anne Murray, CEO, Kakariki Hospital 2. Dr Eamon Merrick, Senior Lecturer – Nursing, Auckland University of Technology 3. Dr Nada Signal, Associate Professor, Auckland University of Technology 4. Dr Nick Garrett, Associate Professor, Auckland University of Technology	
5	**Delivery Means**	According to NZ Private Hospital data transfer protocol	
6	**End Date**	The term of this agreement will end 10 years after completion of the project (the same time when the data will be securely destroyed)	
7	**Purpose**	For the purpose of Doctoral research project. The recipients; Paula Anne Murray (Doctor of Health Science Candidate), Dr Eamon Merrick (Primary Supervisor), Dr Nada Signal (Secondary Supervisor) & Dr Nick Garrett (Secondary Supervisor) can only access the data for the purpose of research project with title " A mixed method study of the impact of a Clinical Decision Support Systems (CDSS) on the incidence of falls and related clinical decision making in a private hospital in New Zealand". All publications and conference papers that result from this research will be shared with and credited to the NZ Private Hospital. The researchers will ensure that 'no individual, facility, and/or support provider' will be identifiable. External communication about this project will at no time include data or analysis other than the anonymous and aggregated reporting of results and methodology. Due to restrictions on data containing information that could compromise the privacy or consent of research participants, the data are not publicly available. If a journal asks for accessibility to data, restrictions will be applied ensuring the data is provided in a non re-identifiable format. Data will only be released following consultation and expressed approval of NZ Private Hospital and AUTEC. At six and twelve months (or at the request of NZ Private Hospital) the researchers will provide a written report and/or presentation of methods and results of this study.	
8	**Additional Security Requirements**	A Patient Reference Number (PRN) will be used as a unique identifer for each administion recorded in the patient management systems (PiMS™ & Trakcare™). This identifier is not digitally accessible by any staff except for the nominated data analyst and Chief Information Officer from the NZ	

		Private Hospital Information Systems department. No staff can identify a patient or access any patient record using a PRN and the data analyst and CIO are required to seek prior approval from the inhouse executive committee to reidentify a patient. The primary researcher does not work at the NZ Private Hospital and therefore unable to reidentify any patient using a PRN. The data and analysis files will be stored in AUT servers. The safety within the server is ensured by controlled access and permission. The files will be kept in a password protected folder, on a password protected AUT server. The access to these files will only be available to Mrs Paula Anne Murray, Dr Merrick, Dr Signal and Dr Garrett
9	**Fees**	Not Applicable
10	**Local Data Laws**	This research project will adhere to NZ Private Hospital policy on Clinical Research/Trials. In accordance with the above policy, the NZ Private Hospital recognises the importance of clinical research/ clinical trials and supports appropriate research/trials being carried out in its hospital. However, this support must be balanced with the primary function to provide safe high quality healthcare to its patients. The policy is also in accordance with the Privacy Act (2020). The strategies taken to maintain the privacy and confidentiality of research participants and data security is discussed in Schedule 1: items 7 & 8 of this document, as well as the attached data management plan. A locality application process is also initiated at NZ Private Hospital to ensure that the research is suitable for conducting a study in a safe and effective manner. The locality application will only be approved once all relevant documents have been received, including an ethics application approved by AUT.

Part B - Special Terms:

[None]

Schedule 2– Security Standards

The overview below represents the minimum security measures that will be taken by Recipient. In the event of a conflict between these standards and the Additional Security Requirements (if any).

1.1 Information Security Policies and Standards

The Recipient has and will retain security requirements that are designed to:

(a) Prevent unauthorised persons from gaining access to Data processing systems (physical access control);

(b) Ensure that persons entitled to use a Data processing system gain access only to such Data as they are entitled to access in accordance with their access rights and that, in the course of Processing or use and after storage, Data cannot be read, copied, modified or deleted without authorization (data access control);

(c) Ensure that the Data cannot be read, copied, modified or deleted without authorization during electronic transmission, transport or storage and that the target entities for any transfer of Data by means of data transmission facilities can be established and verified (data transfer control);

(d) Ensure that the Data is protected against accidental destruction or loss (availability control); and

(a) Ensure all Data security incidents are managed in accordance with appropriate incident response procedures.

1.2 Network Security

The Recipient maintains network security using commercially available equipment and industry standard techniques, including firewalls, intrusion detection and/or prevention systems, access control lists and routing protocols.

1.3 Virus and Malware Controls

The Recipient installs and maintains anti-virus and malware protection software on the system to protect Data from anticipated threats or hazards and protect against unauthorized access to or use of Data.

Signed by or on behalf of the Parties:

The Discloser by:

Signature of authorised signatory

Dr Eamon Merrick (Primary Supervisor)
Name of authorised signatory

[AND]

Signature of authorised signatory

Paula Anne Murray (Researcher)
Name of authorised signatory

The Recipient by:

Signature of authorised signatory

Name of authorised signatory

Appendix E Ethics approval letter - Study 3

Auckland University of Technology Ethics Committee (AUTEC)

2 February 2024

Nick Garrett
Faculty of Health and Environmental Sciences

Dear Nick

Re: Ethics Application: **23/297 A mixed method study of the impact of a Clinical Decision Support System (CDSS) on the incidence of falls and falls related clinical decision making in a private hospital in New Zealand**

Thank you for your request for approval of amendments to your ethics application.

The amendment to broaden the inclusion criteria to include registered nurses working in the admission unit has been approved.

Non-Standard Conditions of Approval

1. Please revise the inclusion criteria in the Information Sheet to include this criteria as well as any materials being used for recruitment.

Non-standard conditions do not need to be submitted to or reviewed by AUTEC unless requested but must be completed before commencing your study.

Standard Conditions of Approval

1. The research is to be undertaken in accordance with the Auckland University of Technology Code of Conduct for Research and as approved by AUTEC.
2. All public facing documents must have the AUTEC approval number and be of a high standard of spelling and grammar. Dates on the Information Sheet(s) and Consent Form(s) must be consistent.
3. Any amendments to the project must be approved by AUTEC prior to being implemented.
4. A progress report is due annually on the anniversary of the approval date.
5. A final report is due at the expiration of the approval period, or, upon completion of project.
6. Any serious or adverse events must be reported to AUTEC, this includes unforeseen issues that might affect continued ethical acceptability of the project.
7. AUTEC grants ethical approval only. You are responsible for obtaining management permission for access from any institution or organisation at which your research is being conducted and you need to meet all ethical, legal, public health, and locality obligations or requirements for the jurisdictions in which the research is being undertaken.

The application number and title need to be referenced on all correspondence related to this project.

All forms are available online http://www.aut.ac.nz/research/researchethics

For any enquiries, please contact ethics@aut.ac.nz

(This is a computer-generated letter for which no signature is required)

The AUTEC Secretariat
Auckland University of Technology Ethics Committee

Cc: Kft9095@autuni.ac.nz; mandie.foster@aut.ac.nz; nada.signal@aut.ac.nz

Appendix F Permission to access staff - Study 3

Permission for researcher to access hospital staff.

For use when permission is being sought from the head of an organisation to undertake research within the organisation or with the organisation's people.

Project title:

A mixed method study of the impact of a Clinical Decision Support System (CDSS) on the incidence of falls and related clinical decision making in a private hospital in New Zealand

Project Supervisor: ***Dr Nick Garrett***

Researcher: ***Paula Murray***

- ☑ I have read and understood the information provided about this research project in the Participants Information Sheet dated October 2023 and the Research Notice.
- ☑ I give permission for the Research Notice to be displayed on the hospital internet and on the wards.
- ☑ I give permission for the primary researcher to undertake research within the private hospital.
- ☑ I give permission for the primary researcher to access the employees of the private hospital.

Hospital CEO's signature: .....

Hospital CEO's name: .....

Date: 01/11/2023

Primary Researcher's signature: P Murray

Primary Researchers name: Paula Anne Murray

Primary Researcher's Contact Details: 027 292 4201

Date: 1/11/2023

Approved by the Auckland University of Technology Ethics Committee on 16th October 2023 AUTEC Reference number 23/297

Note: The CEO of the organisation should retain a copy of this form.

Appendix G Minor change request to ethics - Study 3

29th January 2024

Dear AUT Ethics Committee,

Ethics Application: **23/297 A mixed method study of the impact of a Clinical Decision Support System (CDSS) on the incidence of falls and related clinical decision making in a private hospital in New Zealand**

This letter is to request a minor change to my approved ethics application.

The approved ethics application details one of the criteria for participants is:

- Must be a registered nurse that works on the ward in the private hospital.

Please can I amend this to read:

- Must be a registered nurse that works on the ward, or admission unit in the private hospital.

Rationale:

Through feedback from the advertising for participants, it has become clear that nurses in the admission unit also have an active role in the utilisation of the CDSS with regards to falls assessment and reporting. Therefore, they would also have critical information as to the operation of the CDSS that will add value to my research and contribute the answering my research question. I have discussed this with my primary supervisor, and he is supportive of this amendment.

Thank you in advance for considering my request.

Look forward to hearing from you soon.

Kind regards

Paula Murray
DHSc Student

Assoc. Prof. Nick Garrett PhD
Primary Supervisor

Appendix H Minor change approval letter - Study 3

Auckland University of Technology Ethics Committee (AUTEC)

2 February 2024

Nick Garrett
Faculty of Health and Environmental Sciences

Dear Nick

Re: Ethics Application: **23/297 A mixed method study of the impact of a Clinical Decision Support System (CDSS) on the incidence of falls and falls related clinical decision making in a private hospital in New Zealand**

Thank you for your request for approval of amendments to your ethics application.

The amendment to broaden the inclusion criteria to include registered nurses working in the admission unit has been approved.

Non-Standard Conditions of Approval

1. Please revise the inclusion criteria in the Information Sheet to include this criteria as well as any materials being used for recruitment.

Non-standard conditions do not need to be submitted to or reviewed by AUTEC unless requested but must be completed before commencing your study.

Standard Conditions of Approval

1. The research is to be undertaken in accordance with the Auckland University of Technology Code of Conduct for Research and as approved by AUTEC.
2. All public facing documents must have the AUTEC approval number and be of a high standard of spelling and grammar. Dates on the Information Sheet(s) and Consent Form(s) must be consistent.
3. Any amendments to the project must be approved by AUTEC prior to being implemented.
4. A progress report is due annually on the anniversary of the approval date.
5. A final report is due at the expiration of the approval period, or, upon completion of project.
6. Any serious or adverse events must be reported to AUTEC, this includes unforeseen issues that might affect continued ethical acceptability of the project.
7. AUTEC grants ethical approval only. You are responsible for obtaining management permission for access from any institution or organisation at which your research is being conducted and you need to meet all ethical, legal, public health, and locality obligations or requirements for the jurisdictions in which the research is being undertaken.

The application number and title need to be referenced on all correspondence related to this project.

All forms are available online http://www.aut.ac.nz/research/researchethics

For any enquiries, please contact ethics@aut.ac.nz

(This is a computer-generated letter for which no signature is required)

The AUTEC Secretariat
Auckland University of Technology Ethics Committee

Cc: Kft9095@autuni.ac.nz; mandie.foster@aut.ac.nz; nada.signal@aut.ac.nz

Appendix I Research poster

Approved by the Auckland University of Technology Ethics Committee on 16th October 2023
Reference number 23/297

Participant Information Sheet

Date Information Sheet Produced:

February 2024

Project Title

A mixed method study of the impact of a Clinical Decision Support System (CDSS) on the incidence of falls and falls related clinical decision making in a private hospital in New Zealand.

An Invitation

Hello, my name is Paula Murray. I am a nurse and my current role is Chief Executive Officer of Kakariki Hospital, which is jointly owned by Healthcare Holdings Ltd and a group of surgeons. Kakariki is a new private surgical hospital scheduled to open March 2024.

I am keen to explore nurses' experience and opinions about the use of the falls assessment within the CDSS via the Electronic Medical Record 'Trakcare'. This research is part of my Doctor of Health Science at the Auckland University of Technology (AUT), Auckland.

You have received this participants information sheet via email because you expressed an interest by responding to my research notice. Your participation will be in the form of an interview where I will listen to your experience and opinions about the use of the falls assessment within the CDSS via the Electronic Medical Record 'Trak care'.

Your participation is confidential and entirely voluntary, and it is your decision whether you wish to participate.

What is the purpose of this research?

Phase One has been completed and consisted of me the primary researcher obtaining data from various databases within the organisation pre and post the implementation of the Electronic Medical Record Trak Care.

Phase Two which is the phase you are being invited to participate in consists of a 30-45min confidential interview.

The results of this study will support nurses, executive management, policy makers and other hospitals within the health sector to better understand the nurses lived experience in using an electronic falls assessment via a CDSS to inform future practice and research. The need for this study is critical since the potential of CDSS in improving patient safety and streamlining the patient care process has yet to be fully realised, yet CDSS are continually being implemented into hospitals.

The research project will be reported in a thesis and the findings may be used for academic publications and presentations.

How was I identified and why am I being invited to participate in this research?

You have been included as a nurse that works on the ward or admission unit in the private hospital, who has used the falls assessment tool before and after the implementation of the CDSS, has not had previous management, or supervisory relationship with myself the primary researcher, and has signed the consent form.

These criteria are to ensure the research question is answered and that you as a participant have sufficient experience to be able to provide a meaningful response. The informed consent form is an ethical requirement where participants need to provide voluntary informed signed consent.

Exclusion will include

1. If the primary researcher has had a previous management, or supervisory relationship with you.

2. You are not a nurse.

3. You are a nurse but do not work in the wards or admission unit in the private hospital.

4. nurse but have not used the falls assessment tool, before and after the implementation of the CDSS.

5. You are a nurse but do not wish to sign the consent form.

1.Exclusion is necessary to avoid a power imbalance or coercion of participants.

2,3,4. This is necessary to ensure the research question is answered, and that each participant has sufficient experience to be able to provide a meaningful response.

5. This is an ethical requirement where nurses need to provide voluntary informed signed consent.

The focus of the interview will be your experience and opinions about the use of the falls assessment within the CDSS via the Electronic Record within your clinical practice setting.

How do I agree to participate in this research?

If you are interested in participating email me on kft9095@autuni.ac.nz to confirm your intent to take part in the research. I will give you a quick phone call to screen and ensure that you meet the research inclusion criteria detailed above and also ask the following questions:

- What is the origin of your nurse training?
- How many years' experience do you have as a nurse?
- How many years' experience do you working on surgical ward in the private hospital sector?
- How many years' experience do you have using a falls assessment?
- How many years' experience do you have using a falls assessment via a CDSS in the private hospital setting?

These questions allow me to identify a diverse range of participants. This is known as purposive sampling where the researcher selects participants to ensure a variety of experiences are represented in the sample. The aim is to maximise differences, if the participants are purposefully chosen to be different in the first place, then their views may reflect this difference and provide a complex picture for the research.

This phone call is also an opportunity for you to discuss the information sheet, request further information or ask questions about the research.

Once your participation has been confirmed a consent form will then be sent to you to be signed and returned to me via email before the interview is arranged.

Your participation in this research is voluntary (it is your choice) and whether or not you choose to participate will neither advantage nor disadvantage you.

You are able to withdraw from the research at any time. If you choose to withdraw from the research, you will be offered the choice between having any data which although has been deidentified is identifiable by me and can be removed or you can allow the data to be used. However, once the findings have been produced, removal of an individual's data may not be possible.

What will happen in this research?

If you agree to participate, it will involve an interview which will take approximately 30-45 minutes of your time.

The interview will be conducted at your place of work, in a private meeting room, at a mutually convenient time. To avoid any disruption to your shift and to support your privacy, please select a time outside of work time.

The focus of the interview will be to explore your experience and opinions about the use of the falls assessment via Trak Care in the ward/admission unit setting.

To deidentify the data at no point in the interview will I refer to you by name as it is my intention to record the interview. After the interview the audio tape will be given to a professional transcriber who will transcriber the interview.

It is important to note that the professional transcriber has signed a confidential agreement to ensure:

- they understand that all the material they have been asked to transcribe is confidential.
- they understand that the content of the tapes or recordings can only be discussed within the research team.
- they will not keep any copies of the transcripts nor allow third parties access to them.
- that any transcripts or documents they have in relation to this research project will be kept in a locked cabinet and/or password protected AUT computer.

If on the consent form you identified that you wished to review the final transcript it is at this stage that you will be emailed a copy to validate the information, to check for accuracy and resonance of your experience. Your participation in this review is entirely voluntary.

It is unlikely, but if you would like alterations to be made you will be asked to note the changes in an email and send them to me. I will then add them as an addendum to the end of the word file and return it to you for your final approval.

What are the discomforts and risks?

It is highly unlikely that you will experience any risk or discomfort. It is hoped that you will find participating a worthwhile and stimulating experience, however, should you experience any distress whatsoever during the interview, please do not hesitate to let me know immediately.

As a participant you will be afforded confidentiality, anonymity, and privacy. However, full confidentiality may not be guaranteed if the other participants choose to discuss their involvement in the study with their colleagues. I will strive, to ensure confidentiality, by deidentifying data and findings and ensuring raw data remains private.

How will these discomforts and risks be alleviated?

As a participant you will be treated with respect, dignity and equity honouring the ethical code of conduct in undertaking research.

The interview will be conducted with care and in a professional and transparent way, however if you do experience any emotional responses that are distressing, please let me know. You are also free to withdraw at any point without providing a reason and this decision will be free from prejudice and judgment.

What are the benefits?

The results of this study will support nurses, executive management, policy makers and other hospitals within the health sector to better understand the nurses lived experience in using an electronic falls assessment via a CDSS to inform future practice and research. The need for this study is critical since the potential of CDSS in improving patient safety and streamlining the patient care process has yet to be fully realised, yet CDSS are continually being implemented into hospitals.

This research will also support me to obtain my Doctor of Health Science qualification.

How will my privacy be protected?

Maintaining your privacy and confidentiality is important to me both during and after the interview. All data collected will be deidentified and given codes to ensure confidentiality is protected for all participants. Data will be stored in a highly confidential manner following appropriate processes.

Hard copy information will be stored in a designated locked cabinet for six years, stored correctly with access only for myself and my supervisors. The professional transcriber will sign a confidentiality agreement prior to undertaking the work. Digital material will be stored on a password protected AUT server in a password protected folder.

What are the costs of participating in this research?

The only cost would involve your contribution of no more than 30-45 minutes of your time for the interview.

If you wish to review the final transcript some of your time will be required to complete this review.

What opportunity do I have to consider this invitation?

The research notice requesting volunteers will be displayed on the hospital intranet and on all the wards for 4 weeks. During this time, you can express your interest by emailing me and I will send you a participant information sheet. If you confirm your interest to participate, I will call you to confirm you meet the inclusion criteria, I will also ask you some additional questions which will help me to select a diverse range of participants. Once participation is confirmed you will be asked to sign a consent form before the interview.

Will I receive feedback on the results of this research?

Yes, you will, the results will be sent to you in the form of a written summary.

The final results of this study will also be published in my thesis.

What do I do if I have concerns about this research?

Any concerns regarding the nature of this research should be notified in the first instance to the Project Supervisor, Associate Professor Nick Garrett, Nick.Garrett@aut.ac.nz, 09 921 9999 ext. 7773

In addition to notifying the Project Supervisory Nick, if you still have concerns you may also wish to notify the Executive Secretary of Auckland University of Technology Ethics Committee, ethics@aut.ac.nz, (+649) 921 9999 ext. 6038.

Whom do I contact for further information about this research?

Please keep this Information Sheet for your future reference. You are also able to contact myself or my project supervisor.

Primary Researchers Contact Details: Paula Murray Email: kft9095@autuni.ac.nz; Phone:027 292 4201

Project Supervisor Contact Details: Dr Nick Garrett, Nick.Garrett@aut.ac.nz, 09 921 9999 ext. 7773

Approved by the Auckland University of Technology Ethics Committee on *16th October 2023*, Reference number *23/297*.

Appendix K Participant consent form

Consent Form

For use when interviews are involved.

Project title: A mixed-method study of the impact of a Clinical Decision Support System (CDSS) on the incidence of falls and falls-related clinical decision-making in a private hospital in New Zealand

Project Supervisor: ***Dr Nick Garrett*** *Researcher:* ***Paula Murray***

- I have read and understood the information provided about this study in the Participant Information Sheet dated February 2024.
- I have had an opportunity to ask questions and to have them answered.
- I understand that notes will be taken during the interviews and that they will also be recorded and transcribed.
- I understand that taking part in this study is voluntary (my choice) and that I may withdraw from the study at any time without being disadvantaged in any way.
- I understand that if I withdraw from the study, then I will be offered the choice between having any data that is identifiable as belonging to me removed or allowing it to continue to be used. However, once the findings are produced, removing my data may no longer be possible.
- I agree to take part in this research.
- I wish to receive a transcription of the interview to let the researcher know if the transcribed responses are correct (please tick one): Yes ☐ No ☐
- I wish to receive a summary of the research findings (please tick one): Yes ☐ No ☐

Participant's name: .....

Participant's signature:.....

Participant's Contact Details (if appropriate): .....

Date .....

Primary Researcher's name: Paula Anne Murray

Primary Researcher's signature: .....

Primary Researcher's Contact Details: Email - kft9095@autuni.ac.nz Mobile - 027 292 4201

Date: .....

Approved by the Auckland University of Technology Ethics Committee on 16th October 2023, AUTEC Reference number 23/297

Note: The Participant should retain a copy of this form.

Appendix L Semi-structured interview questions

Research Title: The impact of a Clinical Decision Support System (CDSS) on the incidence of falls and falls-related clinical decision-making in a private hospital in New Zealand

Semi-structured Participant Questions

Participant ID…… **Date……**

Time…….

Before starting the interview, seek verbal consent from the participant to participate in the study and to be recorded. If the participant says yes, then turn the recorder on and ask those questions again and just say to the participant that it is important to have this recorded.

Check that the participant has no questions about the PIS.

Remind the participant of the aim: To explore the nurses' experience and opinions of using an electronic falls assessment via a CDSS within their clinical practice setting.

Explain the format of the interview: Paper Falls Assessment prior to Trakcare, Electronic Patient Assessments, Electronic Falls Assessment in Trakcare, General Questions

Phase Two Question: Is there an association between the use of an electronic falls assessment via a Clinical Decision Support System (CDSS) on nurses fall related clinical decision making within their practice setting.

Questions	Notes
Concepts/domains: benefits, challenges, satisfaction, impact on clinical decision making, efficacy, education received, documentation, implementation to practice, recommendations, exemplars	
Paper Falls Assessment prior to Trakcare	
Can you tell me about your experience using the paper falls assessment prior to Trakcare?	

Can you describe the education you received in relation to the paper falls assessment?	
How accessible was the paper falls assessment?	
Can you describe the information you were required to collect from the patient?	
How user friendly was the assessment?	
You now have the result of the risk assessment (score/low.med.high). and this relates to falls prevention tasks. Can you explain how the fall prevention tasks influenced your care for the patient?	
Can you describe your overall satisfaction with the falls prevention tasks provided?	
Unfortunately, your patient has fallen can you explain the steps you would take?	
Can you explain how you would inform your colleagues and the managers of this fall?	
Can you describe if there were any barriers to you carrying out your duties in caring for a patient who has fallen?	
Can you describe how the fall was to be formally documented?	
Can you describe how this falls assessment supported your clinical decision making?	
Can you describe any failings with the falls prevention tasks provided?	
Can you describe your overall satisfaction with the falls assessment tool?	
Probing questions: Oh, can you tell me more about this, how did this make you fell, what did you do, can you give me an example of this, can you describe this in more detail?	
Electronic Patient Assessments	

Can you tell me about your previous experience using electronic patient assessments?	
If yes: Did this include a falls assessment?	
Can you recall the name of the electronic system?	
Was this experience in a public or private hospital?	
Electronic Falls Assessment in Trakcare	
Concepts/domains: benefits, challenges, satisfaction, impact on clinical decision making, efficacy, education received, documentation, implementation to practice, recommendations, exemplars	
Can you tell me about your experience using the falls assessment in Trakcare?	
Can you describe the education you received in relation to the falls assessment within Trakcare?	
How accessible is the falls assessment?	
Can you describe the information you are required to collect from the patient?	
How user friendly is the assessment?	
You now have the result of the risk assessment (score/low.med.high). and this relate to falls prevention tasks. Can you explain how the fall prevention tasks influence your care for the patients?	
Can you describe your overall satisfaction with the falls prevention tasks provided?	
Unfortunately, your patient has fallen can you explain the steps you would take?	
Can you explain how you would inform your colleagues and the managers of this fall?	
Can you describe if there are any barriers to you carrying out your duties in caring for a patient who has fallen?	
Can you describe how the fall is formally documented?	

Can you describe (examples)how this falls assessment supported your clinical decision making?	
Can you describe any failings with the falls prevention tasks provided?	
Can you describe your overall satisfaction with the falls assessment tool?	
Probing questions: Oh, can you tell me more about this, how did this make you fell, what did you do, can you give me an example of this, can you describe this in more detail?	
General Questions	
In relation to the effect on patient care: Can you describe your thoughts on the effectiveness of overall Trakcare system versus the previously used manual system?	
Can you share your thoughts on the electronic versus the manual falls assessment?	
Can you share your opinion on whether there is a relationship between the papers falls assessment and patient outcomes specifically falls?	
Can you share your opinion on whether there is a relationship between the falls assessment in Trakcare and patient outcomes specifically falls?	
Can you share your opinion on whether there is a relationship between staffing levels and patient outcomes specifically falls?	
How has the implementation of the electronic falls assessment in Trak care informed your clinical decision making?	
How has the implementation of the electronic falls assessment in Trak care informed your clinical practice?	
Do you have any other thoughts or opinions you wish to share in relation to this topic?	