Improving Situation Awareness to Reduce Healthcare-Acquired Urinary Tract Infection

by

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We acknowledge and respect the Lək̓ʷəŋən (Songhees and Esquimalt) Peoples on whose territory the university stands, and the Lək̓ʷəŋən and W̱SÁNEĆ Peoples whose historical relationships with the land continue to this day

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Abstract

Reducing healthcare-acquired urinary tract infections (HAUTI) is a common goal among healthcare providers and organizations. Nurses' situation awareness (SA) skills would likely improve patient status recognition and prevent healthcare-acquired urinary tract infections. Healthcare providers, such as nurses, need eHealth systems that support their situation awareness as they provide care.

Integrating Endsley's design principles with machine learning offers a promising approach for developing an SA-oriented dashboard that could help reduce HAUTI. This study takes an initial step toward this goal by exploring context-based variables contributing to HAUTI. I included a comprehensive list of nursing assessments and implemented multiple methodologies to handle the datasets and address missing data. The XGBoost model emerged as the most effective model in predicting HAUTI, isolating factors such as improving skin integrity and mobility and monitoring neurological status as key factors in reducing HAUTI rates. However, these results should be carefully interpreted, given this study's significant missing data. The finding of this study reinforces the necessity of high-quality data to support the interpretation of Machine Learning (ML) models in clinical settings.

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Dedication

To my beloved wife, whose unwavering love, patience, and support have been my greatest strength throughout this journey. To my precious daughters and son, for filling my life with joy and purpose, and for being my constant source of inspiration. To my brother, for always standing by my side with encouragement and support. And to my late mother and father, whose faith in me and endless encouragement to pursue education continue to guide me, even in their absence. This accomplishment is as much yours as it is mine

List of Abbreviations

Abbreviation	Complete Words
ANOVA	Analysis of Variance
AUC	Area Under the Curve
CART	Classification and Regression Trees
CINAHL	Cumulative Index to Nursing and Allied Health Literature
ED	Emergency Department
EHR	Electronic Health Record
FAMD	Factor Analysis of Mixed Data
GDTA	Goal-Directed Task Analysis
GRADE	Grades of Recommendation, Assessment, Development, and Evaluation
HAUTI	Healthcare-Acquired Urinary Tract Infections
HCI	Human-Computer Interaction
HIRAID	Nursing Assessment Framework
ICU	Intensive Care Unit
IDR	Interdisciplinary Rounds
MAR	Missing at Random
MCA	Multiple Correspondence Analysis
MCAR	Missing Completely at Random
MICE	Multiple Imputation by Chained Equations
ML	Machine Learning
MNAR	Missing Not at Random
NN	The Neural Networks
PCA	Principal Component Analysis
PEWS	Pediatric Early Warning Score
PICOS	Population, Intervention, Comparison(s), Outcome, and Setting
PMM	Predictive Mean Matching
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PRESS	Pediatric Risk Evaluation and Stratification System
QQ	Quantile-Quantile
RoB 2	Risk-of-Bias tool for randomized trials
ROBINS-I	Risk Of Bias In Non-randomized Studies of Interventions
SA	Situation Awareness
SAGAT	Situation Awareness Global Assessment Technique
SBAR	Situation, Background, Assessment, and Recommendation
SVM	Support Vector Machines
TSA	Team Situational Awareness
UTI	Urinary Tract Infection
VIZ	Health data visualization

Chapter 1 Introduction

Chapter 1 introduces the research background, problem domain, and study approach.

1.1 Background and Motivation

Situation Awareness (SA) is one of the cognitive nontechnical skills that is gaining more attention in the healthcare literature (Fore & Sculli, 2013). SA generally refers to perceiving environmental elements, understanding their meaning, and predicting their future status (Endsley, 1995). According to this description, SA is necessary for healthcare providers. The providers need to be aware of patient status, understand changes in patient condition, expect potential patient progression, and then decide on patient care (Phillips, 2014).

Nurses need SA for their practice. They are the largest healthcare workforce and provide 24-hour care in hospital settings (Fore & Sculli, 2013). The nurses' position in the clinical environment allows them to be first in identifying and understanding patient signs and symptoms. Nurses must recognize and realize patients' conditions to provide care (Phillips, 2014).

From a nursing perspective, the SA is a dynamic process involving perceiving clinical cues, assigning meaning to these cues, and using them to project interventions (Sitterding et al., 2012). The awareness of these cues can reflect individual, team, shared or distributed SA (Brady & Goldenhar, 2014). A nurse's personal perception, understanding, and comprehension of patients' status is individual SA (Brady & Goldenhar, 2014). The SA that reflects the role of each healthcare team member is team SA. The common SA among the team members is shared SA. The dynamic awareness supported by devices in the clinical environment is distributed SA (Brady & Goldenhar, 2014). Understanding the definition and variation of SA is essential to studying and supporting this nontechnical skill effectively.

The low SA can result in unfavourable clinical consequences on patient outcomes and providers' performance. Without SA, providers cannot recognize patient status changes, delaying necessary interventions (O'Leary et al., 2014; Padilla & Mayo, 2018). The failure to identify patients' status is one of the root causes of needing a higher level of care and causing acute adverse effects (Jones et al., 2013; van Galen et al., 2016). Studies showed that low SA could result in significant patient harm or even death (Schulz et al., 2017; Uramatsu et al., 2017). SA can also affect the providers' performance (Cha et al., 2019). The nontechnical, SA skill correlates with the providers' ability to perform technical skills and achieve a predefined goal of care (Briggs et al., 2015; Cha et al., 2019; Coolen et al., 2019; Mishra et al., 2008). SA is an essential nontechnical skill when it comes to quality healthcare services.

However, the literature shows that nurses need to improve their SA (Cooper et al., 2010; Cooper et al., 2011; De Meester et al., 2013; O'Meara et al., 2015). In one study, the nurses failed to perceive nearly half of the patients' vital signs (Al-Moteri et al., 2018). In another study, more than half (60%) of participating nurses reported missing patients' signs indicating clinical deterioration (De Meester et al., 2013). Improving SA is necessary to enhance patient outcomes and prevent possible side effects.

One clinical area that can benefit from improved nurses' SA is the prevention of Healthcare-Acquired Urinary Tract Infections (HAUTI). HAUTI is one of the leading quality concerns in healthcare services. HAUTI refers to acquiring the infection while obtaining healthcare in clinical settings. Patients can develop HAUTI for many reasons, such as indwelling catheterization, inadequate nursing care, or poor infection control practices (CPSI, 2016; Castle et al., 2017; Griebling, 2018a). High nurses' SA will likely reduce the adverse event of acquiring HAUTI.

1.2 Problem Statement

HAUTI is a disease that increases mortality, morbidity, and healthcare costs (CPSI, 2016). The prevention of HAUTI is an ideal approach to minimize the consequences of this disease. However, HAUTI's reduction rate is slow in Canada (CPSI, 2016).

The nurses play an integral part in preventing and managing HAUTI. They assess patients regularly and implement interventions that can change the infection rate. For example, the nurses monitor patients' signs, provide meatal care, and practice infection control standards (Gray, 2004; Juthani-Mehta et al., 2007; Lee et al., 2015; Meddings et al., 2017; Willson et al., 2009). The nurses are a core workforce in preventing and managing HAUTI.

Nurse-led initiatives are one method to reduce HAUTI rates. These initiatives focus on enhancing nurses' awareness of evidence-based practices, supporting necessary care, and promoting adherence to infection control practices (Thomas, 2016; Viner, 2020). Most of the evidence around nurse-led initiatives indicates some positive results on patient outcomes (Wu et al., 2020).

Informatics technologies like Electronic Health Records (EHR) can support the nurse-led initiative targeting HAUTI. The EHR can help raise situation awareness around HAUTI by advancing the perception of clinical guidelines, providing feedback about best practices (Quinn, 2015), and analyzing the HAUTI risk factors (Park, 2018). Higher nurses' SA will advance their ability to recognize and understand patients' clinical status, reducing HAUTI incidences.

However, the comprehensive information in the EHR is often scattered and does not necessarily support clinical reasoning (Wisner et al., 2019). There is a need to visualize and contextualize patient information better (Wisner et al., 2019). Here, the dashboards offer a possible solution.

The dashboards can support real-time extraction of necessary EHR data and present it in interactive visualization that supports providers' clinical decisions (Ahmed et al., 2011; Ghazisaeidi et al., 2015). There are two main types of dashboards, including clinical and quality dashboards. The clinical dashboard supports clinicians' daily decisions at the point of care (Dowding et al., 2015). The quality dashboard aims to explore opportunities for quality improvement (Dowding et al., 2015). Regardless of the dashboard type, these displays demonstrated the capacity to display clinical indicators, improve cognitive performance, and reduce the mental workload and frequency of cognition errors (Ahmed et al., 2011; Dolan et al., 2013; Simms et al., 2013).

SA is a cognitive nontechnical skill. If dashboards improve cognitive workload, then it is rational to assume the potential benefit of using dashboards as a point-of-care intervention to improve nurses' SA. An SA-oriented dashboard would offer the opportunity to display health information to support the perception, comprehension, and projection of patients' status and clinical condition.

I conducted a systematic review to explore the use of nurse-targeted SA interventions, specifically dashboards, in a clinical setting (see Chapter 4). In this review, I found a limited number of studies addressing SA-interventions. The studies I found lack the quality to support evidence on the effect of these interventions to enhance nurse SA. The available studies on dashboard interventions did not use an SA model or theory to guide the design process. The information contained in these dashboards represents retrospective data with no indication of supporting prospective reporting. Retrospective and prospective reporting are both important in supporting all levels of SA.

The significance of nurses' SA and the benefits of using dashboards to improve cognitive performance highlights the possibility of employing the dashboards to improve SA in the context of HAUTI. This study addressed this need by initiating the work on developing a nursing SA-oriented dashboard at the point of care. This intervention aims to enhance nurses' SA, enabling them to perceive and understand clinical HAUTI cues, anticipate the infection, and plan preventive measures.

1.3 Research Aim

This study aimed to reduce HAUTI by developing eHealth intervention targeting nurses' SA. This initial step, which is the focus of this study, involve discovering the factors contributing to HAUTI and predicting the risk of the infection. These factors can then be used to inform the design of a situation awareness dashboard that supports the perception of the clinical data, understanding the meaning of this data and projecting the risk of developing HAUIT.

This study includes several questions:

1. What is the best machine learning method and prediction model to predict the probability of Healthcare-Associated Urinary Tract Infection?

2. What are the most important predicting variables of Healthcare-Associated Urinary Tract Infection in the participating organization?

1.4 Summary

SA is an essential cognitive nontechnical skill for nursing practice. Low SA is associated with clinical adverse events and poor patient outcomes. The prevention of HAUTI is one clinical context that can benefit from improved nurses' SA. Here, using eHealth technologies, such as dashboards, can be helpful. Dashboards can extract and present EHR data meaningfully, supporting perception, understanding, and projection of patient status. There are currently no dashboard studies that are built around a SA model or theory. This study aimed to initiate the work on developing SA-dashboard by discovering the factors leading to HAUTI.

Chapter 2 Nature of Problem Domain

Chapter 2 discusses the key concepts of the study, including situation awareness, urinary tract infections, and the use of dashboards in healthcare

2.1 Situation Awareness

Nontechnical skills are essential in healthcare practice (Lewis et al., 2012; Stubbings et al., 2012). These skills include interpersonal skills such as communication, teamwork, and leadership practices, as well as cognitive skills such as situation awareness (SA) and decision-making (Lewis et al., 2012). Researchers link nontechnical skills in clinical settings to minimizing the chances of adverse events and enhancing patient safety (Stubbings et al., 2012).

2.1.1 What is Nursing Situation Awareness

SA is one of the cognitive nontechnical skills that is getting more attention in healthcare literature (Fore & Sculli, 2013). The concept of SA originated in the aviation industry, specifically when studying pilots' awareness and overall performance (Endsley, 1988; Fracker, 1988). Endsley (1995) defined Situation awareness as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future" (p. 36). By this definition, Endsley introduced three SA levels: perception, comprehension, and projection of status (Endsley, 1995).

Understanding the patient's situation is one of the central factors necessary to respond to patient conditions (Tanner, 2006). Like any other healthcare profession, nurses often encounter rapidly changing patient status. Nurses must remain attentive to patient illness, maintain patient surveillance, recognize changes, and generate appropriate decisions (Phillips, 2014).

The nurses' SA is not necessarily the same as that of other professions. The nurses might perceive, understand, and project situations differently. In one study, researchers compared the nurses' and doctor's anticipation of patient development to actual patient outcomes (Reader et al., 2011). The researchers found that the team members had conflicting anticipation for over half of

105 participating patients; senior physicians had the most accurate prediction (Reader et al., 2011). Other researchers reported similar findings (Miller & Sanderson, 2005). Although there was no significant difference between physicians and nurses regarding the perception of the physiological symptoms, there was a significant difference in the SA projection level (Miller & Sanderson, 2005). Changing one SA level will affect the healthcare provider's overall SA (Endsley, 1995). Physicians tend to project patient status over a broader range of physiological functions than nurses, who have a shorter projection timeframe (Miller & Sanderson, 2005). The difference in SA between nurses and other professions necessitates considering nurses' perspective and context when studying the nurses' SA and trying to improve this cognitive skill.

To further study SA as a nursing cognitive construct, it is essential to understand how it is defined in the nursing context. Researchers have defined SA in several ways, many of which apply to the nursing context (Table 1). Learning from Endsley's work, most of these definitions explain SA as being aware of environmental elements and understanding the surroundings. Nurses collect information from their environment as part of their daily practice to understand current and future patients' conditions (Mitchell et al., 2011).

Table 1: *Definitions of situation awareness in literature*

Reference	**Definition of Situation Awareness**
(Endsley, 1995)	"Situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future" (P.36).
(Singh et al., 2006).	A shared understanding of the current process and the progression of health status
(Catchpole et al., 2008)	"the ability of the surgeon to observe, understand, and predict events in the OR" (p. 699)
(Guise et al., 2008)	"Team members vigilantly survey surroundings to be aware of all human and technological resources available and how to access them quickly" (P.219)
(Hicks et al., 2008)	"Avoids fixation errors", "Reassesses and reevaluates situation constantly", "Anticipates likely events" (p.1137).

(Sevdalis et al., 2008)	"System awareness, environmental awareness, and anticipation (p.185)".
(Miller, Riley, & Davis, 2009)	"Conscious, mindful observation of one's own environment or recognition of patient condition" (p.250)
(Fioratou et al., 2010)	"Developing and maintaining an overall dynamic awareness of the situation based on perceiving the elements of the theatre environment: patient, team, time, displays, equipment, understanding what they mean and thinking ahead about what could happen in the near future" (p.83)

One of the most comprehensive attempts to define nursing SA is the work of Sitterding et al. (2012). Sitterding et al. carried out a hybrid concept analysis and performed semi-structured interviews to understand nurses' experience of SA. Then, the researchers completed content and relational analyses (Sitterding et al., 2012). In their conclusion, Sitterding et al. defined SA as "a dynamic process in which a nurse perceives each clinical cue relevant to the patients and their environment; comprehends and assigns meaning to those cues resulting in a patient-centric sense of salience, and projects or anticipates required interventions based on those cues. This projection influences the nurse's cognitive stacking and nursing care actions" (Sitterding et al., 2012, p. 89). I use Sitterding and colleague's definition in this paper to describe SA in nursing.

2.1.2 Types of Situation Awareness

Brady and Goldenhar (2014) have further defined SA into four types. These types include individual SA, team SA, shared SA, and distributed SA (Table 2) (Brady & Goldenhar, 2014). By these definitions, an individual SA, for example, is when a nurse notices signs and symptoms of constipation, understands that these symptoms are related to immobility, and expects to mobilize the patient to improve this clinical status. A team SA is when, for example, each member of a cardiopulmonary resuscitation team has a defined role, such as documenting medication administration or ventilating patients, and has the necessary patient information to support this role. The same member is not necessarily aware of other team members' roles; however, they are sharing a common goal.

Table 2: *Types of situation awareness (Brady & Goldenhar, 2014)*

Type of SA	**Definition**
Individual SA	"individuals' perception of data elements, the comprehension of their meaning in context and the projection of their status in the near future"(p. 154)
Team SA	"degree to which every team member possesses the SA required for his or her responsibilities"(p. 154)
Shared SA	"degree to which team members have the same SA on shared SA requirements"(p. 154)
Distributed SA	"developing and maintaining an overall dynamic awareness of the situation based on perceiving the elements of the theatre environment: patient, team, time, displays and equipment, understanding what they mean and thinking ahead about what could happen in the near future"(p. 154)

The shared SA is evident during patients' rounds. During rounds, all team members share the same information about patient situations and prognoses and can use it to support their decision-making process. The distributed SA is when a nurse working in the Intensive Care Unit (ICU), for example, observes the patient monitor in real-time and adjusts medication perfusion based on the patient's hemodynamics (Brady & Goldenhar, 2014). The monitor, in this example, will influence nurse SA and decision-making.

Based on the examples above, understanding the differences between these SA types can help understand the providers' information needs. The assumption is that the information the nurses need to share during patient rounds (shared SA) is not necessarily the same as the information they require to deliver specific nursing interventions (individual SA). Recognizing the type of SA and its implication in clinical settings is essential.

2.1.3 Importance of Situation Awareness

The importance of SA in a clinical setting is not an area of argument in the literature. The World Health Organization recognizes SA as a necessary measure of patient safety (Flin et al., 2009). Other countries introduce SA as one of the nontechnical skills competencies for health professionals in secondary and tertiary clinical settings (Peddle et al., 2018). One real case example of SA's importance is the Elaine Bromiley incident (Green et al., 2017). In this incident, the physician was trying to insert a breathing tube for Elaine while missing the fact that the patient was in severe cyanosis (decreased oxygen level). The physician should have noticed the perception of a clinical cue (lack of oxygen) and focused on the task at hand. In this case, the low SA led to patient cerebral hypoxia, which eventually led to patient death. This case example indicates how important SA is as a cognitive nontechnical skill and how it might improve healthcare decisions. Low SA can have several consequences in the healthcare context. Below, I discuss the effect of SA on adverse events, technical skills, and nursing practice.

2.1.3.1 Situation Awareness and Adverse Events. Hospital adverse events are not uncommon. Nearly one out of 10 hospitalized patients experience unfavourable outcomes, and 50% of these events being preventable (de Vries, Ramrattan, Smorenburg, Gouma, & Boermeester, 2008). It is possible to prevent these adverse events as patients might demonstrate antecedents' signs and symptoms. For example, most patients (59.4%) had at least one abnormal vital sign 1-4 hours before the arrest, and 13.4% had at least one severely abnormal sign (Andersen et al., 2015). Data from three countries, the UK, Australia, and New Zealand, confirms that 79.4% of the cardiac arrests and 54% of ICU admissions had evidence of abnormal physiological antecedents such as abnormal vital signs (Kause et al., 2004). Kause et al. defined abnormal vital signs as “threatened airway, respiratory rate (<5 and >36 breaths per minute), pulse rate (<40 and >140 beats per minute), systolic blood pressure (<90 mmHg), a fall in Glasgow Coma Scale (GCS) of≥2 points and prolonged seizures” (p. 277). Such changes in these physiological parameters preceded death, cardiac arrest, and unanticipated ICU admission

(Kause et al., 2004). If healthcare providers became aware of antecedents' signs and symptoms before the adverse event, they might prevent such events from occurring.

The failure to monitor patient clinical signs is one of the root causes of patients needing a higher level of care (46%) more than disease-related causes (45%), patient-related causes (7, 5%), or organizational related causes (3%) (van Galen et al., 2016). Suppose nurses do not recognize clinical situations. In that case, the patient's clinical status can worsen, raising their need for higher acuity of care (Padilla & Mayo, 2018). The failure to recognize clinical changes can increase the risk of morbidity, including organ dysfunction, prolonged hospital stay, and disability, or increase mortality (Jones et al., 2013).

In one study, researchers examined the frequency and type of situational awareness errors that led to death or brain damage in closed anesthesia malpractice claims (Schulz et al., 2017). The researchers found that from 2002 to 2013, SA errors existed in 198 out of 266 claims (74%). These errors mainly were related to perception (n = 83, 42%), followed by comprehension (n = 58, 29%) and projection (n = 57, 29%) (Schulz et al., 2017). In a similar study, researchers analyzed death's cause in 73 summary reports of fatal medical accidents. The researchers found that nontechnical skills were the cause of death in 34 cases (46.6%), with fourteen cases (41.2%) involving problems associated with situation awareness, eight (23.5%) with teamwork, and three (8.8%) with decision-making (Uramatsu et al., 2017). Other researchers retrospectively reviewed patient records of 63 serious adverse events in a Belgian teaching hospital. The outcomes in this review were cardiac arrest or unplanned ICU admission (De Meester et al., 2013). During the study, the researchers surveyed 44 nurses regarding their most recent experiences with a deteriorating patient, and 60% of nurses reported they were often unaware that their patients were deteriorating (De Meester et al., 2013).

The loss of SA impairs the healthcare professional's ability to recognize patient status changes and significantly delays lifesaving interventions (O'Leary et al., 2014). Nurses provide care around the hour and represent the largest healthcare workforce (Fore & Sculli, 2013). It is safe to say that nurses are the first to notice and report potential adverse events in hospitals. If the nurses interpret any visual and auditory cues in a clinical setting as significant, they anticipate potential problems and prepare for possible consequences (Marshall & Finlayson, 2018). The benefit of high SA is maximizing the nurse's or healthcare providers' cognitive resources and improving their decision-making process (Fore & Sculli, 2013).

2.1.3.2 Situation Awareness and Technical Skills. Several studies indicated a relationship between SA and providers' technical skills and clinical performance. In one study, researchers tested this relationship in a simulation environment and found that technical skills moderately correlated significantly with nontechnical skills (r = .45, p = .05) (Riem et al., 2012). Two other studies explore the same relationship in the operating room. In one study, researchers examined 26 elective laparoscopic cholecystectomies (Mishra et al., 2008). The researchers found evidence of a negative moderate correlation between the operating room team SA and technical errors during the surgery (r = -.505, p = .009), with a strong negative correlation between the surgeons' SA and technical errors (r_s = -.718, p = .001) (Mishra et al., 2008). In another paper, researchers analyzed the data from 26 laparoscopic cholecystectomies and 22 carotid endarterectomies to find a strong association between the errors in these surgical techniques and the surgical situation awareness in each operation ($F(2,42)$ = 7.93, p < .001) (Catchpole et al., 2008). The researchers noted that this association is stronger with laparoscopic cholecystectomies, possibly related to this procedure's higher cognitive and psychomotor demand (Catchpole et al., 2008).

The providers' level of SA can also help predict healthcare providers' performance and the level of care they provide. Out of multiple nontechnical skills, SA can significantly predict medical students' clinical performance (R^2 = 0.323, p = < .001) (Cha et al., 2019). Other researchers noted the same conclusion in multidisciplinary teams. In a cohort study that involved 20 teams composed of surgical residents, emergency medicine residents, Emergency Department (ED) nurses, and emergency services assistants, the researchers found significant correlation between team’s and team leader’s SA and critical task completion; the correlation coefficients were between .351 and .478 ($p < .05$) (Briggs et al., 2015). In a similar study, Coolen and colleagues measured team SA among 24 teams of two nurses, one resident, and one consultant. They explored the relationship between SA and team effectiveness to achieve a predefined goal (Coolen et al., 2019). The researchers found that the comprehension level of SA led to significantly faster achievement of the predefined goal expected during each scenario ($p < .05$) (Coolen et al., 2019). The relationship between SA and technical skills and clinical performance highlights the unfavourable consequences of low SA on healthcare service quality.

2.1.3.3 Situation Awareness and Nursing Practice. A higher SA in healthcare will advance identifying the patient's condition and diagnosing clinical complaints (Singh et al., 2006). Nurses rate SA as an essential skill in several clinical settings (Afkari et al., 2016; Cemalovic et al., 2016; Hicks et al., 2008; Mitchell & Flin, 2008; Mitchell et al., 2010; Redaelli, 2018). Nurses rely on their SA to care for their patients and carry out daily interventions. As they provide care, nurses use all three levels of SA. The nurses demonstrated Level 1 by noticing and analyzing the patient assessment cues and reviewing admission diagnoses or procedures during hospitalization (Tower et al., 2012). Examples of these cues include information about assessing daily living activities, medication lists, and clinical requirements. The nurses might use previous notes and assessments combined with patient observation and interaction to support their level 1 SA. If the nurses interpreted any of these cues as significant, they anticipate potential problems and prepare for possible events (Marshall & Finlayson, 2018).

Similarly, SA is needed when nurses perform interventions. One example is medication administration. Researchers noticed that nurses used level 1 SA to perceive and process visual and auditory cues, such as hearing the doctor adding new medication orders and the sounds of phones and alarms (Sitterding et al., 2014). The nurses used level 2 SA to assign meaning to the previous cues and level 3 to anticipate necessary medication changes (Sitterding et al., 2014).

Overall, SA is an essential nontechnical skill when exploring adverse events and optimal clinical practice. Providers with low SA can contribute to a higher chance of side effects and unfavourable consequences. Also, their technical abilities can change if their SA is low. SA is an essential skill for all healthcare providers, including nurses.

2.1.4 Current Status of Situation Awareness

2.1.4.1 Opportunity to Improve Nurses' Situation Awareness. Although limited, the studies on nurses' SA show the need to advance this nontechnical skill. Regardless of the clinical setting, clinical experience, or SA measurement method, nurses' and nursing students' SA level is an area of improvement. For example, researchers used two deteriorating patients' simulation scenarios to measure the SA of 35 rural nurses (Cooper et al., 2011). Although Cooper and colleagues found a high average projection score (72.1%-82.1%), SA was low for perception (37.5%) and moderate for comprehension (55.7%-60.3%) (Cooper et al., 2011).

Similarly, researchers explored observation lapses in a sample of 40 nurses using deteriorated case scenarios. They found that the percentage of unnoticed cues per vital sign ranged from 10 to 60, with a mean of 17.58 (*SD* = 17.17) (Al-Moteri et al., 2018). In other words, some nurses failed to perceive more than half of the vital signs. This result is similar to another study where 60% of participating nurses reported that they were unaware their patients were deteriorating (De Meester et al., 2013). Researchers noticed that as the case scenarios deteriorated, the number of missed cures increased (Al-Moteri et al., 2018).

Other studies highlighted similar results when examining nursing students. The average SA among 51 nursing student nurses was generally low (38.2–82.3%; *SD* = 10.7; 95% CI: 55.9–61.9) (Cooper et al., 2010). The student nurses are more successful in identifying the indicators of deterioration and understanding their meaning than having a global perception of these situations (participants' awareness of the total environment) (Cooper et al., 2010). For example, the students noticed the patient's heart rate but did not know if the suction was available at the bedside (Cooper et al., 2010). In another study, researchers explored SA in a sample of nursing and paramedicine students. The researchers found that the students had a moderate overall average score of 52% (O'Meara et al., 2015). Generally, the students were unaware of the presenting medical conditions and the clinical environment and did not recall the patient's vital signs (O'Meara et al., 2015). As SA is vital for patient safety, it is necessary to improve this nontechnical skill.

2.1.4.2 Factors Affecting Nurses' Situation Awareness. According to Endsley, several factors can affect SA. Endsley classified these factors into task and system factors and individual factors (Endsley, 1995). The task and system factors involve system capability, interface design, stress and workload, complexity, and automation (Endsley, 1995). The individual factors include abilities, experience, training, goals and objectives, preconceptions, information processing mechanisms, long-term memory, and automaticity (Endsley, 1995). When studying nurses' SA, it is important to consider task, system, and individual factors. The nursing literature mostly explored the effect of individual factors on SA. These factors include knowledge, anxiety, age, experience, and fatigue.

2.1.4.2.1 Knowledge. Studies show no clear evidence regarding the relationship between knowledge and SA. For example, Cooper and colleagues (2011) found that rural nurses' knowledge did not correlate with SA scores (Cooper et al., 2011). The lack of correlation was also evident in nursing students (Cooper et al., 2010) Other researchers found that the mean knowledge score had weak correlation with the SA (Bogossian et al., 2014; Cooper et al., 2012; Cooper et al., 2013). One study reported a correlation of r = .359 (p = .040) (Cooper et al., 2012), and another reported a correlation of r = .298 (p = .001) (Cooper et al., 2013). Researchers explained the reason behind the relationship between SA and knowledge as some of the SA measurement questions included some knowledge elements (Cooper et al., 2012).

2.1.4.2.2 Anxiety. Anxiety seems to affect SA negatively. The nurses' performance and nontechnical skills decline as the patient's status changes from stable to a more deteriorated condition (Briggs et al., 2015; Cooper et al., 2011). The declined performance appeared to be related to high anxiety levels (Cooper et al., 2011). An alternative explanation is a deviation from the memorized algorithm as the providers discovered multiple patient conditions requiring immediate action (Briggs et al., 2015).

2.1.4.2.3 Age and Experience. The relationship between age and experience and SA is also not consistent. One study showed that younger registered nurses have significantly higher SA (r = .346, p = .021) (Hudson et al., 2015). Spearman's rho revealed as age increases, SA decreases (r_S = -.598, p = .04) (Hudson et al., 2015). However, age and experience did not affect student nurses equally. Age did not add value in explaining variance in SA (Wright & Fallacaro, 2011) and did not significantly correlate with this nontechnical skill.

Similarly, when it comes to experience, researchers reported differences between experienced and less experienced nurses during medication administration (Sitterding et al., 2014). The expert nurses used visual and auditory cues and continuously scanned them while in a clinical environment (Sitterding et al., 2014). The less experienced nurses relied almost entirely on visual cues (Sitterding et al., 2014). However, this conclusion might not apply to student nurses. Researchers found that experience did not significantly correlate with students' SA (Cooper et al., 2010).

2.1.4.2.4 Fatigue. Fatigue might also be associated with SA. Nurses commonly work night shifts and extended hours shifts, increasing fatigue. As fatigue affect human cognitive functions (Abd-Elfattah et al., 2015), it will probably affect SA. Researchers noticed that day shift nurses were more likely to have a higher SA score ($\chi2 = 4.29$, $p = .04$) (Hudson et al., 2015). A study by Dara, Helander, and Park (2019) found that when fatigue increased, sleepiness increased, and SA decreased. Although the changes in SA were not significant, the SA showed improvements in reducing fatigue after implementing the fatigue risk management system.

Overall, considering the SA factors is important when studying this nontechnical skill. The literature reported factors such as knowledge, anxiety, age, experience, and fatigue; however, more evidence is yet to be established. An interesting observation is that the SA of student nurses is likely different from licensed nurses and depends on the student's level. The SA scores of senior students are significantly higher than those of sophomore ones ($F(1,31) = 10.394$, $p = .002$) (Phillips, 2014, 2016). Such observation is important to remember when reviewing interventions to improve SA.

2.2 Urinary Tract Infection

2.2.1 What is Urinary Tract Infection

Healthcare-associated Urinary Tract Infection (HAUTI) is one of the leading quality concerns in healthcare services (CPSI, 2016). Urinary Tract Infection (UTI) refers to a group of diseases that affect the upper urinary tract (Pyelonephritis) or lower urinary tract (cystitis, urethritis, and prostatitis), and bacteria or fungi commonly cause it (CPSI, 2016). HAUTI is an infection that patients acquire while obtaining health care in various settings, including acute-care hospitals, long-term care, family medicine clinics, home care, and ambulatory care (Haque et al., 2018). For patients admitted to hospitals, the diagnosis of HAUTI is associated with a positive urine culture obtained two days after admission (Zachariah et al., 2020). A positive urine culture reflects the growth of more than 100,000 colony-forming units of an organism and more than five white blood cells per high-power field (Zachariah et al., 2020). According to the Canadian Patient Safety Institute (2016), HAUTI is the fourth leading cause of healthcare-associated infections. In this paper, I use the acronym HAUTI to refer to Healthcare-associated UTIs that affects adult patients within a hospital or long-term settings.

2.2.2 Signs and Symptoms of UTI

There are many signs and symptoms of UTI, and disease management is different in each patient population (Frerick, 2004). The infection can cause behavioural, functional and mental status symptoms and non-specific symptoms such as fever and costovertebral tenderness (Caterino et al., 2012; Juthani-Mehta et al., 2009; Juthani-Mehta et al., 2008; Mayne et al., 2018). UTI can also change the voiding pattern and urine characteristics, causing symptoms like hematuria, dysuria, frequency, and urgency (D'Agata et al., 2013).

The percentage of patients presenting these signs and symptoms depends on the patient population and the clinical settings. For example, fever and urinary tract symptoms can be absent in most adults with urinary tract infections over 65 years old (Caterino et al., 2012). Also, disease management is more challenging for older patients because of other comorbidities in this population (Frerick, 2004). Fewer UTI clinical features lead to diagnostic uncertainty (Juthani-Mehta et al., 2009), which could affect patient outcomes.

There are several consequences of HAUTI. Some examples are increased mortality, morbidity, and length of stay (CPSI, 2016). The effect of the later complications on patient outcomes is also associated with higher healthcare costs (CPSI, 2016). In one study, the prevention of HAUTI led to an annual net saving of USD $34,037 in a 120-bed care center (Griebling, 2018b). In another study, the prevention of catheter-related UTI for admitted patients led to USD $403,000 in savings over 18 months (Goetz et al., 1999). The prevention of HAUTI will benefit both payers' and patient's outcomes (Griebling, 2018b).

2.2.3 Prevention of HAUTI

It is possible to improve patient outcomes by preventing HAUTI. Up to 69% of HAUTIs are preventable, as many risks are modifiable factors (CPSI, 2016). The duration of indwelling catheterization is the most common factor that causes HAUTI (CPSI, 2016). An indwelling catheter is a tube that is left in the bladder to continuously drain urine. Around 80% of HAUTI is attributed to indwelling catheters (CPSI, 2016). Other factors include patient factors, such as incontinence and diabetes; provider factors, such as poor hand hygiene and suboptimal catheter insertion skills (CPSI, 2016), and facility-related factors, such as staffing level and education and infection control practices (Castle et al., 2017; Griebling, 2018a).

Although many HAUTI risk factors are modifiable, progress in reducing the infection, especially catheter-related infections, is slow compared to other device-associated infections (CPSI, 2016). The slow progress highlighted HAUTI as a priority for quality improvement initiatives. In British Columbia, one of the largest health authorities indicated that the quality initiatives to reduce HAUTI did not achieve the target and are still an area of improvement (FHA, 2019).

2.2.4 Importance of Nursing Practice

The nurses play an integral role in the prevention and management of UTIs. There is a negative relationship between nursing care hours per patient day and HAUTI (Park, 2018; Sujijantararat et al., 2005). In other words, with more nursing hours per day, there are fewer HAUTI cases. The nurses represent a core workforce to fight and prevent infection.

The nurse practice affects the patient care process in many ways. The nurses collect patient data such as UTI signs and symptoms, maintain the necessary care of catheters, plan for nursing interventions, and treat the infection. (Brown & Nay, 2007). The nurses are also the most frequent urinary catheter inserters (Fink et al., 2012). They contribute to decisions around urinary tract care, including catheter insertion and removal (Durant, 2017). The nurse's decisions to avoid catheter utilization, if deemed unnecessary, and their catheter maintenance technique, if a catheter was inserted, can reduce the incidence of HAUTI (Mody et al., 2015). The nurses can also decide on the type of catheter used for patients depending on their needs. Some types of catheters, such as a silver alloy-coated catheter and antimicrobial catheter, can affect the risk of developing HAUTI (Parker et al., 2009). Other nursing practices such as technique of catheter insertion, hand hygiene, meatal care, bladder or catheter irrigation, changing urinary bags managing incontinence without catheters, barrier precautions, bedside dipstick test, and the involvement of the family in patient care all appear to affect the risk of developing HAUTI (Gray, 2004; Juthani-Mehta et al., 2007; Lee et al., 2015; Meddings et al., 2017; Willson et al., 2009). It is within nurses' core responsibility to implement interventions to prevent HAUTI and promote the treatment of this infection.

The importance of nursing practice necessitates empowering the nursing staff to recognize and report HAUTI improvement opportunities (Carter et al., 2016). The nurses should be involved in designing and implementing practice changes and evaluating the effect of nursing practices on patient outcomes (Carter et al., 2016). Nursing leadership can enhance HAUTI prevention by enforcing nurses' autonomy to make patient care decisions (Landerfelt et al., 2020) and foster their communication around HAUTI prevention and management (Carter et al., 2016). One way to implement such a change is through nursing-led initiatives and protocols.

2.2.5 Nurse Initiatives and HAUTI

Improving nursing practice through nursing-led initiatives can help cut HAUTI rates (Murphy et al., 2007). These projects increase compliance with evidence-based practice (Thomas, 2016) and improve staff education (Viner, 2020). The nursing initiatives that increase nurses' adherence to evidence-based practice and nursing protocols are essential for successfully reducing HAUTI (Fink et al., 2012). Researchers identified practices such as wearing gloves, handwashing, maintaining a sterile barrier, and using a no-touch insertion technique as practical prevention approach (Fink et al., 2012). Nursing-led interventions can also minimize catheter use and select appropriate catheters depending on patient status (Johnson et al., 2016). The clinical benefits will be evident if nurses comply with recommended prevention strategies.

Education is also crucial for HAUTI prevention. Education can improve the nurses' awareness and knowledge of evidence-based practice, clinical indicators, and assessment variables that seem to affect the development of HAUTI (Viner, 2020). If nurses' knowledge and understanding of these indicators improve, they will implement interventions that positively influence patient outcomes (Gesmundo, 2016; Jain et al., 2015; Olatunji, 2020; Seyhan Ak & Özbaş, 2018; Woolforde & Castro, 2013).

Although the evidence on the effectiveness of nurse-led projects is limited, most studies around this domain reported some positive outcomes (Wu et al., 2020). For example, in one study, nursing-led protocols led to a 28% reduction in catheter-associated urinary tract infections in intensive care units (Johnson et al., 2016). In another study, a nursing-led protocol leads to a 50% hospital-wide reduction in catheter use and a 70% reduction in UTIs (Parry et al., 2013). A nursing-let protocol that included early removal of urinary catheters significantly decreased HAUTI from 5.1 to 2.0 infections per 1000 catheter days (Tyson et al., 2020). Other researchers found similar results in large-scale implementations of a nurse-led program (Mody et al., 2017). Through these initiatives, nurses' involvement seems to have a promising result on HAUTI incidences and patient outcomes.

2.2.6 Technological Opportunities and HAUTI

Implementing the nursing-led initiative implies the importance of the nurses' awareness of patient clinical status. The assumption is that nurses' awareness of the patient clinical condition and evidence-based practice will promote implementing required interventions to improve the patient outcome. For example, suppose nurses are aware of individual patient risk of HAUTI. In that case, they will select the appropriate catheter type, work on the patient's hydration status, and optimize the patient's blood sugar level. If the nurses are unaware of the patient's condition, they might not provide the necessary care.

EHealth technologies provide an opportunity to improve nurses' SA. The EHR and other information technologies, such as dashboards, can offer a medium that promotes the perception of clinical guidelines and provides feedback regarding evidence-based practice (Quinn, 2015). These technologies can also advance the analysis of HAUTI risk factors to project patient conditions (Park, 2018). Generally, nurses find such use of technology more beneficial than paper-based methods as it provides a faster and more clear method to share patient information.

2.2.6.1 EHR Support for Clinical Guidelines. The EHR promotes the perception of clinical guidelines through electronic documentation. The nurses can collect data related to HAUTI prevention criteria (Quinn, 2015). The EHR can integrate evidence-based, nurse-driven daily checklists or protocols. These checklists and protocols can enhance nurses' awareness of urinary catheter care and reduce HAUTI (Fuchs et al., 2011; Giles et al., 2015). The protocols provide a systematic approach to care that will standardize the nursing practice and inform nurses of the pathway to prevent infection (Giles et al., 2015). Evidence-based guidelines generally appear to positively affect patient outcomes (Mendes-Rodrigues et al., 2017; Newswire, 2012).

2.2.6.2 EHR and Feedback on Healthcare Practice. The EHR can provide feedback regarding evidence-based practice. The nurses can use the patient data in the EHR to generate reports and track and monitor patient clinical status (Quinn, 2015). The EHR makes it feasible and sustainable to collect patient data and provide HAUTI and catheter care surveillance (Wald et al., 2014). A surveillance system can generate reminders to enforce nurses' compliance with treatment protocols (Meddings et al., 2014). It is also possible to create unit-specific feedback about the HAUTI rate, which researchers found to reduce the infection rate (Goetz et al., 1999).

The surveillance system can act as an evaluation process to monitor the quality of care related to preventing HAUTI (Moreira Arrais et al., 2017).

2.2.6.3 EHR and Analysis of Healthcare Data. The EHR can advance the analysis of HAUTI risk factors. The EHR contains a large amount of information from multiple sources. This data can be beneficial for creating a predictive model for UTIs. A predictive model will illustrate the factors contributing to UTI. If these factors are modifiable, it will be possible to reduce their effect. Here, machine learning methods can be of great benefit (Park, 2018). Machine learning can analyze large amounts of data and provide additional knowledge of UTI. Machine learning offers data mining methods such as decision trees, logistic regression, and support vector machines, which all can create a predictive model for HAUTI (Park, 2018).

Using eHealth technologies, such as EHR, can support the success of nursing-led initiatives. If eHealth technologies improve the nurses' perception, understanding, and projection of patient clinical needs, their overall SA will improve. A higher nurse SA will foster achieving clinical decisions that promote desired outcomes and reduce HAUTI rates.

2.3 Dashboards

2.3.1 Dashboards and EHR Data

While the EHR contains comprehensive healthcare data, the increased volume of information in these systems, often scattered, does not necessarily support clinical reasoning (Wisner et al., 2019). Some thoughts to solve the issue of extensive EHR data were using template-driven patient summaries and reports (Wisner et al., 2019). However, the favourable outcome of these documents is yet to be proven. While the goal of these documents is to organize the health data and make meaning of clinical conditions (Wisner et al., 2019), they are error-prone and can result in static, inconsistent, and incomparable data (Farri et al., 2012; Ghazisaeidi et al., 2015). Suboptimal reports can create a cognitive challenge for clinicians and decrease their SA (Wisner et al., 2019), technology acceptance, and satisfaction (Dziadzko et al., 2016). With lower satisfaction, the providers tend to use paper-based notes instead of electronic tools (Wisner et al., 2019).

Interactive data management tools, such as information displays or dashboards, are possible solutions to improve patient outcomes (Wisner et al., 2019). The dashboards can offer current and standardized data elements and scores to promote healthcare performance (Brady & Goldenhar, 2014).

Dashboards have promising benefits that make this technology a potential solution to improve the use of EHR data. One benefit is data standardization. The EHR data is commonly compiled from multiple sources, including clinical, operational, financial, and organizational outcomes (Battié, 2009). The dashboard can utilize these various data sources to facilitate common language and terminology and use this language for tasks such as statistical analysis and external benchmarking of healthcare outcomes (Battié, 2009; Frith et al., 2010).

Standardizing patient data helps advance patient care knowledge and create a collective understanding of the patient's condition (Battié, 2009; Brady & Goldenhar, 2014).

Another benefit of dashboards is the possibility of using real-time health information feeds. The use of current information is likely to promote the clinical decision-making process (Frith et al., 2010). These displays support real-time filtration and extraction of EHR data and provide interactive visualizations that measure and monitor patient data and support providers' decisions (Ahmed et al., 2011; Ghazisaeidi et al., 2015). The use of a dashboard presents a possibility to reduce clinicians' task load and cognition errors and optimize information aggregation at the point of care (Farri et al., 2012).

2.3.2 Types of Dashboards

The literature describes a wide variety of dashboards. The differences between these dashboards are related to the type of organization, the type of users, and the purpose of using the dashboard (Wilbanks & Langford, 2014). Dowding et al. (2015) classified the dashboards into two main types: clinical and quality dashboards. Both types provide a visual representation of quality or productivity indicators. The difference is that the quality dashboard is directed to managers and administrators to find quality improvement areas. In contrast, the clinical dashboards are directed to clinicians to support their daily clinical decisions (Dowding et al., 2015).

2.3.2.1 Clinical Dashboards. As discussed above, dashboards commonly collect patient information from the EHR and facilitate data visualization. Clinical dashboards can use data visualization to improve the synthesis of patient information (Farri et al., 2012), which can benefit clinical practice in several ways.

The use of the clinical dashboard has a time-saving benefit. In two separate studies, the dashboard helped to decrease the time to gather patient information from 12 (10–15) to 9 minutes (7.3–11) ($p = .03$) and from 5.5 to 1.3 minutes from 5.5 to 1.3 minutes ($p < .001$) (Koopman et al., 2011). Similarly, Farri et al. (2012) found that dashboard use led to a shorter patient review time (43±4 mins vs. 36±4 mins, $p = .35$). Although the latter study results were insignificant, reducing patient review time is still important. If a long time is needed to find the patient information, the providers would continue without the information or repeat the test (Koopman et al., 2011).

The clinical dashboards can also promote the accurate collection of patient data. The dashboard seems to reduce missing patient information and improve accurate inferences (Farri et al., 2012). Koopman et al. (2011) found that using the dashboard, physicians identified 100% of required patient data compared to 94% using traditional EHR screens ($p < .01$). A possible explanation is that the dashboard can provide continuous monitoring of patient physiological reading (Sebastian et al., 2012) and make gathering data significantly easier with reduced mental demand (Pickering et al., 2015). Additionally, in some instances, the dashboard automatically calculates disease-related scores in real-time (Harrison et al., 2013), a functionality clinicians can use to develop an accurate diagnosis. The use of information display significantly reduces task load, time to task completion, and frequency of cognition errors linked to identifying and using patient data (Ahmed et al., 2011). This technology supports routine tasks and fosters teamwork (Dziadzko et al., 2016). All these benefits can enhance efficiency and clinical data management compared to the standard EHR.

2.3.2.2 Quality Dashboards. The complexity of health information can hinder informed decision-making and quality improvement in the healthcare sector. Interactive quality dashboards can be helpful here. Quality dashboards can reduce the cognitive effort associated with non-linear health information to decide and improve clinical practice (Dolan et al., 2013). Such dashboards aim to increase awareness of key performance indicators and quality improvement opportunities (Sprague et al., 2013).

The dashboards can help improve healthcare quality by using key quality indicators to promote staff compliance with clinical standards. In one paper, researchers explained a dashboard supporting patients' daily clinical management with multisystem injury (Salazar et al., 2011). The dashboard enhanced compliance with clinical management indicators from 64% to 100% over 3 years. The electronic tool allowed instant improvement of deficiencies, monitored patient trends, and supported clinical performance and patient safety (Salazar et al., 2011). Other researchers found similar results regarding decreasing the risk of central line-associated bloodstream infection. The dashboard reduced infection rates from 2.6 per 1000 line-days to 0.7 per 1000 line-days (Pageler et al., 2014). Pageler and colleagues found that the dashboard improved staff adherence to infection prevention practices such as dressing and port needle changes. The dashboard promoted providers' compliance with best practices and prevented potential patient harm (Pageler et al., 2014).

Another two examples of using quality dashboards to improve compliance with clinical standards are minimizing the prolonged use of urinary tract catheters and improving medication management. Shaw and colleagues (2015) examined data from 450 patients before and after using dashboards. They found that the number of patients who had urinary catheters in place for more than 96 hours decreased from 16 (32%) to 11 (19%) ($p = .01$). The researchers also noticed that the completion of medication reconciliation improved from 80% to 92%-93% ($p = .002$) (Shaw et al., 2015). The dashboard can summarize medication management information such as medication effectiveness, side effects, drug-drug interactions, costs, and ease of use (Dolan et al., 2013). Overall, the dashboard improves providers' awareness of needed interventions to enhance care and patient safety (Shaw et al., 2015). Using dashboards to reduce the cognitive load can identify hospitals' ongoing issues and support quality assurance systems (Simms et al., 2013).

2.3.3 Dashboards and SA

Out of the two types of dashboards, the clinical dashboard seems more relevant to supporting nurses' efforts to reduce HAUTI rates. Based on the discussion above, the clinical dashboard would provide a data visualization that supports nurses during their clinical practice and promotes their clinical decisions. Would the dashboard be an effective approach to improving the nurses' SA? If the dashboard improves the SA, it will likely enhance the nurses' decisions and reduce HAUTI.

As discussed in the first section of this chapter, SA is a cognitive non-technical skill. The clinical dashboards seem to support the provider’s cognitive tasks. This is evidenced by reducing errors in cognition (Ahmed et al., 2011), reducing the time needed to complete tasks (Pickering et al., 2015), and improving providers' ability to identify required patient data (Koopman et al., 2011). If providers could use dashboards to minimize the task completion time, this would indicate a higher SA of the patient's condition (Cornell et al., 2014). Also, providers' ability to use the dashboard to identify the required clinical information accurately reflects a high SA level 1 (perception). Overall, the dashboards seem to have a promising approach to tackling nurses' SA; however, this claim needs validation. An initial approach would be a comprehensive literature review exploring dashboards' effect on nurses' SA. The literature review would help investigate the interventions used, their effectiveness, and the current knowledge gap.

2.4 Summary

SA is a crucial nontechnical skill for nurses. The nurses provide ongoing care that requires careful attention to patient signs and accurate comprehension of their condition. Nursing SA is a dynamic process that involves perceiving clinical cues, assigning meaning to them, and using them to project clinical interventions. The low SA can increase patient care acuity and increase the chance of clinical deterioration and patient death. As the current studies show a low SA level, improving the nurses' SA is necessary to enhance patients' outcomes.

HAUTI is a main quality concern in clinical settings. Altering the modifiable factors leading to HAUTI can reduce the risk of HAUTI. However, progress in lowering UTI is still slow. Nurses and nurse-led initiatives play an essential role in reducing HAUTI infection. Integrating eHealth technologies can improve these initiatives further.

EHealth technologies such as dashboards can reduce HAUTI rates by improving information visualization and providing alerts and notifications. The dashboards support the providers in performing cognitive tasks such as managing a large amount of data and fostering informed clinical decisions. As SA is a cognitive non-technical skill, it is reasonable to think that an SA-oriented dashboard can improve nurses' SA when caring for patients at risk of developing HAUTI. If effective, the SA-oriented dashboard can collect EHR data and make it easier to monitor, perceive, and understand the patient's clinical condition (Brady & Goldenhar, 2014). However, conducting a comprehensive literature review is necessary to examine and confirm the effect of dashboards on nurses' SA and identify the research gap in this field. A literature review (Chapter 4) established the basis for future research studies in SA-oriented dashboards.

Chapter 3 Theories of Human-Computer Interaction

Chapter 3 discusses the application of activity theory and Endsley's model of situation awareness in the study context

3.1 Human-Computer Interaction

Theories are important in scientific inquiry. They provide a systematic abstract explanation of a phenomenon and predict how it will act in real work (Polit & Beck, 2008a). The explanation and prediction of a phenomenon can guide modelling research on system development in the health informatics domain. The selection of an appropriate theory is essential in conducting health informatics research.

Theories of Human-Computer Interaction (HCI) can help understand and explain what affect a SA dashboard might have on nursing practice. HCI investigates the relationship between people or users and computer systems and applications (Su & Liu, 2012). Users of a computerized dashboard do not necessarily understand the computer's technical operation but understand this technology through its interface, texts, and images (Su & Liu, 2012). The nurses will interact with a dashboard by perceiving and understanding the health information on the display. A theory that addresses this interaction will promote understanding and prediction of this phenomenon.

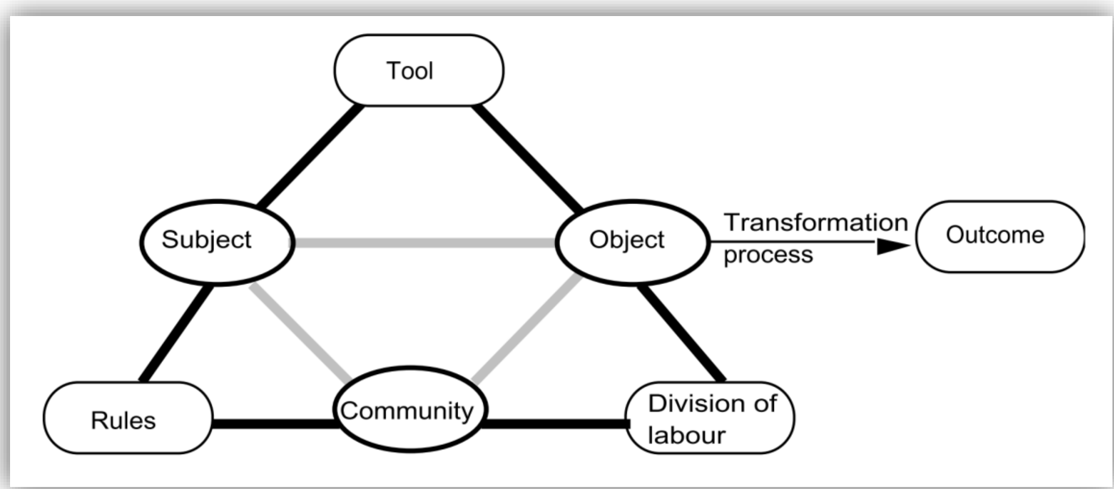
Various theories address HCI in the health informatics domain. However, I argue that integrating the Activity Theory and Endsley SA model will best achieve this goal. Compared to other theories, activity theory is suitable to examine the dynamics of provider-computer interactions within the healthcare domain. The providers here refer to healthcare professionals such as nurses and physicians. The AT describes the healthcare environment and defines the information technology systems as mediators between providers and patients (Wiser et al., 2018). The use of AT will emphasize the separate roles of providers, patients, and technology. Therefore, the theory allows the investigation of technology's role in healthcare settings (Wiser et al., 2018). The AT illustrates the actions generated by a provider toward a patient using mediators or tools such as the dashboard, which makes it suitable for explaining provider-dashboard interaction.

However, the use of AT alone does not clearly describe the role of context or situation. Understanding context is important to conceptualizing the role of SA during the user-computer interaction. Here, Endsley's SA model offers a framework to promote the situated understanding of environmental elements within the time and place of decision-making (Endsley, 1995). To utilize the benefits of both the AT and Endsley's SA model, I combined both to promote the understanding of the interaction between SA-oriented dashboards and providers in clinical settings.

3.4 Activity Theory

The Activity Theory illustrates the relationship between the subject and the object that forms an activity (Hasan & Kazlauskas, 2014). The subject is a human doer and their motive, while the object is the activity being done, including its focus and purpose (Hasan & Kazlauskas, 2014). As encouraged by the object, the subject will direct the activity toward the object to achieve an outcome (Wiser et al., 2018).

Figure 1: *Basic structure of activity (Kuutti, 1996) with permission*



The activity system incorporates several elements, which all translate into an outcome (Wiser et al., 2018). These elements include subject, object, community, and mediating objects, such as tools, rules, and labour division (Figure 1). According to Kutti (1996), The human subject has a goal of transforming the object (tangible or not tangible) into a particular outcome. The activity of transforming the object is carried out within a community of interested teams or stockholders. The AT defines the roles and hierarchy of the community as a division of labour. The interactions between the subject and object are mediated by tools (Kuutti, 1996). These tools have a material or non-material nature. The tools are the core dimension a subject uses to fulfil a motive. The interaction between the subject and object is also determined by explicit rules or implicit norms and expectations (Kuutti, 1996). This activity system can evolve over time and adapt to a changing environment (Wiser et al., 2018).

Wiser and colleagues (2018) further explained that the activity is divided into the activity, action, and operational layers. The first layer, the activity layer, is at the highest level. The subject directs their activity towards a motive, which can be achieved in multiple ways. In nursing practice, the nurse can initiate the motive of, for example, preventing urinary tract infections. There are several solutions the nurses can use to avoid these infections. To achieve this motive, the subject (the nurse) will take out several goal-related actions representing the second layer. Actions such as increasing fluid intake are associated with a goal in mind. In turn, these actions consist of operations (the third layer) that can be unconscious (facial expression when talking) or automated operations. A nurse, for example, can adjust the intravenous fluid pump in an automated way without consciously thinking about it. If the automated operation fails, the subject will switch into manual and conscious action (Wiser et al., 2018), like the need to reprogram the pump.

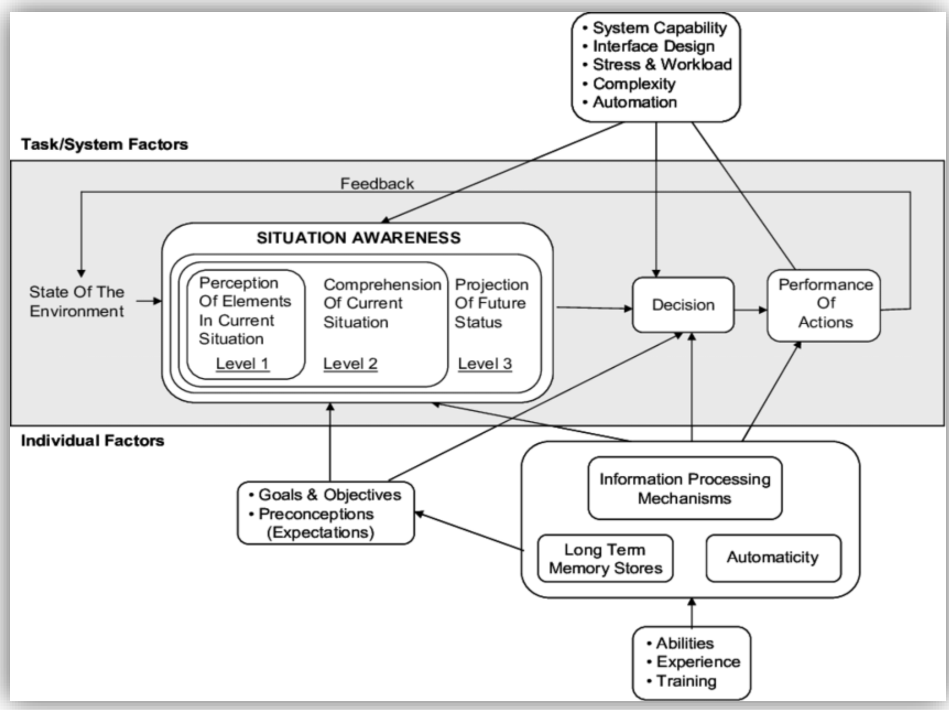
From the nursing context, a general example that represents the AT perspective is when a nurse (subject) would assess a patient (object) using a tool (dashboard) in an in-hospital setting (community). This community also includes other nurses and healthcare providers (a division of labour). The nursing assessment process follows the guidelines and standards of practice (rules). After completing the assessment, the nurse will document the findings and carry out nursing interventions. The outcome of the activity can be either intended or unintended (Hasan & Kazlauskas, 2014). A nurse providing care for a patient might carry out an intervention to treat a condition but end up with an unfavourable adverse event.

3.5 Situation Awareness Model

The activity theory explains how interactions between a subject (nurse) and an object (patient) are mediated by a tool (the dashboard); however, the theory does not clearly explain the situation awareness within the subject and how the SA can change an activity. Here, Endsley's SA model is of great benefit.

Endsley's SA model illustrates the role of SA in a dynamic environment as a separate entity that proceeds decision-making and activities (Figure 2) (Endsley, 1995). Endsley defined situation awareness as “the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future” (p. 36). The model explains three levels of SA: perception, comprehension, and projection (Endsley, 1995). According to Endsley, the person's SA is determined initially by the perception of relevant environmental elements. The environmental elements are context-specific things the person needs to perceive, understand, and project their status. The perception, or level 1 SA, is directed by systems display or a person's senses. The individual perceives the status, attributes, and dynamics of environmental elements. After perception, the SA is formed by the comprehension (level 2 SA) of environmental elements. The individual goes beyond perceiving the elements into understanding the significance of these elements as directed by personal goals. Here, the individual forms a holistic view that reflects realizing the importance of the environmental elements. The third level of SA is projection. This level reflects the individual projection of actions and the status of the environment's elements that are valuable for decision-making. Therefore, the SA results from perceiving information about the environment, comprehending the meaning of this information, comparing it to personal goals, and then projecting the future status and dynamics of the relevant elements in the environment.

Figure 2: *Model of SA in dynamic decision-making (Endsley, 1995) with permission*



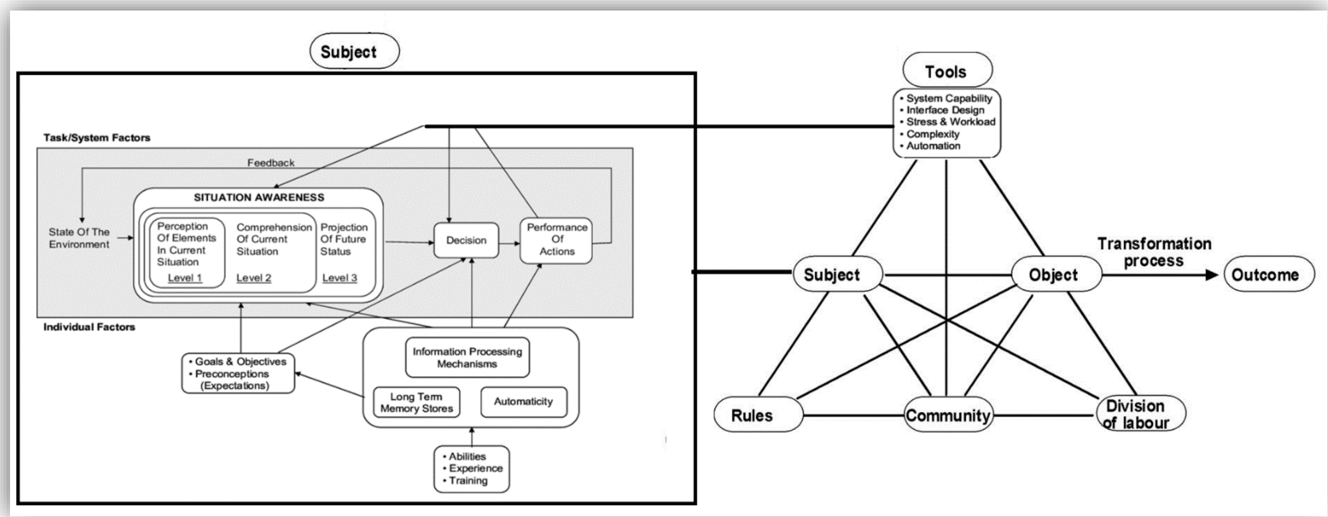
Endsley also explained the importance of time and space to SA (Endsley, 1995). The perception, comprehension, and project processes are temporal and spatial in many contexts. In other words, the SA depends on elements that rely on the spatial, temporal, or functional relationships of these elements to an individual's goals. Although SA reflects the individual knowledge of the environment at any point in time, it also builds up over time and in relation to a subset space of the environment. According to particular spatial information, the SA can be acquired concerning the environment's past and future status. This information determines what environmental elements are essential to developing SA. The necessity of environmental elements to build SA varies across time and space without completely losing their value.

Endsley's SA model illustrates several factors that can influence SA, including individual and system factors (Endsley, 1995). Individual factors explain how individuals receiving the same data input might acquire different SA. Examples of these factors include an individual's information processing, abilities, experience, training, preconceptions, and objectives. Similarly, the system factors, such as system design, workload, stress, and complexity, change the individual's SA. The system design, for example, affects whether necessary information is provided in an appropriate format. Various designs are not equal in the type and form of information they provide and the effect of the design on individual information processing. Individuals can filter and interpret the environment differently depending on the system factors.

3.6 Combining Activity Theory and Endsley's Model

The AT is suitable to promote the understanding of technology in healthcare settings. The AT theory explains the roles of and interaction between providers, patients, and technology. However, the AT alone does not describe the situatedness of activity. Functionalities from Endsley's SA theory will provide advanced insight into how the SA is developed within the individual and how it will affect the performance and activities. Combining the AT and SA model will expand the AT's subject entity to include aspects and levels of an individual's SA (Figure 3). This integration will allow going beyond explaining the sociotechnical context of using the dashboard as knowledge and evidence-based tool to illustrate the role of contextual and situated awareness in optimizing clinical decisions and activities. Therefore, I combined AT and Endsley's SA theory to promote the understanding of dashboard implementation in clinical settings.

Figure 3: *The Combination of the AT and SA model*



3.7 Summary

EHealth interventions, such as dashboards, can help reduce HAUTI by improving human-computer interactions. To help understand this interaction's dynamics, I employed the activity theory and Endsley's SA model. The activity theory explores providers, patients, and technology's independent roles and interactions in healthcare (Wiser et al., 2018). Endsley's SA model explains how SA is developed within the individual and describes the relationship between SA and decisions (Endsley, 1995). The combination of the AT and SA models will guide the effort to understand the interaction between nurses' SA and dashboards.

Chapter 4 Systematic Literature Review

Chapter 4 illustrates the details of the methodology and results of a systematic review of the literature. The review addresses the questions and objectives relevant to the discussion in Chapter 2

4.1 Objectives

I carried out a systematic review to explore SA interventions to support nurses' SA at the point of care. This systematic review identifies the clinical interventions that improve the nurse SA. The specific questions include: What are the interventions used to enhance nurse SA? What are the types of SA that these interventions aim to improve? What are the SA theoretical backgrounds or design approaches that guided the development of the interventions? What affect these interventions have on nurse SA?

Table 3*: PICOS framework*

PICOS Framework	The focus of the literature review
Problem or Patient or Population	Nurses
Intervention/indicator	Any SA intervention
Comparison	Any comparison
Outcome of interest	Changes in Situation Awareness
Setting	Any clinical setting

4.3 Method

I carried out a systematic review to explore SA interventions to support nurse SA at the point of care. To organize our review report and highlight its focus, I used the PRISMA statement and the Population, Intervention, Comparison(s), Outcome (PICO) Framework. I used PICO to format our review question and organize the search methodology (Table 3).

The SA is a dynamic process in which a nurse perceives clinical cues relevant to care goals, understands and assigns meaning to those cues, and uses them to project required interventions (Sitterding et al., 2012). I describe the SA intervention in this study as any device, technology, tool, or non-educational activity defined to improve nurse SA at the point of care. The PICO in this review includes nurses as the population of interest, any SA intervention regardless of its comparison, and SA as the primary outcome irrespective of the clinical settings (Table 3).

4.3.2 Eligibility Criteria

Based on the PICO framework, I developed the inclusion and exclusion criteria for two screening processes (Appendix A). One reviewer tested and refined both processes' inclusion and exclusion criteria using a sample of full-text articles. The refined inclusion and exclusion criteria allowed selecting articles that include interventions to improve nurse SA within any context. I did not define a specific intervention type, such as EHR dashboards, to ensure a comprehensive review and discover other types of SA interventions. I focused on practising nurses as their SA is likely different compared to other providers, such as physicians, and compared to nursing students (Cooper et al., 2010; Miller & Sanderson, 2005; Phillips, 2014, 2016; Sitterding et al., 2014).

4.3.3 Information Sources

We consulted research librarians, Carol Gordon and Liz Hansen, to review the process of identifying the information sources and developing a search strategy. I identified four databases for electronic searching: Cumulative Index to Nursing and Allied Health Literature (CINAHL), Medline, PsycInfo, and Web of Science. I added no restriction to the publication year. I searched these four databases on April 6, 2020, an updated search was done on September 29, 2022, to add any possible new research.

4.3.4 Search

In our search strategy, I used keywords and subject headings related to SA and nursing. Examples of keywords include Nursing, Situation Awareness, non-technical skills (Appendix B). I did not specify the type of intervention to ensure sensitive results. I only included English articles from our searches due to the limited capacity for translation. I also used the Web of

Science database to complete a comprehensive forward citation review by finding articles that cite back to the ones in the initial search and backward review by reviewing cited references.

4.3.5 Study Selection

Both the first and second screens have inclusion and exclusion criteria (Appendix A). The first screen focused on finding at least one of the key terms, including awareness or situation awareness, anywhere in the article. I directed the second screen on uncovering articles with intervention to improve situation awareness. I completed the first screen and then worked with Dr. Roudsari to complete the second one. In the second screen, we screened the articles independently and then compared our selections to come up with a final list. Whenever there was a discrepancy, we discussed the articles in question to reach an agreement. Once we reached the final list of selections, I double-checked the list to confirm that there are no missing articles and that all articles matched the inclusion criteria. This approach enhanced the rigour of the review process by promoting mutual understanding of the articles and, therefore, their relevance to the inclusion criteria. In addition, the double-checking step added a quality assurance component to the review process.

After implementing the search strategy, I imported the articles to Endnote version X9.3.3 (Clarivate, 2020) and removed duplicates. Then, I manually checked the remaining articles for additional duplications.

4.3.6 Data Items and Data Collection Process

I created data collection forms in Endnote (Appendix C). The data items in the form follow recommendations from the Cochrane method (Li et al., 2019) and are relevant to the PRISMA statement and PICO framework. The data collection forms included study methods, participant characteristics, a description of the intervention, and a description of the outcomes and limitations.

4.3.7 Critical Appraisal of Individual Studies

Risk of Bias within Quantitative Studies. I completed a risk of bias assessment for quantitative studies using two tools: version 2 of the Cochrane Risk-of-Bias tool for randomized trials (RoB 2) and the Risk of Bias In Non-randomized Studies of Interventions (ROBINS-I). Both tools were recommended in the Cochrane literature review process (Higgins et al., 2019; Sterne et al., 2019).

The use of RoB2 and ROBIN-I allowed a detailed assessment of the risk of bias by exploring several research domains (Table 4). One reviewer evaluated the quantitative studies and reported the grade of each study.

Table 4: *Risk domains in RoB 2 and ROBIN-I tools*

RoB 2	ROBIN-I
Bias arising from the randomization process	Bias due to confounding
Bias due to deviations from intended interventions	Bias in the selection of participants into the study
Bias due to missing outcome data	Bias in the classification of interventions
Bias in the measurement of the outcome	Bias due to deviations from intended interventions
Bias in the selection of the reported result	Bias due to missing data
	Bias in the measurement of outcomes
	Bias in the selection of the reported result

4.3.7.2 Critical Appraisal of Qualitative Studies. I completed a critical appraisal for the qualitative studies using the qualitative critical appraisal tool from the Joanna Briggs Institute (Joanna Briggs Institute, 2020). The purpose of this tool is to evaluate the methodological quality of the qualitative studies and to explore the extent the researchers addressed potential bias in study design, conduct, or analysis (Joanna Briggs Institute, 2020). I have appraised the qualitative studies. Then, Dr. Roudsari took a random sample of the studies and validated methodological quality.

4.3.8 Quality of Evidence Across Studies

4.3.8.1 Risk of Bias Across Quantitative Studies. I completed the risk of bias across the quantitative studies using the GRADE framework. GRADE, which refers to the Grades of Recommendation, Assessment, Development, and Evaluation, is a widely accepted framework to grade certainty of the evidence for each outcome (Schünemann et al., 2019). There are five domains to consider in GRADE: risk of bias, consistency of effect, imprecision, indirectness, and publication bias. A second reviewer validated the risk of bias to ensure the quality of the appraisal.

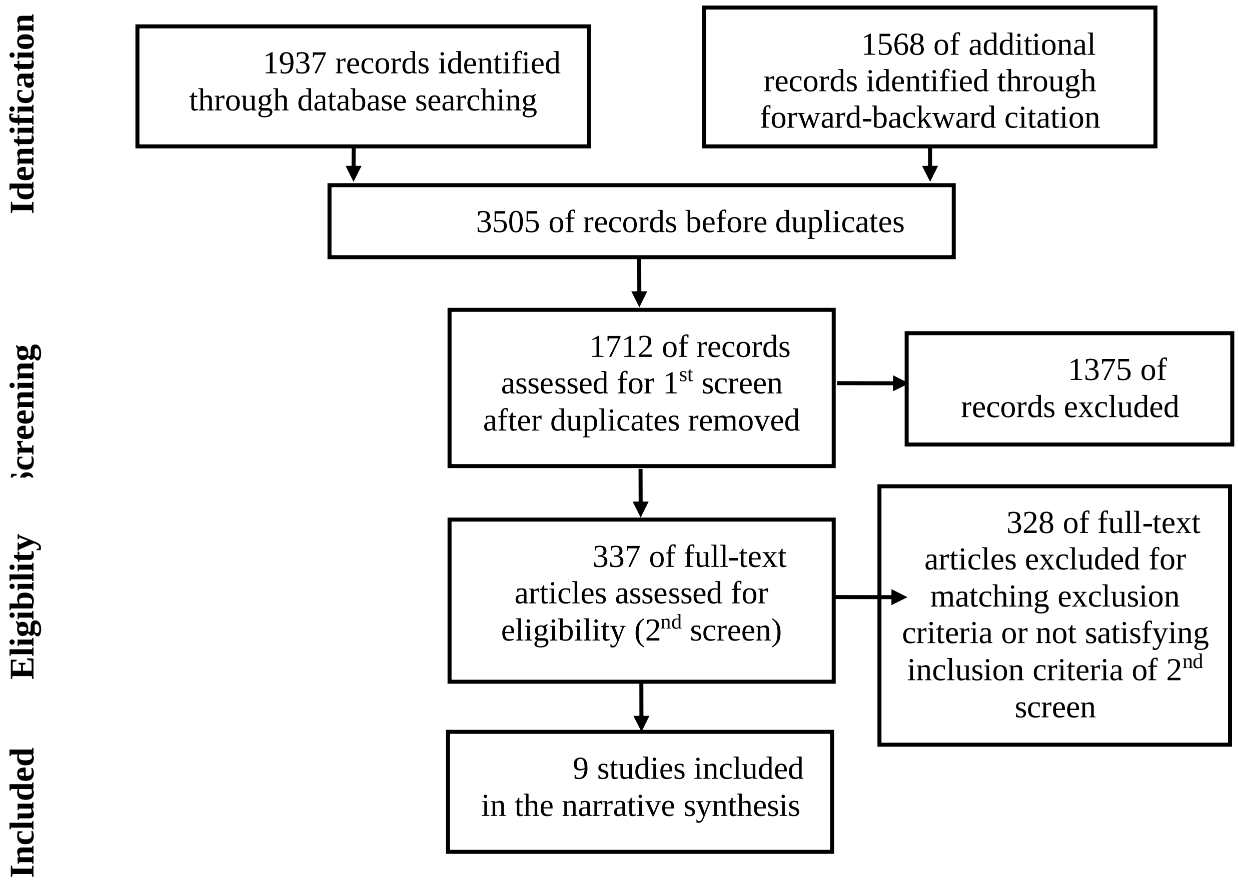
4.4 Results

4.4.1 Study Selection

The search of the databases returned a total of 1,937 articles. After removing duplicates, I screened the 1,285 articles using the first-screen criteria, resulting in 254 articles for the second screening. I used the 254 articles for the forward and backward citation search process. The forward-backward citation search added additional 1,568 articles to the number of articles before duplicate removal (total 3,505). After removal of duplicates, 1,712 records proceeded to the first screening, of which 337 qualified for the second screening. After completing the second screening, only nine articles were included for the final review (Figure 4).

I searched the databases on September 29th, 2022, to review new articles. The search returned a total of 614 new articles. After removing duplicates, I screened 402 articles using the first-screen criteria. None of the articles were eligible for a second screening.

Figure 4: *Flow diagram of the citation search*



4.4.2 Article Characteristics

The nine articles included six quantitative studies and three qualitative studies (Appendix D). I found two articles that involved nurses as research participants (Koch et al., 2013; Munroe et al., 2016) and seven articles that involved nurses as part of health care teams (Calder et al., 2018; Cornell et al., 2014; de Vries et al., 2017; Kettelhut et al., 2017; McGeorge et al., 2015; Parush et al., 2017; Stapley et al., 2018).

The SA interventions in this review targeted several clinical conditions and settings. These conditions include caring for ICU patients (Koch et al., 2013), reporting patient condition (Cornell et al., 2014), caring for patients in emergency departments (McGeorge et al., 2015; Munroe et al., 2016), exploring patients resuscitation and risk of clinical deterioration (Calder et al., 2018; de Vries et al., 2017; Parush et al., 2017; Stapley et al., 2018), and exploring patients at risk of exposure to infection (Kettelhut et al., 2017).

To design the SA interventions, researchers used a user-centred design approach in four studies (Calder et al., 2018; Koch et al., 2013; McGeorge et al., 2015; Parush et al., 2017), and a conceptual model (antibiotic-resistant infection transmission) in one study (Kettelhut et al., 2017). The remaining articles did not explain the intervention development process (Appendix D). I found no SA interventions addressing UTI.

4.4.3 Critical Appraisal of Individual Studies

4.4.3.1 Risk of Bias Within Quantitative Studies. Our review has six quantitative studies. These studies included the use of repeated measure design (Koch et al., 2013; Parush et al., 2017), observational design (Cornell et al., 2014), two-group post-test design (McGeorge et al., 2015), and pre-test post-test design (Kettelhut et al., 2017; Munroe et al., 2016). I used RoB 2 to assess the risk of bias in the studies with randomized repeated measure design and ROBIN-I for the remaining studies.

For repeated measures studies, I found some concerns regarding the integrity of the randomization process (Koch et al., 2013; Parush et al., 2017). The concerns are related to the lack of information about the differences between the participants who received the intervention first and those who received the control intervention (or no intervention) first. One study was at a high risk of deviation from the intended intervention (Parush et al., 2017). This high risk is mainly because of a lack of sufficient time for any carry-over effects to have disappeared before assessing SA in the second period. Both studies were at high risk of bias due to the selection of reported results. The selection of report results is evident as both studies did not clearly report the baseline differences in randomized groups at the start of the cross-over design.

All studies that used a non-randomized design method received high or moderate risk of bias in the confounding domain. This result is mainly related to a lack of information on controlling confounding variables. One study was at risk of bias in the classification of interventions dues to the lack of clear definitions of study groups (Cornell et al., 2014). I found two studies with moderate bias in measuring the outcome (Cornell et al., 2014; Kettelhut et al., 2017); this was related to the potential effect of knowing the intervention received by study participants (Table 5). Finally, due to lack of reporting full study results, three studies have a moderate risk of bias (Cornell et al., 2014; Kettelhut et al., 2017; Munroe et al., 2016), and one has serious risk bias (McGeorge et al., 2015) in the domain of selection of the reported result (Table 6).**Error! Reference source not found.**

Table 5 : *Results of version 2 of the Cochrane risk-of-bias tool*

Results of Version 2 of the Cochrane risk-of-bias tool						
Reference	**Bias arising from the randomization process**	**Bias due to deviations from intended interventions**	**Bias due to missing outcome data**	**Bias in measurement of the outcome**	**Bias in selection of the reported result**	**Total**
(Koch et al., 2013)	Some concerns	Low Risk	Low Risk	Low Risk	High Risk	High Risk
(Parush et al., 2017)	Some concerns	High Risk	Low Risk	Low Risk	High Risk	High Risk

Table 6: *Results of risk of bias in non-randomized studies of interventions*

Results of Risk of Bias In Non-randomized Studies of Interventions

Reference	Confounding	Selection of participants	Classification of interventions	Deviations from interventions
(Cornell et al., 2014)	Serious Risk of Bias	Low risk of bias	Serious risk of bias	Low risk of bias
(McGeorge et al., 2015)	Serious Risk of Bias	Low risk of bias	Low risk of bias	Low risk of bias
(Munroe et al., 2016)	Serious Risk of Bias	Low risk of bias	Low risk of bias	Low risk of bias
(Kettelhut et al., 2017)	Moderate risk of bias	Low risk of bias	Low risk of bias	Low risk of bias
Reference	**Missing data**	**Outcome measurement**	**Reported result**	**Total**
(Cornell et al., 2014)	No Information	Moderate risk of bias	Moderate risk of bias	Serious risk of bias
(McGeorge et al., 2015)	No information	Low risk of bias	Serious risk of bias	Serious risk of bias
(Munroe et al., 2016)	No Information	Low risk of bias	Moderate risk of bias	Serious risk of bias
(Kettelhut et al., 2017)	Low risk of bias	Moderate risk of bias	Moderate risk of bias	Moderate risk of bias

4.4.3.2 Critical Appraisal of Qualitative Studies. I critically appraised all three qualitative studies in this review (Calder et al., 2018; de Vries et al., 2017; Stapley et al., 2018).

All three studies are of low quality. Although the authors described their qualitative work, the main concern is that they did not explain their philosophical orientation or qualitative methodology. Without a clear explanation, it was challenging to evaluate the philosophical orientation and methodology's congruity. It was also difficult to assess the congruity between methodology and other domains, such as study objectives or questions, data collection, data analysis, and result interpretation. However, the conclusions drawn in all three studies were relevant to the collected data, described analyses, and illustrated data representing the participants.

4.4.4 Quality of Evidence Across Studies

4.4.4.1 Risk of Bias Across Quantitative Studies. The assessment of bias across studies examines the certainty of the evidence of an intervention's effect on a particular outcome. Our review includes three types of interventions: EHR dashboards, communication tools, and structured assessment. Out of the six quantitative studies, four examined the effect of EHR dashboards on SA (Kettelhut et al., 2017; Koch et al., 2013; McGeorge et al., 2015; Parush et al., 2017), one study examined a communication tool (Cornell et al., 2014) and one study explored a structured assessment (Munroe et al., 2016). I used GRADE to evaluate evidence across the quantitative studies examining the dashboards, as it is the only intervention examined by more than one study. Overall, I downgraded the level of certainty to very serious low certainty. I explain our judgment using the five domains of certainty of evidence.

4.4.4.1.1 Risk of Bias. Out of the four studies, I rated one study as moderate risk (Kettelhut et al., 2017), two studies as high risk (Koch et al., 2013; Parush et al., 2017), one study as serious risk (McGeorge et al., 2015) of bias. Therefore, I graded the risk of bias as a serious limitation, indicating low certainty of evidence.

4.4.4.1.2 Unexplained Heterogeneity or Inconsistency of Results. The four studies have inconsistent results in terms of the effect of the dashboard on SA. Two studies showed significant results (Kettelhut et al., 2017; Koch et al., 2013), and two studies reported insignificant changes (McGeorge et al., 2015; Parush et al., 2017). Generally, these studies are different in terms of study participants, intervention used, the method to develop the intervention, and clinical settings. It is reasonable to assume that this heterogeneity explains the inconsistent result; therefore, I did not further downgrade the evidence because of this domain.

4.4.4.1.3 Indirectness of Evidence. All four studies meet the main review question's criteria regarding population, intervention, comparator, outcomes. However, one source of indirectness is the inclusion of participants other than nurses in three studies (Kettelhut et al., 2017; McGeorge et al., 2015; Parush et al., 2017). In the latter studies, the results did not distinguish between participants, such as physicians, consultants, and respiratory therapists. The SA of nurses is not necessarily the same as other providers. Therefore, I further downgraded the evidence in this domain.

4.4.4.1.4 Imprecision of Results. Due to heterogeneity, it was not possible to conduct a meta-analysis in this review.

4.4.4.1.5 High Probability of Publication Bias. In terms of bias in the selection of the reported result, I rated one study as moderate risk (Kettelhut et al., 2017), two studies as high risk (Koch et al., 2013; Parush et al., 2017), and one study as serious risk (McGeorge et al., 2015). Therefore, I graded the risk of bias as a serious limitation as researchers failed to report studies based on results.

4.4.4.2 Appraisal of Evidence Across Qualitative Studies. As mentioned above, I found three qualitative studies in this review. One study examined dashboards (Calder et al., 2018), one explored a communication tool (Stapley et al., 2018), and one reviewed a structured assessment (de Vries et al., 2017). The differences between these interventions do not allow an evaluation of the evidence across the studies.

4.5 Results of Individual Studies

4.5.1 Narrative Synthesis

We included all nine studies in our narrative synthesis (Appendix D).

4.5.2 Types of Interventions

The first two questions in this review were: What are the interventions used to enhance nurse SA? What are the types of SA did these interventions aim to improve? I found several types of interventions to improve nurse SA. Five studies used EHR dashboards (Calder et al., 2018; Kettelhut et al., 2017; Koch et al., 2013; McGeorge et al., 2015; Parush et al., 2017), two studies examined communication interventions (Cornell et al., 2014; Stapley et al., 2018), and two studies examined structured nursing assessment (de Vries et al., 2017; Munroe et al., 2016). Each type of these interventions targeted different SA type and included different information depending on the clinical context (Table 8).

4.5.2.1 EHR Dashboards. Five studies examined the use of EHR dashboards on SA. One study examined individual SA (Koch et al., 2013), and four studies explored team SA (Calder et al., 2018; Kettelhut et al., 2017; McGeorge et al., 2015; Parush et al., 2017). To improve individual SA, Koch and colleagues integrated the dashboard information from multiple devices and designed it for individual ICU nurses. EHR dashboards addressing team SA integrated information used by multidisciplinary providers such as nurses, physicians, consultants, respiratory therapists, and other professions.

The SA information varied between studies (Table 8). In the context of ICU and patient resuscitation, the electronic display included patient clinical information such as vital signs, clinical interventions, and due medications (Calder et al., 2018; Koch et al., 2013; Parush et al., 2017). Other displays included information about the patient location and special hospital data to track patients in the Emergency Department (ED) (McGeorge et al., 2015) and infection-related information (Kettelhut et al., 2017).

4.5.2.2 Communication Interventions. Two studies, one quantitative and one qualitative, examined the use of interdisciplinary rounds or huddles to improve shared SA (Cornell et al., 2014; Stapley et al., 2018). The use of rounds and huddles facilitated sharing patient SA information between staff members. Examples of this information included current patient situations, assessment results, and patient issues (Cornell et al., 2014; Stapley et al., 2018).

4.5.2.3 Structured Assessment. Two studies, one quantitative and one qualitative, used structured nursing assessment to examine individual SA (de Vries et al., 2017; Munroe et al., 2016). The structured assessment involved the use of tools that guide assessments carried out by individual nurses. Using these tools, the nurses collected information such as patient history, red flags, vital signs, and mental status (de Vries et al., 2017; Munroe et al., 2016).

4.5.3 SA Theory and Design Approaches

The third and fourth questions in this review were: What are the SA theoretical backgrounds or design approach that guided the development of the interventions?; and What affect did these interventions have on nurse SA? In terms of theoretical background, I found all nine studies used terms related to Endsley's work to define SA (Cornell et al., 2014; de Vries et al., 2017; Kettelhut et al., 2017; Koch et al., 2013; Munroe et al., 2016; Parush et al., 2017;

Stapley et al., 2018), measure SA (Kettelhut et al., 2017; Koch et al., 2013; McGeorge et al., 2015; Munroe et al., 2016; Parush et al., 2017), or report results of a qualitative study (Calder et al., 2018; de Vries et al., 2017; Stapley et al., 2018). I found multiple operational definitions of the SA (Table 7); however, none of the studies explained the SA theory or model that guided the intervention development process (Table 7). Some researchers explained their design approach. Below, I discussed these approaches based on the intervention type, and then I elaborated on their effect on SA.

Table 7: *Situation awareness definitions in included studies*

Study	**SA Definition**	**SA Measurement**
(Koch et al., 2013)	"operators' awareness, understanding, and anticipation of the future development across three levels: perception, comprehension and projection" (p.666)	SAGAT
(Cornell et al., 2014)	"a level of understanding that enables the individual to make a decision or formulate a plan." SA "involves the individual's perception, comprehension, and projection of the current situation" (p.165)	Patient review time
(McGeorge et al., 2015)	Not clearly defined.	SAGAT
(Munroe et al., 2016)	"gathering information, recognising and understanding, anticipating" (p.6)	Emergency Nurses' Nontechnical Skills
(de Vries et al., 2017).	Used Endsley's model to define SA levels	N/A
(Kettelhut et al., 2017)	perception and comprehension of risk of exposure to an antibiotic-resistant infection	SA Questionnaire measuring subjects' perception (Level 1 SA) and comprehension (Level 2 SA)
(Parush et al., 2017)	"Team Situational Awareness (TSA) is a meta-construct referring to cognitive processes involved in team members acquiring and sharing situational information and knowledge about the situation" (p. 154).	SAGAT
(Calder et al., 2018)	"knowing what is going on around you" (p. 17)	N/A

(Stapley et al., 2018)	"situation awareness means that staff gather information, recognize its significance, and systematically report on the information in real time to facilitate a shared and timely understanding of potential risk" (p. 45)	N/A

4.5.3.1 EHR Dashboards Interventions. There are two main design approaches for EHR dashboards: the user-centred approach and a clinical conceptual model.

4.5.3.1.1 User-Centered Approach Design. Four studies explained a user-centred approach to design EHR dashboards; three were quantitative studies (Koch et al., 2013; McGeorge et al., 2015; Parush et al., 2017), and one was qualitative (Calder et al., 2018). All studies listed the type of data included in the design to support SA, such as vital signs and lab results, which appears to be retrospectives in nature (Table 8). None of the studies clearly explained the link between this information and each SA level. For example, how the data or the system design would improve the projection level of the user's SA.

The researchers measured SA using the Situation Awareness Global Assessment Technique (SAGAT) in the three quantitative studies (Koch et al., 2013; McGeorge et al., 2015; Parush et al., 2017). Of these, one reported significant result, and two reported insignificant results. Koch and colleagues reported significant SA improvement (p = .001) (Koch et al., 2013). Compared to the traditional display, the researchers reported that the new SA display significantly improved all levels of SA, the perception, comprehension, and projection (OR = 3.96, 5.59, 2.56, respectively (p < .5)) (Koch et al., 2013). Other researchers examined the use of the ED display and tested its effect on SA but found no significant difference (McGeorge et al., 2015; Parush et al., 2017).

The qualitative study included the examination of an ED Dashboard (Calder et al., 2018). Overall, the researchers reported that the display was beneficial. The display enhanced the staff's ability to perceive key elements of patient data, comprehend their meaning, and develop a future projection of clinical status and required tasks (Calder et al., 2018).

4.5.3.1.2 Clinical Conceptual Model. One study used a conceptual mode, antibiotic-resistant infection transmission, to design the dashboard (Kettelhut et al., 2017). In this study, the researchers focused on improving the first two levels of SA (perception and comprehension) and included information to support these two levels. The researchers measured SA using a questionnaire and found a significant result (p = .008) (Kettelhut et al., 2017). Compared to EHR, the use of health data visualization display significantly increased median level 1 SA (1.8 vs. 4.6, p < .001) and median level 2 SA (2.0 vs. 4.5, p < .001) (Kettelhut et al., 2017).

Table 8: *Description of interventions*

Reference	**Intervention/Comparison**		**Type of data supporting SA**
(Koch et al., 2013)	Intervention	Integrated Information display	Integrates information about patient medications (administered, due, and side effect), vital signs, ventilator values, input/output values, and alarms of the nurse's second patient.
	Comparison	Traditional display	Multiple displays of different devices including ventilators, infusion pumps, patient monitor, information from EMR, and medication reference
(Cornell et al., 2014)	Interventions	SBAR and IDR	SBAR: scripted protocol for communication about patients, including information about a patient situation, background, assessment, and recommendation. IDR: Interdisciplinary Rounds attended by a staff nurse, charge nurse, pharmacist, dietitian, case manager, and others when appropriate.
	Comparison	N/A	
(McGeorge et al., 2015)	Intervention	Emergency Department Information Display Prototype	Displays information about the waiting room, ED patient flow, ED status, ED beds, Resources and equipment, staff workload, patient progress overview.

	Comparison	Control display	Display of existing information system and include patient demographic, chief complaint, vital sign, order/result information, and comments
(Munroe et al., 2016)	Intervention	Nursing Assessment Framework (HIRAID)	Patient assessment framework includes information about History, Identify Red flags, Assessment, Interventions, Diagnostics, reassessment, and communication
	Comparison	N/A	
(de Vries et al., 2017).	Intervention	PEWS and PRESS	PEWS: Pediatric Early Warning Score aims to improve early recognition of clinical deterioration PRESS: Pediatric Risk Evaluation and Stratification System that includes a subset of predefined risk factors, vital parameters, and patient's responsiveness (alert, verbal, pain, unresponsive score)
	Comparison	N/A	
(Kettelhut et al., 2017)	Intervention	Health data visualization (VIZ)	Display the "hospital spatial data linked to individual patients' clinical-laboratory data for tracking diseased patients' locations, antibiotic administrations, contact data, and infection prevention intervention data" (p. 322-323)
	Comparison	EHR	Not clearly explained
(Parush et al., 2017)	Intervention	Situational Awareness Display (same as Calder)	Information about whether the team code was called, interventions (treatments, medications), visible notifications for the key activities as they take place, patient information and vital signs at arrival, current resuscitation team, key vital signs in digital format and a trends graph, all key events, and activities along with their timestamp, graphic timeline depicting all events and activities
	Comparison	N/A	
(Calder et al., 2018)	Intervention	Situational Awareness Display	Displays information about clinical interventions, patient demographics and clinical history, team members, patient's current vital sign information with temporal trends, a summary of information requests, and a timeline of interventions.

	Comparison	N/A	
(Stapley et al., 2018)	Intervention	Huddle: Situation Awareness For Everyone (SAFE)	A frequent brief meeting to share information about patients and detect the risk of deterioration and other current issues. The huddle is a central component of a safety improvement program known as Situation Awareness for Everyone.
	Comparison	N/A	

4.5.3.2 Communication Interventions. None of the two studies examining communication interventions explained the design approach; however, the researchers found favorable results regarding SA outcomes. In a quantitative study, the researchers examined the use of Interdisciplinary Rounds (IDR) and Situation, Background, Assessment and Recommendation (SBAR) to improve SA (Cornell et al., 2014). SBAR is a structured reporting tool which stands for Situation, Background, Assessment, and Recommendation. The researchers measured SA using review time and found that the time was shorter for IDR and SBAR with a significant analysis of variance ($F = 17.25$, $p < .001$). In the qualitative study, the researchers examined huddle use and SA (Stapley et al., 2018). They found that huddles provided the staff with an opportunity to share information, raise concerns, and develop their awareness (Stapley et al., 2018).

4.5.3.3 Structured Assessment. Like the communication interventions, none of the studies examining structured assessments explained the design approach. They reported, however, an improvement in users SA. In a quantitative study, (Munroe et al., 2016) examined the effect of a structured nursing assessment tool on SA. The researchers used Emergency Nurses' Nontechnical Skills (ENNTs) scale to measure SA and found that the mean score significantly improved from 4.68 ($SD = 1.77$) to 5.58 ($SD = 2.11$) ($p =< .01$) (Munroe et al., 2016).

For the qualitative study, the researchers used the Pediatric Early Warning Score (PEWS) and Pediatric Risk Evaluation and Stratification System (PRESS) to improve SA. The researcher found that the combination of PEWS and PRESS has an added value to SA compared to PEWS alone (de Vries et al., 2017). The use of PEWS focuses on the perception and, to a lesser extent, SA's comprehension levels. The use of PRESS improved SA's projection level (de Vries et al., 2017).

4.6 Discussion

SA is an essential nontechnical skill for nurses. However, the current literature has limited studies that examined SA-targeted interventions aiming to improve nurse SA at the point of care. I did not find any studies examining the SA interventions in the context of preventing UTI. For those studies exploring dashboards, the researchers established weak evidence to support the use of this technology to enhance the nurse SA. The number and quality of current evidence indicate that the work in this domain is still at an early stage, with a need for conducting higher quality research.

4.6.1 Types of Interventions

One objective of our study was to explore the effect of using EHR dashboards to improve SA. In this review, information display or dashboards emerged as the most common intervention to enhance nurse SA. Depending on the goal of using technology, the displays included information about the patient clinical status or unit resources. This information was used to improve individual and team SA in various clinical settings, including ICU, ED, and medical-surgical units (Calder et al., 2018; Kettelhut et al., 2017; Koch et al., 2013; McGeorge et al., 2015; Parush et al., 2017).

The use of the dashboard to improve SA was not a surprise. Previous literature shows that the dashboards support the provider cognitive tasks through better information visualization (Ahmed et al., 2011; Dolan et al., 2013; Farri et al., 2012). The dashboards help to manage large data and enhance the decision-making process (Dowding et al., 2015; Dziadzko et al., 2016).

It is reasonable to think that the dashboard would improve SA. However, I could not establish evidence to support this claim. Our review includes three studies that reported favourable outcomes from using dashboards (Calder et al., 2018; Kettelhut et al., 2017; Koch et al., 2013), and two articles reported insignificant outcomes (McGeorge et al., 2015; Parush et al., 2017). I associated the inconsistent results among studies with possible research bias. I judged all studies in this review to have a moderate to serious risk of bias. The main reason behind this appraisal is the possible confounding effect in some studies and the potential selection of study results in others.

Although the focus of this paper is technological solutions such as dashboards, I found other types of interventions that can support SA, including communication interventions and structured assessment. However, I could not conclude the benefits of these interventions over the dashboards due to limited quality studies in this domain.

Communication interventions, such as huddles and rounds, are communication methods between two or more healthcare providers and include sharing patient conditions (Cornell et al., 2014; Stapley et al., 2018). These interventions help create common ground between staff and establish agreement about patient clinical status; hence, they are used to improve shared SA. Studies in our review showed favourable results in terms of using communication interventions to improve SA. Staff were able to share important patient information and improve their level of awareness. In one study, the team use of a structured communication tool (SBAR) shortened the time needed for interdisciplinary rounds (Cornell et al., 2014). The SA in the latter study is defined based on staff review time of patient data. A shorter review time indicated that the staff developed their awareness of required patient information. However, it is important to mention that although the patient review time can be associated with improved SA, the patient review time is not a precise measure of staff SA.

Structured nursing assessment is another intervention used to improve SA. The structured evaluation guides the nurses' assessment process and confirms data completeness regarding patient history, clinical issues, assessments, patient vital signs, and responsiveness (de Vries et al., 2017; Munroe et al., 2016). These assessment tools were used to improve individual SA in ED and pediatric wards. Generally, the assessment tools seem to positively affect nurse SA (Munroe et al., 2016). However, the latter study used a pre-post design. There is a need for a more rigorous research design to confirm these results.

4.6.2 Theory and Design Approaches

The design and content of a SA intervention will likely affect the intervention's effectiveness to achieve the desired outcome (Endsley, 1995). The most common method to design the SA intervention in our review was the user-centred approach. However, there is no clear evidence that studies in this review used a SA model or theory to support the design process. Although all studies used terms referring to Endsley's SA model, it is not clear how the model guided the design approach and how the dashboard information is linked to each SA level.

4.6.2.1 Theoretical Models and User-Centered Approach. In general, the user-centred approach involved collecting data from end-users about design requirements, followed by the development of prototypes, and then refine the prototypes by user testing (Koch et al., 2013). The engagement of healthcare providers would support the design of acceptable and usable dashboards (Hartzler et al., 2015). Compared to technology-centred design, the user-centred approach defines the system interface around user needs rather than the capabilities of the technology operating the interface (Endsley & Jones, 2012c). The optimization of dashboards around the user's goals and tasks improve user acceptance and satisfaction and reduce potential errors (Endsley & Jones, 2012c).

However, the design around user needs alone is insufficient and requires a theoretical model to support it. Users do not necessarily have complete ideas on how the system design can improve their current practice and effectively present clinical information (Endsley & Jones, 2012c). Also, different users can have other ideas about dashboard design. The exact translation of what specific users ask into a computerized design will likely miss the perspectives of broader users and lead to an ongoing cycle of system development (Endsley & Jones, 2012c).

If the goal was to develop a system that supports SA, it is safe to say that such a design would require a SA theoretical model. The use of a SA model or theory will probably ensure that the designed system will match how SA is conceptualized. However, none of the studies clearly explain the SA theoretical model that guided their design, representing a gap in the literature.

4.6.2.2 SA Levels and Dashboard Designs. An SA-oriented dashboard would have a design that demonstrates all levels of SA (Endsley & Jones, 2012b). In this review, the researchers designed the dashboards using retrospective reporting of data (perception and comprehension), with no evidence of using a prospective prediction of data. Information such as vital signs and patient medication does not directly report the expected patient status in the future. Researchers argue that useful dashboards would integrate retrospective data and prospective prediction of decisions (Frith et al., 2010). A potential explanation for not including the projection level is the complexity of healthcare data and the difficulty associated with representing this SA level. Indeed, the difficulty of representing SA level 3 is acknowledged by Endsley when describing how to design SA-oriented systems (Endsley & Jones, 2012b).

4.7 Conclusion of the Literature Review

The use of SA interventions in a clinical setting can be of great benefit for patient health outcomes and the reduction of clinical adverse events such as HAUTI. I founded a limited number of studies exploring SA interventions to improve nurse SA at the point of care, with no studies addressing HAUTI. The studies I found lack the quality to support evidence on the effect of the interventions to enhance nurse SA. The available studies on dashboard interventions did not use a SA model or theory to guide the design process. The information contained in these dashboards represents retrospective data with no indication of supporting prospective reporting. The retrospective and prospective reporting are both important to support all levels of SA.

Designing a dashboard using SA principles would identify factors leading to HAUTI and estimate the probability of developing the infection. The literature lacks such studies; hence, the significance of conducting research in the context of SA and HAUTI. This research addresses the need to developing a nursing SA-oriented dashboard at the point of care. This intervention aims to enhance nurses' SA, enabling them to perceive and understand clinical HAUTI cues, anticipate the infection, and therefore, implement measure to prevent the infection.

Chapter 5 Research Methods

Chapter 5 describes the study design and research method to address the gap in literature explained in Chapter 4

5.1 Research Aim and Objectives

This study aimed to discover the factors contributing to developing HAUTI and predicting the risk of acquiring the infection. These factors will be used to design a situation awareness dashboard for nurses. The dashboard will incorporate a machine-learning algorithm to discover HAUTI factors and display these factors to nurses based on Endsley's' situation awareness principles. The specific objectives of the study were

1. to collect de-identified EHR data and prepare it for machine learning tasks
2. to develop the best predictive model for the outcome of developing UTI.
3. to explore the key factors leading to HAUTI in the study clinical context.

5.2 Research Questions

There are several questions that I am trying to answer in this study. These questions include the following:

1. What is the best machine learning method and prediction model to predict the probability of Healthcare-Associated Urinary Tract Infection?
2. What are the most important predicting variables of Healthcare-Associated Urinary Tract Infection in the participating organization?

5.3 Designing SA-Oriented Dashboard

5.3.1 Endsley's Methodology

Endsley described a methodology for developing SA designs. The first step in this methodology is the Goal-Directed Task Analysis (GDTA), which defines the necessary information to support SA. Then, in the second step, the information is organized according to Endsley's design principles. The detailed explanation of these principles is beyond the scope of this paper. This research study focuses on the first step of Endsley's methodology.

It is essential to organize the technology around users' goals and tasks and the way they make decisions (Endsley & Jones, 2012c). The GDTA's main objective is to discover information requirements relevant to a particular domain and understand what is needed to support the understanding of user SA (Endsley & Jones, 2012a). The GDTA includes an extensive interviewing process with subject matter experts to explore which data users need to perceive, how the users should understand the data from the perspective of users' goals, and what projections the users need to achieve (Endsley & Jones, 2012c). This information represents the users' SA. The interviews will then be combined with other resources, such as protocols, and validated with many experienced users (Endsley & Jones, 2012a). Once these requirements are specified, it will be possible to create dashboards to present this information to maximize the users' SA in a given context (Endsley & Jones, 2012a).

The dashboard I intend from this study focuses on preventing HAUTI by improving the nurses' SA. A higher SA reflects the staff's awareness of factors causing the infection, promoting an understanding of these factors and the probability of developing the disease. Here, the use of GDTA to design this dashboard is problematic. The interviews do not necessarily result in optimal and accurate data (Endsley & Jones, 2012a). The interviewees will provide expert opinions, which is the lowest level of evidence (Ingham-Broomfield, 2016). In addition, the interviewees are unlikely to give an accurate probability estimate of each factor affecting HAUTI. In that case, the overall SA will not be supported. For example, the nurses can define factors contributing to HAUTI, such as the number of catheter days, blood sugar, and perineal care, as necessary information to decide what needs to be done to prevent HAUTI. The staff opinions, although valuable, do not confirm these variables' probabilistic on developing the infection and might not lead to an accurate prediction of HAUTI. Indeed, Endsley described SA's projection level as the most challenging to represent in designing a SA system (Endsley & Jones, 2012b). It is necessary to find an effective method to support the projection of future patient status.

5.3.2 Machine Learning

Machine Learning (ML) can resolve the challenge of using the GDTA to reduce HAUTI. ML supports discovering the data by analyzing datasets and using algorithms to project the probability of developing HAUTI. ML prediction model can then be integrated with the second step in Endsley's methodology, which is the design principles of a SA-oriented system.

While the performance benefit of ML over traditional statistics is still an area of argument (Christodoulou et al., 2019; Zachariah et al., 2020), I maintain that ML is a better fit to design an SA-oriented dashboard than traditional statistics. Compared to conventional statistical methods, the ML methods do not pre-specify the variables and their relationships. Instead, the ML methods allow discovering new variables and models within a specific context, which is important for designing SA systems. As described in Chapter 2.1, the SA reflects the user's knowledge of a particular environment. ML learning will help analyze datasets representing elements of this environment and build prediction models based on available information. On the other hand, the traditional statistical method uses theories and assumptions around possible factors (Christodoulou et al., 2019). These factors might or might not represent the context under study, leaving a possibility of missing context-specific variables.

ML is a type of artificial intelligence that allows learning from previous examples and detecting data patterns in a large and complex dataset (Nithya & Ilango, 2017). ML employs statistical and probabilistic techniques to iteratively learn and find hidden insights and trends in the data (Nithya & Ilango, 2017). Such capacity can support accurate predictions and optimize decisions in healthcare and many other industries (Nithya & Ilango, 2017).

5.3.2.1 Machine Learning and UTI. The research on using ML in the context of HAUTI is a relatively new domain in literature (Luz et al., 2020). In a recent literature review, the researchers found 11 studies exploring hospital-acquired infections, with one study examining HAUTI (Luz et al., 2020). The HAUTI study investigated the use of ML to predict HAUTI in emergency patients (Taylor et al., 2018). Other work has explored the use of ML to reduce the microbiological screen for patients suspected to have HAUTI (Burton et al., 2019), build a classification method to support the diagnosis of HAUTI (Checcucci et al., 2020; Ozkan et al., 2018), predict HAUTI in dementia patients at home settings (Enshaeifar et al., 2019), and discover data patterns and relationships between variables such as nursing hours per patient-day and nursing education, and catheter-associated UTI (Park et al., 2018). None of the studies above addresses the datasets that include nurses' assessments and interventions and the effect of these features on HAUTI.

In addition to limited research on ML and UTI, the generalization from previous ML studies to a new population and settings can be challenging. Studies can have heterogeneous definitions of the outcome of interest (Luz et al., 2020). Also, there are technical differences between health organizations, especially when using complex EHR (Kelly et al., 2019). The EHR can include nursing assessments with a coding definition that varies across organizations. Also, diverse populations, lab equipment, and various administrative practices among facilities can yield results that might not apply to other sites (Kelly et al., 2019). The limited literature and the generalization challenges necessitate implementing site-specific ML training to achieve a well-performing model.

5.3.2.2 Types of Machine Learning. There are two main types of ML, including supervised and unsupervised ML (Roth et al., 2018). Supervised learning uses clear instructions on what the algorithm needs to learn (Nithya & Ilango, 2017). The algorithm requires training on a given input data and known output (Nithya & Ilango, 2017). Supervised learning can help in regression or classification problems. The regression algorithms aim to predict the value of one variable using other values in the dataset (Roth et al., 2018). The classification will differentiate between two classes: healthy/unhealthy patients (Roth et al., 2018).

On the other hand, unsupervised methods have no specific output to learn (Nithya & Ilango, 2017). Unsupervised learning aims to summarise the data and discover new data structures (Roth et al., 2018). As this study seeks to find variables that best predict a known output (HAUTI), I used supervised ML methods as they are a better fit. However, unsupervised learning can be a good approach to investigate data missingness, a common problem in EHR data (Garcia Olea et al., 2022; Weller et al., 2018). In this study, I used unsupervised learning to investigate the patterns of data missingness and evaluate the relationship between missingness and the outcome variable.

5.3.2.2.1 Supervised Machine Learning Methods. I used several supervised learning methods in this study, including Decision Trees, Random Forests, XGBoost, Neural Networks, Logistic Regression, and Support Vector Machines. It is possible to apply most supervised methods to complex data structures (a combination of categorical and continuous predictors) commonly found in the EHR (Jiang et al., 2020). These methods, however, can result in better or worse performance depending on the type of input variables (binary vs. continuous variables). There was no single algorithm that was better than all others. In this study, I evaluated these algorithms in the context of EHR data and HAUTI to find the best-performing learning method. These evaluation methods are explained in detail later in this chapter.

Each supervised machine learning method works differently. The decision trees method, for example, involved dividing possible values for input variables into distinct, non-overlapping regions, a method known as classification (Jiang et al., 2020). This method allows for predicting categorical outcomes, like the presence or absence of HAUTI, by assigning observations to the most common category within a node, termed terminal nodes. The tree then grows based on various calculation methods, depending on the outcome variable (Crisci et al., 2012).

Decision Trees can also be further developed into Random Forests. Random Forests develop predictions using a collection of individual decision trees. Random Forests can help explore classification trees and discover specific combinations of variables associated with a high risk of developing HAUTI. XGBoost, which stands for Extreme Gradient Boost, is also relevant to Decision Trees. XGBoost Gradient boosting works by sequentially training multiple models to boost weak Decision Trees and improve model performance (Azmi, 2020).

The Neural Networks (NN) perform regressions or classification (or both) tasks at the same time (Osisanwo et al., 2017). The NN mimics the human brain's neurons on a much smaller scale. Each Neuron or node connects to layers on each side, known as input and output layers. The input layers are the ones receiving input variables. The output layers are the ones responsible for the information learned. Between the input and output layers are the hidden layers. Commonly, each hidden and output layer is connected, forming a fully connected Neural Network. These connections are represented by weight that reflects the influence one unit has on another. The weight is initially set randomly and then adjusted to bring output values close to the desired outcome (Osisanwo et al., 2017).

Logistic Regression is a technique borrowed by machine learning from traditional statistics (Gamiz et al., 2023). Logistic regression is a predictive analysis that performs binary classification (i.e., positive HAUTI, negative HAUTI). The algorithm estimates probabilities using logistic functions to ensure an output between 0 and 1. This output can then be used to estimate the probability of the input being classified as a positive case (Muhamedyev, 2015).

Support Vector Machine (SVM) can help classify the outcome of interest into HAUTI and non-HAUTI cases in a multidimensional space (Jiang et al., 2020). In this study, the multidimensional space is represented by various EHR variables. The SVM transforms data into a higher dimensional space and identifies the boundary, known as a hyperplane, that provides optimal separation of classes. The separation between the classes is represented by the margin on either side of the hyperplane (Bhavsar & Ganatra, 2012). The bigger the margin, the larger the distance between the hyperplanes.

***5.3.2.2.2 Unsupervised Learning Algorithms*.** Missing data in EHR is a common issue (Garcia Olea et al., 2022; Weller et al., 2018). As a method to further analyse missingness, I used an unsupervised learning algorithm, K-Means Clustering, where K refers to number of clusters. The K-means algorithm is the most known and commonly used method to find cluster structure in a data set (Sinaga & Yang, 2020). I used this algorithm to discover missingness structures and create clusters with the same observations missingness patterns and dissimilar missingness patterns between different clusters. Then, I evaluated the relationship between being a member of one cluster and the probability of developing HAUTI.

To do so, I Initially created a binary indicator for missing values in the dataset. This transformed each value in the dataset into a binary format (1 indicating missing, 0 for not missing). This transformation simplifies the identification of missing values and the understanding of their distribution.

After the binary format transformation, I used the Elbow Method, an established technique in data analysis, to identify the optimal number of clusters for the dataset (Puli, 2024). The optimal number of clusters would balance the similarity of pattern within a cluster and the difference between clusters. In other words, minimize the variance within a cluster and maximize it between clusters. The elbow method involved calculating and plotting the total within-cluster sum of squares for varying numbers of clusters. The elbow method involved calculating and plotting the total within-cluster sum of squares for varying numbers of clusters. The result is an elbow-like plot that indicates the ideal value of K (Puli, 2024).

5.4 Research Design

This study is a quantitative retrospective observational case-control study. Data measurement is essential when calculating predictions; thus, quantitative research is necessary. Qualitative research, on the other hand, focuses on collecting narrative materials. The retrospective approach focuses on linking a present phenomenon to another phenomenon that occurred in the past; the prospective approach starts with a presumed cause of a phenomenon and moves forward in time to confirm the presumed effect (Polit & Beck, 2008b). This study aimed to discover variables that cause HAUTI in a particular organizational context, so a retrospective approach is more appropriate.

5.5 Setting and Data Source

I conducted the study in a regional hospital in British Columbia, Canada. This regional hospital was the first to implement electronic documentation for nurses. The average HAUTI at the hospital was 13.4 per 1000 hospitalizations, and the HAUTI was one of the hospital's priorities of quality care.

I retrieved the data from four medical-surgical units. These units accept various medical and surgical conditions for the adult population. These four units experienced frequent HAUTI at the targeted institution.

I extracted the nursing assessment data from August 2019 to August 2021. The electronic documentation was implemented in the target hospital through 2018. Around July 2019, the project implementation team reached a stable EHR, requiring fewer revisions and enhancements, thus August 2019 was selected as a starting point for data collection.

5.6 Outcome Variable

The Canadian Patient Safety Institute defines UTI as a group of diseases that affect the upper or lower urinary tract. In this study, HAUTI refers to urinary tract infections acquired after hospitalization that were not present or incubated at admission (Monegro et al., 2020). These infections typically start to manifest at least 48 hours after admission (Monegro et al., 2020). The operational definition of HAUTI depended on the hospital's coding system. As it is one of the quality measurements, the patients' diagnoses were electronically coded to have HAUTI. The case patients are those with HAUTI codes. For the date of acquiring the infection, I selected the date of sending the urine culture sample to the laboratory.

5.7 Extracted Data

The study focuses on provider factors, specifically the variables documented in electronic nursing assessments. The aim is to enhance the nurse's awareness of the variables they record in

EHR, which are associated with developing HAUTI. Understanding these variables is crucial for reducing the incidence of HAUTIs and improving patient care.

5.8 Sample Method

We collected data for all HAUTI patients admitted to one of the four participating medical-surgical units who were at least 18 years old and had a length of stay of two or more days. I also collected the demographic data of all non-HAUTI patients admitted to the participating hospital using the same parameters of HAUTI patients. Then, I matched the HAUTI patients (case group) with a sample of non-HAUTI patients to serve as the control group.

5.9 Matching Method

I employed a Nearest Neighbour matching process to create cases and control groups. The goal is to create a quasi-experimental scenario where case and control groups are comparable in terms of observed confounders, thereby isolating the effect of independent variables on the outcome variable.

The Nearest Neighbor matching method is one type of distance matching. This matching considers the case group and selects members of a control group to pair with each observation of the case group, a process that uses the distance between observations (Greifer, 2023). Observations with no matches were dropped from the sample.

Unlike other types of distance matching, the Nearest Neighbour allows matching based on each demographic instead of calculating the average of all demographics (Greifer, 2023). This matching process allowed for control of the parameters of the matching variables and minimized the differences between the case and control groups, reducing the chances of bias.

The factors I used to complete the matching process included:

1. patient age (AgeNumber),

2. sex (genderdesc),
3. admission location (FromFHAUniDplMnemonic),
4. year of admission and discharge (StartYear, EndYear),
5. length of stay in the hospital (LOSDays),
6. and length of stay in the admission location (`DurationOfLocation).

The name between brackets reflects the name of the table in the database. I used these variables to ensure that the case and control groups had similar demographic profiles and were exposed to similar hospital environments and care conditions. The sex (genderdesc) variable was inconsistently reported in the database and could not be interpreted as sex or gender. The options available for each patient were male/female.

I employed a calliper (or distance threshold) for the continuous variables (AgeNumber, LOSDays, DurationOfLocation). I used a Data-Driven approach to decide on the caliper width. I started with a width equal to 0.2, which can eliminate approximately 99% of bias (Austin, 2011a), and kept it higher than 0.4 which eliminate 95% of bias (Austin, 2011b). Then, I gradually increased the caliper to balance the sample size and matched the pairs' similarity. I finally selected a caliper width of 0.25.While I don’t have the exact estimate of bias at the caliper of 0.25 (range from 95%-99%), it is reasonably close to 0.2, and therefore effective in minimizing bias (Austin, 2011a). For categorical variables (genderdesc, FromFHAUniDplMnemonic), I used an exact match between the case and control groups. The overall matching strategy aimed to mitigate potential confounding and bias and improve the robustness of the analysis.

5.10 Evaluation of the Matching Process

I used multiple techniques to evaluate the matching process, including standardized mean difference, histograms, quantile-quantile plots, and the Kolmogorov-Smirnov test. When closer to zero, the standardized mean difference indicates a negligible difference in means between the case and control groups for a particular variable. The histograms and quantile-quantile (QQ) plots offered a visual analysis of value distributions. The histogram graphs the data into non-overlapping intervals and displays the count of data points for each interval (Ariel, 2014). The bar in the histogram reflects the average data point of each interval. The QQ plots graph the quantiles of the covariate for the case group against the quantiles of the covariate for the control group (Ariel, 2014).

I employed the Kolmogorov-Smirnov test to ensure that the matched cases and controls were comparable. This non-parametric statistic helps compare the case and control distributions and defines the largest absolute difference between them as a measure of disagreement (Lopes et al., 2007). In case of divergence between the case and control histogram and QQ plots, the Kolmogorov-Smirnov test evaluates whether the difference is significant.

5.11 Deciding on Cut-Off Date

Nurses commonly document their assessments on an ongoing basis. As patients' length of stay ranges from a few days to several weeks, each patient can have a large amount of nursing assessment data. It is necessary to decide which data to include to serve the study's objectives.

As per the definition of HAUTI, the patient needs to be admitted for at least 48 hours before the diagnosis of HAUTI. I used 48 hours as a standard data collection period for all patients. In other words, I collected 48 hours' worth of nursing assessment data for patient analysis. The assumption is that, within these 48 hours, there might be changes in the patient's condition that indicate an increasing risk of HAUTI.

However, I needed to decide on a cut-off point that marks the end of 48 hours. For HAUTI patients, I used the date of sending the urine culture sample (which was positive) as the cut-off point. In other words, I collected the data 48 hours before sending the urine culture.

For non-HAUTI patients, there are no necessary urine culture samples, which poses a challenge in how to decide on the cut-off point. To solve this issue, I evaluated multiple options. First, I selected a random date within each patient's length of stay. The assumption is that randomization will help control confounding variables and reduce bias. However, randomizing a date might not provide a cut-off date with at least 48 hours preceding it. A second approach is calculating the mode for the number of days from admission to the cut-off point for HAUTI patients and then using the same mode for the non-HAUTI patients. However, this approach posed the same challenge as the first approach without reducing bias. To solve this challenge, I adopted a third approach. In this approach, I started by reviewing the paired groups that resulted from the matching process. For each HAUTI patient in the paired group, I counted the days from admission to sending the urine culture. Then, I used the same number of days to calculate the cut-off date for the non-HAUTI patients in the same paired group. This method did not only solve the challenge of the first two approaches; it also standardized the cut-off point for patients matched on other demographic factors.

5.12 Steps of Machine Learning and Data Analysis

I implemented the ML steps using R Studio version 4.3.1. R Studio (Posit, 2024) is one of the most common applications for ML (Nithya & Ilango, 2017). It is an open-source language with several ML packages appropriate for analyzing the retrieved dataset. R Studio was also an approved application at the participating hospital.

After data collection, I used ML steps from the work of Park et al. (2020) and Hu et al. (2017). These steps include data preprocessing, feature selection, model training, model evaluation, and model performance improvement. Each supervised learning algorithm required a different package in R studio (Table 9).

Table 9: *R packages used in the study*

Machine Learning	R Packages
Decision Trees	rpart
Random Forest	randomForest
Neural Networks	h2o
XGBoost	xgboost
Logistic Regression	glmnet
SVM	caret

5.12.1 Data Preprocessing

Data preprocessing is essential for reducing variables, finding useful features to represent the data, and allowing statistical modelling (Fayyad et al., 1996).

5.12.1.1 Initial Preprocessing. I started by using my domain knowledge to remove factors irrelevant from a clinical perspective. Then, I standardized the variables to maintain a consistent coding scheme, facilitating a more streamlined analysis. For example, variables that I deemed categorical underwent factorization, while I considered others as numeric, integer, or ordinal based on their intrinsic properties. Such systematic sub-setting ensured that each variable received appropriate preprocessing tailored to its type. Ensuring data was in its optimal format was critical for maintaining the integrity and reliability of the later stages of analysis.

The study included a structured nursing assessment. In some instances, the nurses added additional non-standard textual answers instead of selecting one of the optional selections. I have recorded these non-standard answers as “other” to ensure uniformity.

As the nursing assessment is collected 48 hours before the cut-off date, I aggregated the variables to get a single value for each variable per observation. To do so, I used the mean for continuous variables and mode for categorical ones. In the case of ties-in mode, I used the most recent observation based on the time and date of the observation. I also summed the values over the 48 hours for specific continuous variables including fluid intake and output.

5.12.1.2 Domain-specific Features. I employed my domain knowledge to review, update, and extract new features. This feature engineering method helped find variables with the same meaning and optional answers and combine them into one feature. The combination process included replacing the null values of one variable with values from the other variable, which reduced missing data. Also, this method led to deriving meaningful features by analyzing the values of predefined features.

5.12.1.3 Management of missing data. There are several mechanisms of missing data, including Missing Completely at Random (MCAR), Missing at Random (MAR), and Missing Not at Random (MNAR) (Hu et al., 2017). An example of MCAR is missing lab results due to a broken urine culture sample. MAR occurs, for instance, when a patient leaves the hospital without completing the full assessments or when a nurse completes a patient's assessment but does not document it. An example of MNAR is when a nurse does not conduct a nursing assessment, or a physician does not order a specific test, perhaps due to a clinical judgment about the patient's condition. As the data in this research is retrospective, it is impossible to differentiate between MAR and MNAR from observed data (Carreras et al., 2021). In this study, I assumed the mechanism of missing the data to be MAR. I used the imputation method, multivariate imputation by chained equations, that applies to both MAR and MCAR (Hu et al., 2017; Madley-Dowd et al., 2019).

5.12.1.3 Missing Data Quantification. I quantified the missing values per each column and row in the dataset. I computed the missingness percentage of each column (variables) and each row's (patients), ensuring comprehensive insight. This was essential to decide on subsequent analysis and missing data management.

5.12.1.4 Clustering Missing Data. I used an unsupervised learning algorithm, K-Means Clustering to evaluate the missing data further. Initially, I created a binary indicator for missing values in the dataset. This transformed each value in the dataset into a binary format (1 missing, 0 not missing). This transformation simplifies the identification of missing values and the understanding of their distribution. Then, I used the Elbow Method, to identify the optimal number of clusters for the data.

After identifying the clusters, I calculated the percentage of HAUTI infection in each cluster. I then performed a Chi-square test to determine whether the infection rate differed significantly between clusters. In other words, I used the *p* results from the Chi-square to evaluate whether the observed differences in infection rates between clusters are related to the missingness distribution.

5.12.1.5 Missing data deletion. One of the methods to manage missingness is deleting variables with a high missingness rate (Beaulieu-Jones et al., 2018). I followed a structured approach to data deletion. I divided the dataset into five new datasets using the fraction of missing values for each variable. The fraction values that I used are 20%, 30%, 40%, 50%, 60%, 70%, 80%, and 90%. In other words, I used the results of the missing data quantification and retained columns with missingness equal to or less than 20% for the first dataset, less or equal to 30% for the second one and so on. This resulted in eight datasets, which I named Dataset 20 to Dataset 90. The plan is to perform imputation for each of these datasets, run supervised learning algorithms, and then perform sensitivity analysis, where I compare the results of the supervised learning algorithms between these datasets. The sensitivity analysis evaluated the effect of variable deletion on the ML performance. I did not perform multiple imputations for variables missing above 90% as I assumed no value of variables with such a high missingness rate.

5.12.1.6 Imputation of missing values. I used Multiple Imputation by Chained Equations (MICE) method to input the missing values (Beaulieu-Jones et al., 2018). MICE is a statistically rigorous method that creates multiple regression models to impute missing values of one variable using known and imputed values of other variables (Jazayeri et al., 2020). The MICE process is iteratively repeated with updated estimations of missing values. The result of MICE is multiple complete datasets to acknowledge the uncertainty inherited in imputing missing values and produce more reliable estimates than single imputation methods. Several studies indicate the effectiveness of multiple imputation to impute values of variables of high missingness of up to 90% (Javadi et al., 2021; Jazayeri et al., 2020; Madley-Dowd et al., 2019)

The multiple imputation method included two sub methods. For categorical variables, I ran imputed using Classification and Regression Trees (CART) and Predictive Mean Matching (PMM) (Slade & Naylor, 2020). CART is effective for categorical data as it can model complex interactions and non-linear relationships, and I used PMM for numeric and integer variables.

5.12.2 Feature Selection

Feature selection is essential in ML (Delzell et al., 2019) (Spooner et al., 2020). The selection methods will help to reduce dimensionality and noise (Delzell et al., 2019) and facilitate the selection of input variables with a strong relationship with the target variable.

Principal component analysis (PCA) and Multiple Correspondence Analysis (MCA) are widely used dimensionality reduction techniques, especially with large datasets (Karamizadeh et al., 2013; Khangar & Kamalja, 2017). PCA handles continuous data, while Multiple Correspondence Analysis (MCA) deals with categorical data. As nursing assessments usually include a combination of numerical and categorical variables, I combined both methods, PCA and MCA, using Factor Analysis of Mixed Data (FAMD) (Han et al., 2021).

FAMD performs as PCA when dealing with numeric variables and as MCA when treating categorical variables. The results of the FAMD are several dimensions that retain at least 80% of the total variance (Han et al., 2021). Each dimension has different loading magnitude for each variable, which enables the discovery of the most informative features for further analysis.

5.12.3 Model Training

After preparing the data, I ran the supervised ML algorithms explained in section 5.1.2 to create prediction models using HAUTI diagnosis as an output. Each algorithm offers unique strengths and approaches to data analysis. By integrating these diverse algorithms, I broadened the modelling process, allowing for a more inclusive and better understanding of the underlying patterns in the data.

5.12.4 Model Evaluation

I used Area Under the Curve (AUC) and sensitivity analysis to compare the ML model's performance. AUC is a commonly used biomedical informatics method and conducts a sensitivity analysis to evaluate classification and prediction models and predict a given condition's presence or absence (Lasko et al., 2005) . An AUC of 1.0 is a perfect test, while a value of .5 results from random chance (Lasko et al., 2005). I compared the different models and selected the one with the highest AUC. In general, .7 to .8 is acceptable, .8 to .9 is excellent, and above .9 is outstanding model performance (Mandrekar, 2010).

I used sensitivity analysis to evaluate the effect of missing data deletion and multiple imputation on ML model performance. The approach helped assess the extent to which missing data could affect study results (Beaulieu-Jones et al., 2018).

To conduct sensitivity analysis, I first calculated the mean and standard deviation of the AUC for the imputed datasets within each missingness category, which was 20% to 90%. The mean and standard deviation indicate how missingness affects model performance on average and how stable the performance is across different imputations. Then, I performed a visual trend analysis by plotting the average AUC against the percentage of missing data. Finally, I used Analysis of Variance (ANOVA) to evaluate whether the AUC difference between different missingness categories is significant.

5.12.5 Model Performance Improvement

This step includes finding opportunities to improve the model's performance or change its type. I employed K-Fold cross-validation (Vabalas et al., 2019) in all ML algorithms. Such approaches are essential to ensure unbiased performance estimates are achieved (Vabalas et al., 2019).

After reaching a predictive model with acceptable accuracy, I investigated the variables contributing to the model and introduced them as the component for the perception level of the SA dashboard (Endsley & Jones, 2012b).

5.12.6 Variables extraction

After completing the model performance evaluation and improvement, I analyzed the dimensions produced by the FAMD. Each dimension has different loading magnitude for each variable, which enables the discovery of the most informative features for further analysis. After extracting the variables' loading magnitude, I reviewed variables with high magnitude as the most important variables contributing to HAUTI. A common rule of thumb is to consider loading above 0.3 or 0.4 as minimally acceptable and loadings of 0.5 or higher as significant variables (Hair et al., 2009). However, sample size might affect the optimal loading (Hair et al., 2009). The loading threshold decreases progressively with larger samples to become 0.45 for 150, 0.4 for 200, 0.35 for 250, and 0.3 for 350 participants (Hair et al., 2009). Therefore, in this study, I used a threshold of 0.35 as the sample size was 266 cases.

5.13 Summary

Endsley described a methodology for developing SA designs consisting of two steps: implementing GDTA to discover relevant factors and implementing design principles to organize these factors into a dashboard. This research focused primarily on the first step. I employed ML to support GDTA and explore the most important variables contributing to HAUTI. I used several supervised learning techniques to discover these variables and an unsupervised method to evaluate data missingness. The study's primary goal is to discover the factors contributing to developing HAUTI and predicting the risk of acquiring the infection. These factors will set the ground for designing a situation awareness dashboard for nurses.

The research design is a quantitative, retrospective, observational study targeting HAUTI as an outcome Variable. I conducted the study in a regional hospital in British Columbia, Canada. The study involved nursing assessment data for adult patients who were admitted to medical-surgical units and had a hospital stay of at least two days. Using patient demographic data, I employed a Nearest Neighbour matching process to create cases and control groups. Then, I validated the matching process using standardized mean difference, histograms, quantile-quantile plots, and the Kolmogorov-Smirnov test. I used five main steps in ML, including data processing, feature selection, model training, model evaluation and model performance improvement. While implementing these steps, I followed an extensive approach to manage missing data and minimize bias and performed data imputation to produce a reliable ML model. I also implemented sensitivity analysis to evaluate the effect of missing data deletion and multiple imputation on ML model performance. Then, after deciding on the best ML model, I used the dimensions produced by FAMD to extract the most important variables contributing to HAUTI.

Chapter 6 Research Results

Chapter 6 describes the research results.

6.1 Overview of Initial Data Collection

The initial sample included 135 HAUTI patients (cases) and 11,437 non-HAUTI patients (controls). The HAUTI patients were admitted to the four medical-surgical units, and 11,437 were admitted to the same hospital at any location.

6.2 Balancing Outcome Post Matching

After employing the Nearest Neighbor matching method I retained 95 HAUTI patients and matched them with 171 non-HAUTI patients (total 266), ensuring a 2:1 matching ratio (Figure 5). This resulted in a well-balanced cohort, allowing for better comparability between groups when evaluating the outcome. I tried other matching ratios such as 1:1 and 1:3. However, the 1:1 ratio resulted in a smaller sample size, while the 1:3 ratio results in less consistent groups, with many groups lacking the complete four observations expected from the 1:3 ratio. This inconsistency might overrepresent some matching groups and introduce potential bias (Rassen et al., 2012).

Figure 5: *Final matched groups*

Sample Sizes:

	Control	Treated
All	11437.	135
Matched (ESS)	158.33	95
Matched	171.	95
Unmatched	11266.	40
Discarded	0.	0

I then evaluated the case and control group balance. This is to ensure similar distributions between cases and controls and reduce bias due to confounding variables. Balanced groups support robust conclusions in the subsequent analyses.

6.2.1 Standardized Mean Difference

The matching process minimized the standard mean differences across all variables, with many approaching zero. This indicates a good match and suggests that the two groups are comparable in terms of the observed characteristics (Figure 6).

Figure 6: *Result of the matching process*

```
Summary of Balance for Matched Data:
                              Means Treated Means Control
distance                             0.0254        0.0252
AgeNumber                           77.6842       77.8684
genderdescFemale                     0.6000        0.6000
genderdescMale                       0.4000        0.4000
StartYear                         2020.1895     2020.1474
EndYear                           2020.2211     2020.2000
LOSDays                             19.5263       19.0789
FromFHAUniDplMnemonic2BAKER          0.3474        0.3474
FromFHAUniDplMnemonic2CHEAM          0.2632        0.2632
FromFHAUniDplMnemonic3BAKER          0.2737        0.2737
FromFHAUniDplMnemonic3CHEAM          0.1158        0.1158
DurationOfLocation                  16.2414       16.0852
                              Std. Mean Diff. Var. Ratio
distance                               0.0014     0.8986
AgeNumber                             -0.0138     1.0089
genderdescFemale                      -0.0000          .
genderdescMale                         0.0000          .
StartYear                              0.0601     0.9241
EndYear                                0.0332     0.9083
LOSDays                                0.0176     0.9454
FromFHAUniDplMnemonic2BAKER            0.0000          .
FromFHAUniDplMnemonic2CHEAM            0.0000          .
FromFHAUniDplMnemonic3BAKER            0.0000          .
FromFHAUniDplMnemonic3CHEAM            0.0000          .
DurationOfLocation                     0.0071     0.9898
```

The variables Gender (genderdesc) and admission Location (FromFHAUniDplMnemonic) were used as exact matching criteria, ensuring that for these categorical variables, pairs had identical values, resulting in a standard mean difference of zero.

6.2.2 Histogram Analysis

The histograms illustrate that the matching process has effectively aligned matched cases and matched controls in several key parameters including sex, admission location, and year of admission and discharge (Appendix E). However, there were areas of divergence regarding Age

(AgeNumber) and length of stay in the admission location (DurationOfLocation). In addition, there was an observable difference in the distribution pattern of length of stay in the hospital (LOSDays). These differences highlighted the opportunity for further analysis to confirm a robust matching.

6.2.3 QQ (Quantile-Quantile Plot) Plot Analysis

Upon reviewing the QQ plots for Matched Cases and Matched Controls, it was evident that there were still visible differences in the distributional properties for AgeNumber, DurationOfLocation, and LOSDays (Appendix F). The divergence in QQ distributions between Case and control groups required further analysis to confirm its significance.

6.2.4 Kolmogorov-Smirnov Test

I used the Kolmogorov-Smirnov test to examine the significance of the distribution differences observed in the Histogram and QQ distribution. The result of the test was as follows:

1. AgeNumber, StartYear, and EndYear: No significant differences in distributions between cases and controls, ensuring balanced matching (p ~1).

2. LOSDays: Distributions were similar ($p = .628$), suggesting that the length of stay did not differ substantially between groups.

3. DurationOfLocation: The matched groups showed no significant distributional differences ($p = .807$), implying balanced durations across locations.

The Kolmogorov-Smirnov test results indicate effective matching between the cases and controls in the study. For variables like AgeNumber, StartYear, and EndYear, the distributions between the groups were almost identical, as suggested by p value close to 1. Similarly, LOSDays and DurationOfLocation showed no significant distributional differences. I did not perform the test for Sex (Genderdesc) and FromFHAUniDplMnemonic as they were set to be exact matches.

6.3 Nursing Assessment

I collected patient data from electronic nursing assessments. I included the standard of care assessments for Medical-Surgical units. The standard of care assessments are assessments that nurses add to the electronic documentation for all patients admitted to their units. The final list included nineteen assessments (Table 10). I also added nursing assessments relevant to the standard of care assessments and shared similar data with them. I included the additional assessments to ensure comprehensive data collection.

After collecting the assessments, I extracted the variables included in these assessments. The total number of variables was 266.

Table 10: *Included nursing assessments*

Standard of Care Assessments	**Additional relevant assessments**
ADL Record	Vital Signs
Adult Trend and Trigger Tool	Neurovascular Assessment
Braden Scale	Personal Care Record
Cardiovascular Assessment	Nutrition & Glycemic Management
Confusion Assessment Method	
Gastrointestinal Assessment	
Genitourinary Assessment	
Intake and IV Infusions	
Integumentary Assessment	
Mobilization Record	
Neurological Assessment	
Nutrition Risk Screening	
Oral Nutrition Assessment	
Output Record	
Pain Assessment	
Patient and Family Education	
Peripheral IV Management	
Respiratory Assessment	
Toileting Record	

6.4 Pre-processing

6.4.1 Missing Data Quantification

I quantified the missing values for each column (variable) and row (case). For variables, the median percentage of missing data per variable stands at 77.82%. The range of missingness stretched from no missing data (0%) to nearly complete absence (99.62%) (Appendix G). This indicates that while some variables have complete records, others are almost entirely missing.

There is also a substantial rate of missing data per case. The median percentage of missing data per patient is approximately 69.66%, with the data missingness ranging from 54.31% to as high as 89.89%. This suggests that, on average, many patients have around 72% of their data missing. The high percentage of missing data per variable and per case could pose challenges in interpreting downstream analyses and model building.

6.4.2 Domain-Specific Features

Out of the 266 variables, I found variables with the same meaning and optional answers and combined them to reduce missing data (Appendix H). When appropriate, I replaced the null values of one variable with values from another variable with similar meaning and answer selections (Appendix H). This result in removing 10 variables from the dataset (Appendix I).

I also created new features by analyzing the values of predefined features (Appendix H). For instance, I introduced a new feature, "Best cap refill". The observation value of this feature is determined by evaluating multiple features such as "Capillary refill left foot", "Capillary refill right foot", "Capillary refill left hand", and "Capillary refill right hand". I used the values from these variables that fall within the normal capillary refill range first; if there was none, I selected the best next value, and so on. This added additional new 11 variables in total.

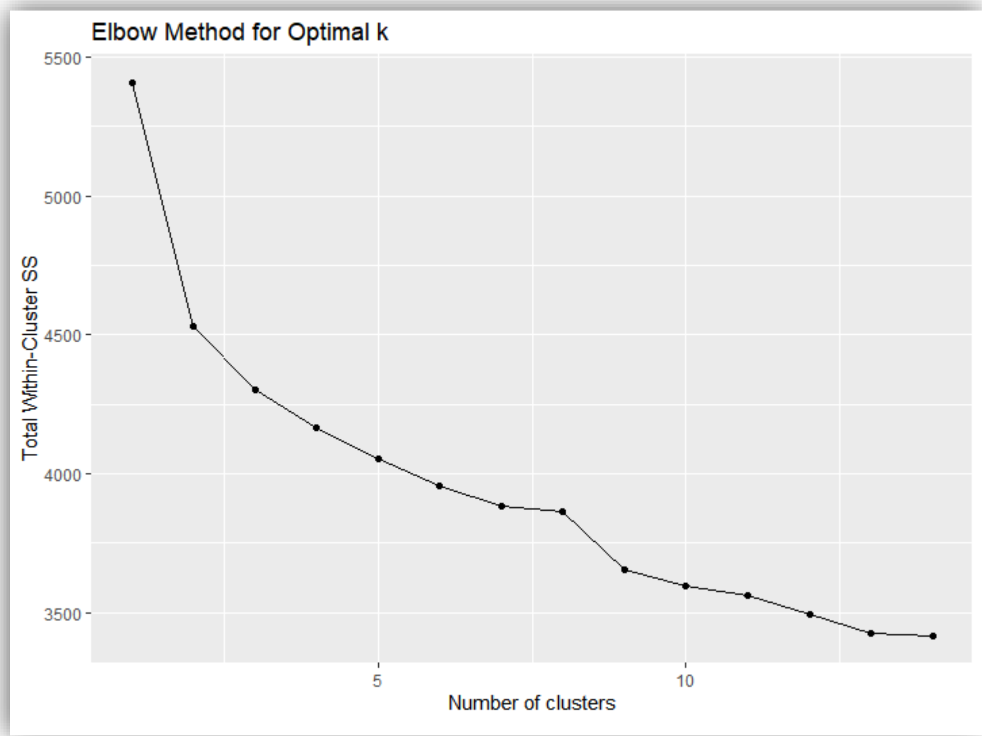
6.4.3 Variables removal

I reviewed all variables processed during the pre-processing step and I applied my clinical knowledge to remove 88 of them (Appendix I). This resulted in reducing the original list from 266 to 178 variables. Then, I added the 11 newly created variables (Appendix H) along with the outcome variable (infected), bringing the total number of variables to 190.

6.4.4 Clustering Missing Data

The Elbow Method revealed that five clusters would promote a balance between maximizing inter-cluster variance and minimizing intra-cluster variance (Figure 7). I used this optimal number to segregate the data into distinct, non-overlapping subgroups using the K-means Clustering algorithm. The proportion of infected individuals within clusters one to five was 37.9%, 35.7%, 36.9%, 42%, and 30.9%, respectively. The Chi-square test yielded a Chi-square value of 1.9322 with 4 degrees of freedom and a $p = .748$. The high p value suggests no significant association between the clusters and infection rates, indicating that the observed differences in infection rates are unrelated to missingness distribution. In other words, the distribution of missing values as a variable does not affect the chances of conducting HAUTI.

Figure 7: *Elbow Method*



6.4.5 Missing Data Deletion

As discussed in the previous chapter, the missing data deletion process resulted in eight datasets, which I named Dataset 20 to Dataset 90. I ran the Multiple Imputation Method for each of these datasets.

6.4.6 Imputation of Missing Values

I performed the multiple imputations with five imputations (m = 5) and 50 iterations (maxit = 50). This ensures a thorough exploration of the data's variability and uncertainty due to missingness. The result of the multiple imputation is five complete datasets for each of the original eight datasets (20 to 90). In other words, Dataset 20 became five datasets with complete values (Dataset 20-1, Dataset 20-2, Dataset 20-3, Dataset 20-4, and Dataset 20-5. I have performed a similar process for Datasets 30 to 90. The result is forty complete datasets with different variables (Appendix J).

I have evaluated the results of the imputation. The imputation method successfully estimated the values of all variables with some exceptions. The imputation resulted in some variables having one level only (Appendix H). Due to a lack of variance, I removed these variables. The total number of these variables was twelve. In addition, the imputation did not successfully compute the values for two variables, including Neurovascular right foot temperature (Neurovascularrightfoottemperature) (77.44 % missing values) and Output urine (Outputurine) (65.41 % missing values). As these variables still retain a high level of missingness, I excluded these variables from the study (Beaulieu-Jones et al., 2018).

6.6 Supervised Learning Algorithms

I employed multiple supervised learning algorithms to ensure a comprehensive and robust modelling approach. These algorithms included Decision Trees, Random Forests, Neural Networks, XGBoost, Logistic Regression, and Support Vector Machines (SVM). All algorithms were set to include 10-fold cross-validation with a training-test split ratio of 70:30. I ran the supervised algorithms for all forty datasets from the multiple imputation method.

6.7 Machine Learning Performance

I calculated the AUC and pooled AUC (Table 11) for all supervised models for the 40 datasets. An observed inconsistency exists in how AUC changes from Dataset 20 to Dataset 90 (Table 12). All ML performed poorly, with most AUCs < 60 for all algorithms. Notably, XGBoost performed better than the others, evident by the higher pooled AUC across all datasets (Table 11).

Table 11: *Pooled AUC results for all ML algorithms*

	Decision Trees	**Random Forests**	**Neural Networks**	**XGBoost**	**Logistic Regression**	**SVM**
Average Pooled AUC	.52	.45	.54	.56	.54	.51

Table 12: *AUC results for all ML algorithms*

AUC	Decision Trees	Random Forests	Neural Networks	XGBoost	Logistic Regression	SVM
Dataset 20-1	.50	.40	.51	.56	.50	.50
Dataset 20-2	.50	.39	.51	.51	.51	.47
Dataset 20-3	.50	.42	.52	.47	.54	.49
Dataset 20-4	.50	.41	.52	.52	.58	.47
Dataset 20-5	.50	.41	.60	.59	.49	.52
Pooled AUC	.50	.41	.53	.53	.52	.49

AUC	Decision Trees	Random Forests	Neural Networks	XGBoost	Logistic Regression	SVM
Dataset 30-1	.59	.46	.60	.58	.53	.57
Dataset 30-2	.51	.39	.56	.53	.53	.50
Dataset 30-3	.51	.42	.59	.64	.57	.54
Dataset 30-4	.50	.40	.64	.50	.54	.43
Dataset 30-5	.57	.52	.49	.50	.51	.46
Pooled AUC	.54	.44	.58	.55	.54	.50

AUC	Decision Trees	Random Forests	Neural Networks	XGBoost	Logistic Regression	SVM
Dataset 40-1	.54	.45	.58	.65	.52	.51
Dataset 40-2	.45	.40	.63	.58	.60	.50
Dataset 40-3	.50	.42	.53	.52	.53	.51
Dataset 40-4	.53	.41	.58	.61	.54	.53
Dataset 40-5	.46	.41	.53	.53	.53	.50
Pooled AUC	.50	.42	.57	.58	.54	.51

AUC	Decision Trees	Random Forests	Neural Networks	XGBoost	Logistic Regression	SVM
Dataset 50-1	.51	.44	.53	.54	.57	.62
Dataset 50-2	.52	.50	.53	.47	.45	.48
Dataset 50-3	.40	.43	.57	.53	.56	.50
Dataset 50-4	.51	.41	.51	.45	.52	.48
Dataset 50-5	.53	.44	.59	.60	.46	.44
Pooled AUC	.49	.44	.55	.52	.51	.51

AUC	Decision Trees	Random Forests	Neural Networks	XGBoost	Logistic Regression	SVM
Dataset 60-1	.55	.40	.47	.55	.54	.51
Dataset 60-2	.52	.38	.49	.44	.51	.50
Dataset 60-3	.62	.50	.55	.58	.52	.48
Dataset 60-4	.45	.41	.57	.47	.54	.52
Dataset 60-5	.55	.42	.60	.56	.59	.50

Pooled AUC	.54	.42	.54	.52	.54	.50

AUC	Decision Trees	Random Forests	Neural Networks	XGBoost	Logistic Regression	SVM
Dataset 70-1	.48	.50	.54	.52	.54	.46
Dataset 70-2	.51	.47	.60	.62	.49	.53
Dataset 70-3	.50	.41	.49	.51	.46	.57
Dataset 70-4	.57	.40	.54	.55	.56	.51
Dataset 70-5	.70	.70	.51	.77	.75	.48
Pooled AUC	.55	.49	.54	.59	.56	.51

AUC	Decision Trees	Random Forests	Neural Networks	XGBoost	Logistic Regression	SVM
Dataset 80-1	.59	.68	.48	.77	.61	.62
Dataset 80-2	.48	.40	.50	.62	.50	.53
Dataset 80-3	.53	.43	.55	.60	.50	.47
Dataset 80-4	.62	.60	.54	.74	.63	.48
Dataset 80-5	.39	.44	.52	.59	.57	.47
Pooled AUC	.52	.51	.52	.66	.57	.51

AUC	Decision Trees	Random Forests	Neural Networks	XGBoost	Logistic Regression	SVM
Dataset 90-1	.49	.45	.58	.50	.50	.49
Dataset 90-2	.50	.57	.55	.52	.57	.63
Dataset 90-3	.71	.43	.52	.65	.63	.55
Dataset 90-4	.50	.40	.50	.46	.53	.62
Dataset 90-5	.56	.46	.57	.52	.47	.55
Pooled AUC	.55	.46	.54	.53	.54	.57

6.8 FAMD Analysis

I recalculated the AUC and pooled the AUC (Table 13) for all supervised models after running the FAMD. I observed inconsistency in how AUC changes starting from Dataset 20 to Dataset 90 (Table 14). Again, all ML performed poorly, with the vast majority of AUCs < .60 for all algorithms. XGBoost is still performing better than the other algorithms, evident by higher pooled AUC across all datasets (Table 13).

Table 13: *Pooled AUC results after FAMD*

	Decision Trees	**Random Forests**	**Neural Networks**	**XGBoost**	**Logistic Regression**	**SVM**

Average Pooled AUC	.51	.51	.54	.55	.51	.54

Table 14: *AUC results after FAMD*

AUC	Decision Trees	Random Forests	Neural Networks	XGBoost	Logistic Regression	SVM
Dataset 20-1	.50	.53	.51	.59	.51	.53
Dataset 20-2	.49	.58	.55	.56	.48	.54
Dataset 20-3	.53	.52	.47	.66	.50	.59
Dataset 20-4	.50	.58	.52	.58	.50	.50
Dataset 20-5	.46	.46	.45	.53	.51	.59
Pooled AUC	.49	.53	.50	.58	.50	.55

AUC	Decision Trees	Random Forests	Neural Networks	XGBoost	Logistic Regression	SVM
Dataset 30-1	.45	.53	.48	.60	.50	.50
Dataset 30-2	.50	.47	.54	.60	.50	.53
Dataset 30-3	.55	.63	.52	.58	.46	.59
Dataset 30-4	.49	.52	.52	.56	.51	.55
Dataset 30-5	.57	.53	.53	.64	.59	.57
Pooled AUC	.51	.54	.52	.60	.51	.55

AUC	Decision Trees	Random Forests	Neural Networks	XGBoost	Logistic Regression	SVM
Dataset 40-1	.50	.51	.53	.57	.55	.53
Dataset 40-2	.65	.55	.52	.56	.50	.46
Dataset 40-3	.50	.45	.58	.50	.49	.53
Dataset 40-4	.63	.49	.56	.67	.52	.56
Dataset 40-5	.48	.53	.58	.55	.50	.48
Pooled AUC	.55	.51	.55	.57	.51	.51

AUC	Decision Trees	Random Forests	Neural Networks	XGBoost	Logistic Regression	SVM
Dataset 50-1	.55	.51	.59	.44	.52	.50
Dataset 50-2	.46	.51	.59	.50	.51	.52
Dataset 50-3	.50	.55	.55	.55	.49	.56
Dataset 50-4	.61	.51	.59	.52	.50	.56
Dataset 50-5	.50	.53	.51	.50	.47	.59
Pooled AUC	.52	.52	.56	.50	.50	.55

AUC	Decision Trees	Random Forests	Neural Networks	XGBoost	Logistic Regression	SVM
Dataset 60-1	.41	.41	.58	.56	.50	.51

Dataset 60-2	.48	.46	.57	.55	.50	.52
Dataset 60-3	.50	.50	.49	.45	.52	.54
Dataset 60-4	.53	.53	.53	.52	.50	.58
Dataset 60-5	.46	.47	.57	.51	.54	.49
Pooled AUC	.47	.47	.55	.52	.51	.53

AUC	Decision Trees	Random Forests	Neural Networks	XGBoost	Logistic Regression	SVM
Dataset 70-1	.60	.53	.59	.62	.50	.53
Dataset 70-2	.50	.55	.55	.45	.50	.58
Dataset 70-3	.49	.57	.55	.51	.53	.57
Dataset 70-4	.50	.49	.59	.54	.52	.52
Dataset 70-5	.54	.55	.53	.51	.49	.52
Pooled AUC	.52	.54	.56	.53	.51	.54

AUC	Decision Trees	Random Forests	Neural Networks	XGBoost	Logistic Regression	SVM
Dataset 80-1	.60	.52	.65	.61	.53	.54
Dataset 80-2	.49	.49	.58	.55	.50	.55
Dataset 80-3	.50	.53	.50	.52	.48	.56
Dataset 80-4	.53	.53	.48	.50	.55	.48
Dataset 80-5	.50	.48	.53	.49	.50	.58
Pooled AUC	.52	.51	.55	.53	.51	.54

AUC	Decision Trees	Random Forests	Neural Networks	XGBoost	Logistic Regression	SVM
Dataset 90-1	.41	.48	.55	.50	.50	.53
Dataset 90-2	.50	.58	.59	.63	.52	.51
Dataset 90-3	.50	.35	.52	.50	.54	.54
Dataset 90-4	.50	.55	.46	.50	.49	.48
Dataset 90-5	.50	.47	.54	.57	.55	.53
Pooled AUC	.48	.49	.53	.54	.52	.52

6.9 Sensitivity Analysis

6.9.1 Average AUC and Standard Deviation per Algorithm

The first step in preparing for sensitivity analysis is to calculate the mean (*M*) and standard deviation (*SD*) for the AUC for each algorithm (Table 15). This step allowed the trend analysis and ANOVA testing.

Table 15: *Average AUC and Standard Deviation per algorithm*

Missingness percent	**Decision Trees *M***	**Decision Trees *SD***	**Random Forests *M***	**Random Forests *SD***
20	0.49	0.02	0.53	0.04
30	0.51	0.04	0.54	0.05
40	0.55	0.08	0.51	0.03
50	0.52	0.05	0.52	0.01
60	0.47	0.04	0.47	0.04
70	0.52	0.04	0.54	0.03
80	0.52	0.04	0.51	0.02
90	0.48	0.03	0.49	0.09

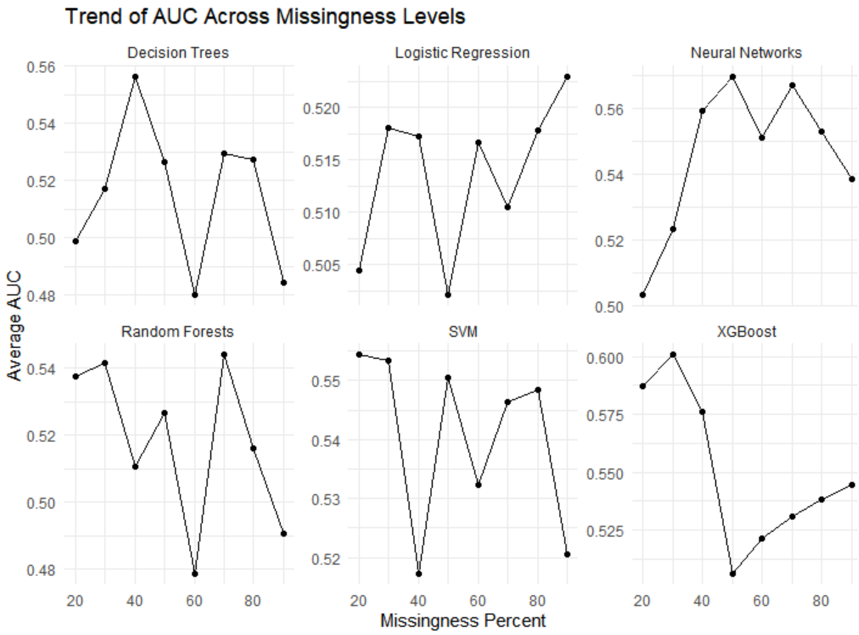
Missingness percent	**Neural Networks *M***	**Neural Networks *SD***	**XGBoost *M***	**XGBoost *SD***
20	0.50	0.04	0.58	0.04
30	0.52	0.02	0.60	0.03
40	0.55	0.02	0.57	0.06
50	0.56	0.03	0.50	0.04
60	0.55	0.03	0.52	0.04
70	0.56	0.02	0.53	0.06
80	0.55	0.06	0.53	0.04
90	0.53	0.04	0.54	0.06

Missingness percent	**Logistic Regression *M***	**Logistic Regression *SD***	**SVM *M***	**SVM *SD***
20	0.50	0.01	0.55	0.03
30	0.51	0.04	0.55	0.03
40	0.51	0.02	0.51	0.04
50	0.50	0.01	0.55	0.03
60	0.51	0.01	0.53	0.03
70	0.51	0.01	0.54	0.02
80	0.51	0.02	0.54	0.03
90	0.52	0.02	0.52	0.02

6.9.2 Trend Analysis

I plotted the trend of AUC across missingness levels for all algorithms (Figure 8). The analysis shows no consistent trend that indicates a direct relationship between the percentage of data missingness and AUC. This trend can result from the original significant missingness in the data, the nature of the data, or the imputation method. Without further statistical analysis, it is difficult to conclude whether the observed fluctuations in AUC are statistically significant or result from random variation, hence the need for an ANOVA test.

Figure 8: *AUC across missingness levels for all algorithms*



6.9.3 ANOVA Analysis for Each Algorithm

For all algorithms and at the 5% significance level, the ANOVA testing shows no statistically significant difference between the AUCs levels across all missingness levels (Table 16). This implies that the model performance was not affected by levels of missing data, at least within the range of missingness percentages tested.

The closest algorithm to indicate a potential effect was XGBoost, with a $p = .063$, which may indicate some effect of data missingness on model performance. XGBoost best performed at a 30% missingness rate, and the AUC consistently fell for subsequent percentages.

Table 16: *ANOVA Results*

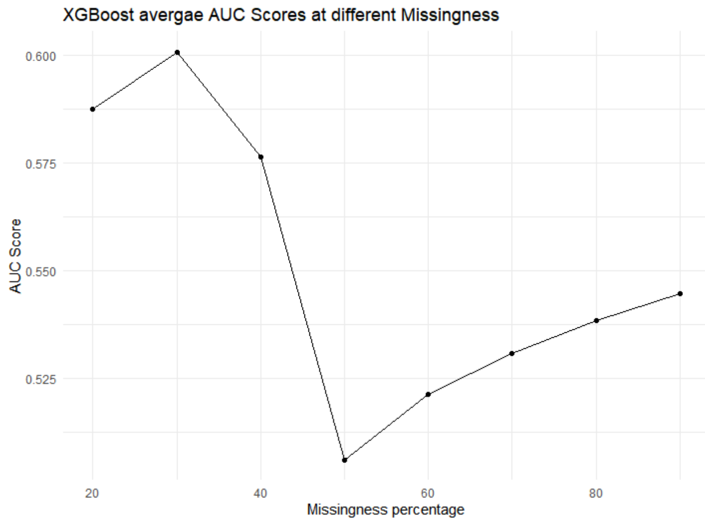
Algorithm	Factor /Residual	*df*	Sum Sq	Mean Sq	*F*	*p*
Decision Trees	Missingness percent	7	0.02	0.003	1.286	.289
	Residuals	32	0.08	0.002		
Random Forests	Missingness percent	7	0.02	0.002	1.185	.339
	Residuals	32	0.07	0.002		

Neural Networks	Missingness percent	7	0.01	0.002	1.587	.175
	Residuals	32	0.05	0.001		
XGBoost	Missingness percent	7	0.03	0.005	2.179	.0631
	Residuals	32	0.08	0.002		
Logistic Regression	Missingness percent	7	0.001	0.0002	0.402	.894
	Residuals	32	0.02	0.0006		
SVM	Missingness percent	7	0.007	0.001	0.909	.512
	Residuals	32	0.03	0.001		

6.10 Further Investigation on XGBoost

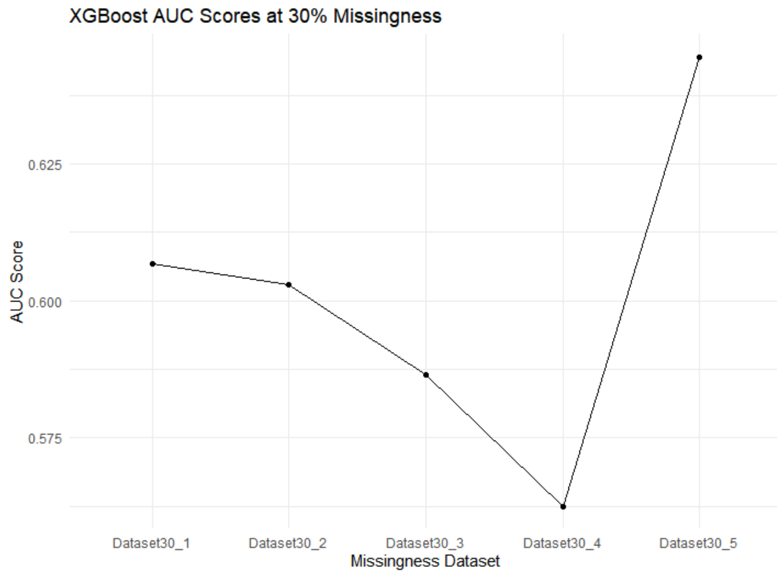
XGBoost is still the best-performing algorithm, with an average AUC of .55 across all datasets. XGBoost performed best at a 30% missingness rate, and then declined for subsequent percentages from 30% to 70% (Figure 9).

Figure 9: *XGBoost average AUC*



A closer look at the five 30% missing rate datasets shows considerable variation in AUC scores across them. The fifth dataset had the highest AUC of .64 (Figure 10). I further analyzed this dataset to extract the dimensions that contributed most to the algorithm's performance.

Figure 10: *XGBoost average AUC at 30% Missingness*



6.10.3 Most Important Dimension by XGBoost

Four dimensions resulted from the FAMD reduction (Figure 11). The gain, a measurement of the average contribution to the model's performance, of the top three dimensions explains 82% of the total variance. Dimension one has the highest gain, cut, and frequency, which indicates that it is used frequently to make splits. This result indicates that dimension one was the most influential across the four dimensions.

I performed further analysis for dimension one to understand the variables with high loading magnitude of each variable and, therefore, highlight those contributing to the development of HAUTI.

Figure 11: *Dimensions for Dataset five*

	Feature	Gain	Cover	Frequency	Importance
1:	Dimension1	0.2982382	0.3423283	0.3378378	0.2982382
2:	Dimension4	0.2657809	0.2234608	0.2432432	0.2657809
3:	Dimension2	0.2615429	0.2802923	0.2162162	0.2615429
4:	Dimension3	0.1744380	0.1539185	0.2027027	0.1744380

6.10.4 Investigating Variables Contributing to Important Dimensions

As Dimension One is the most important dimension contributing to predicting HAUTI, I extracted the variables contributing to this dimension along with the loading magnitude of each variable (Table 17). As the sample size in this study is 267, I considered a loading of 0.35 to be significant (Hair et al., 2009) (Table 18).

Table 17: *Variables loading magnitude for dimension one*

Variables	Variable Name	Loading Magnitude
BradenSkinRiskAssessmentScore	Braden Skin Risk Assessment Score	0.83
BradenScalerisklevel	Braden Scale risk level	0.81
BradenScalesensoryperception	Braden Scale sensory perception	0.57
GCSscore	GCS score	0.56
GlasgowComaScaleVerbalResponse	Glasgow Coma Scale Verbal Response	0.54
BradenScalemobility	Braden Scale mobility	0.53
Currentfeedingsupportrequired	Current feeding support required	0.47
BradenScaleactivity	Braden Scale activity	0.47
Toiletingassistance	Toileting assistance	0.46
BradenScalemoisture	Braden Scale moisture	0.33
GlasgowComaScaleMotorResponse	Glasgow Coma Scale Motor Response	0.32
Bowelflatuspresent	Bowel flatus present	0.24
GlasgowComaScaleEyeOpening	Glasgow Coma Scale Eye Opening	0.23
Levelofconsciousness	Level of consciousness	0.16
Nothingbymouth	Nothing by mouth	0.15
Oxygentherapydeliverymethod	Oxygen therapy delivery method	0.09
Respiratorydepth	Respiratory depth	0.07
Bestlegstrength	Best leg strength	0.07
Breakfastamountconsumed	Breakfast amount consumed	0.05
Lunchamountconsumed	Lunch amount consumed	0.04
Pulseoximetryoxygensaturation	Pulse oximetry oxygen saturation	0.02
Respiratoryrate	Respiratory rate	0.01
Respiratorypattern	Respiratory pattern	0.01
Temperature	Temperature	0.01

Urinecolour	Urine colour	0.01
Skinmoisture	Skin moisture	0.008
Workofbreathing	Work of breathing	0.007
Skintemperature	Skin temperature	0.0008
Painassessment	Pain assessment	0.0004
Bestcaprefill	Best cap refill	0.0003
Edema	Edema	0.0003
Urineoutputadequate	Urine output adequate	0.0002

According to the loading magnitude, the top performing variables are those related to the Braden scale assessment, including Braden Skin Risk Assessment Score (0.83), Braden Scale risk level (0.81), Braden Scale sensory perception (0.57), and Braden Scale mobility (0.53); and variables related to patient level of consciousness including Glasgow Coma Scale score (0.56) and Glasgow Coma Scale Verbal Response (0.54) (Table 18).

Table 18: *Top contributing variables by loading magnitude*

Top Contributing Variables	**Variable Name**	**Loading Magnitude**
BradenSkinRiskAssessmentScore	Braden Skin Risk Assessment Score	0.83
BradenScalerisklevel	Braden Scale risk level	0.81
BradenScalesensoryperception	Braden Scale sensory perception	0.57
GCSscore	GCS score	0.56
GlasgowComaScaleVerbalResponse	Glasgow Coma Scale Verbal Response	0.54
BradenScalemobility	Braden Scale mobility	0.53
Currentfeedingsupportrequired	Current feeding support required	0.47
BradenScaleactivity	Braden Scale activity	0.47
Toiletingassistance	Toileting assistance	0.46

6.11 Summary

The Nearest Neighbourhood matching yielded 266 patients (95 HAUTI patients and 171 non-HAUTI patients), resulting in well-balanced groups. I analyzed nineteen nursing assessments with a total of 267 variables. The median percentage of missing data per variable stood at 77.82%, and per patient was approximately 69.66%. The clustering method revealed that the distribution of missing data does not significantly influence the likelihood of HAUTI occurrence. The data deletion method resulted in 8 datasets, while the imputation method increased this number to 40, accounting for variability and uncertainty introduced by missing data.

The initial run of ML showed that all ML performed poorly, with most AUCs < .60 for all algorithms. Notably, XGBoost performed better than the others, evident by the higher pooled AUC across all datasets. The FAMD data reduction method did not improve model performance, although XGBoost consistently outperformed other algorithms. The sensitivity analysis showed no consistent trend, which indicates the absence of a direct relationship between the percentage of data missingness and the AUC of each ML technique. However, the sensitivity analysis of XGBoost showed some effect of data missingness on model performance ($p = .063$). XGBoost best performed at a 30% missingness rate; the fifth dataset had the highest AUC of .64.

The XGBoost model demonstrated that dimension one is the most important FAMD dimension. In this dimension, the top-performing variables are the Braden scale assessment, including the Braden Skin Risk Assessment Score (0.839728291), the Braden Scale risk level (0.818078689), the Braden Scale sensory perception (0.575611741), and the Braden Scale mobility (0.537155875), and variables related to patient level of consciousness, including the Glasgow Coma Scale score (0.564173469) and the Glasgow Coma Scale Verbal Response (0.543687126).

Chapter 7 Discussion

Chapter 7 discusses the research results, reviews the study objectives, explains the study's strengths and limitations, and provides an overall summary.

7.1 Study Overview

Situation Awareness is one of the cognitive nontechnical skills gaining more attention in the healthcare literature (Fore & Sculli, 2013). The literature shows that nurses need to improve their SA (Cooper et al., 2010; Cooper et al., 2011; De Meester et al., 2013; O'Meara et al., 2015). Low SA can result in unfavourable clinical consequences on patient outcomes and provider performance. One of these consequences can be increased HAUTI rates for inpatients.

In my systematic review, I explored the use of SA interventions, such as dashboards, and found limited studies exploring SA interventions to improve nurse SA in the context of HAUTI. The studies I found are of low quality and did not use a SA model or theory to guide the design process. The information contained in these dashboards represents retrospective data with no indication of supporting prospective reporting. As the retrospective and prospective reporting are both important to support all levels of SA, I found an opportunity to initiate the work on designing a SA-dashboard that supports all SA levels and focus on the prevention of HAUTI.

7.2 Study Objectives

The overall aim of the study was to discover the factors contributing to developing HAUTI and predicting the risk of acquiring the infection. This study had three objectives: the first objective was to collect de-identified EHR data and prepare it for machine learning tasks; the second objective was to develop the best predictive model for the outcome of developing UTI; and the third objective was to explore the key factors leading to HAUTI in the study clinical context.

7.2.1 First Objective

The first objective was to collect de-identified EHR data and prepare it for machine learning tasks. I started the data collection by identifying the study samples. The study's initial sample of HAUTI patients (135 cases) indicates a relative prevalence of HAUTI at the study site. I matched the HAUTI sample with another sample of non-HAUTI patients with close age and length of stay in the hospital and similar length of stay in the admission location, year of admission and discharge, gender, and admission location. Several studies indicated that these factors contribute to the risk of developing HAUTI (Akram, 2022; Alanazi et al., 2022; Laupland et al., 2002).

The final matched dataset consisted of 95 HAUTI patients and 171 non-HAUTI patients, with a 2:1 matching ratio. I deemed this ratio optimal for maintaining balance and sample size for meaningful analysis. The post-matching analysis indicated that the matching process successfully minimized the standard mean difference between the case and control groups across all variables. While the histograms and QQ plots indicated areas that are not fully aligned between the case and control groups, especially in age and length of stay, I found this divergence statistically insignificant. The post-matching analysis affirmed the matching process's effectiveness and laid the groundwork for a reliable study finding.

After identifying and creating case and control groups, I collected the clinical data from the nursing assessments. The study included twenty-three nursing assessments. My approach ensured the capture of frequently documented assessments, representing a broad spectrum of patient care activities and a comprehensive list of variables.

I initially extracted 266 variables from the nursing assessments. Some of these variables have similar meanings and optional answers, which allowed me to consolidate variables and extract new ones. Consolidating existing features and creating new ones is not new to data preparation for ML (Misra et al., 2021; Ru et al., 2023). By creating new features, I aimed to derive additional clinically meaningful insights from the raw data, enhancing the study's utility for predicting the risk of HAUTI.

One approach to evaluating the data quality and preparing it for machine learning is understanding the missingness and how it might affect the outcome of interest (Weiskopf & Weng, 2013; Weller et al., 2018). The quantification of the missing data in this study revealed substantial missingness, with a median percentage of 77.82% missing per variable and approximately 69.66% missing per patient. This highlights a significant gap in the available patient records.

Although EHR improved the quality of nurses documentation (Khairunisa, 2023; Martin et al., 2018), other studies also reported high missingness rate in electronic health records (Garcia Olea et al., 2022; Weller et al., 2018), with studies reported up to 90% missing rate (Ejima et al., 2020; Idri et al., 2020; Stiglic et al., 2019). Reasons that can affect the nurse’s documentation include the design of the EHR and the nurse’s documentation strategies. The electronic documentation at the study site is new. EHR can increase the number of steps or subtasks to complete patient documentation. Nurses can interpret such an increase in steps in patient documentation as a complex and difficult EHR system (Rinkus & Chitwood, 2002). Other nurses found nursing documentation excessive and took them away from patient care (Charalambous & Goldberg, 2016). Another design aspect is the mismatch between the documentation workflow and EHR (Baird et al., 2024). The assessments can be scattered in many locations, which increases the chance of missing documentation (Baird et al., 2024). The EHR design can affect the nurse’s documentation practices.

Nurses’ documentation strategies can also affect the quality of the record. Nurses can change their documentation practice at the point of care to prevent infection (Yang et al., 2019).

Also, they can document afterward to minimize contamination, which is consistent with nurses' intention to minimize healthcare-associated infections. However, these practices may delay documentation and increase the chances of data missingness.

In this study, I used K-means as an innovative approach to estimate the effect of missingness on the risk of developing HAUTI. The Elbow Method and K-means identified five clusters, with infection rates varying across clusters. I found no statistically significant association between cluster membership and infection rates, as indicated by a Chi-square test p = .748. The absence of a significant association suggests that the patterns of missingness are not systematically related to developing HAUTI. This finding implies that the missing data might be MAR or MCAR rather than MNAR. A MNAR indicates that the missingness may bias the outcome estimates (Carreras et al., 2021). The insignificant association between cluster membership and HAUTI occurrence supported my assumption of MAR in this study. However, this result should be interpreted carefully as it does not completely eliminate the effect of missingness on calculating the risk of HAUTI. The high missingness rate will affect the quality of data and, therefore, the trustworthiness of findings.

The extensive missing data presented a substantial analysis challenge in this study. I followed a comprehensive approach to managing the data missingness using three main approaches: data deletion, Multiple Imputation, and sensitivity analysis. The combination of these approaches created forty datasets out of the original one. These datasets allowed the consideration of variability in the calculation method and consideration of the multiple missingness percentages. The sensitivity analysis gave an overview of how the results can change with different missingness rates.

7.2.2 Second Objective

The second objective was to discover the best predictive model for the outcome of developing HAUTI. The objective aims to answer the research question: What is the best machine learning method and prediction model to predict the probability of Healthcare-Associated Urinary Tract Infection? To this end, I applied multiple supervised ML algorithms to the 40 datasets, including Decision Trees, Random Forests, Neural Networks, XGBoost, Logistic Regression, and SVM, each utilizing a 70:30 training-test split ratio and 10-fold cross-validation. The overall performance for all these ML models was modest, with most AUC scores below .60. This suggests that the models may struggle to predict HAUTI accurately based on the available data. The performance of these ML algorithms did not significantly improve after using FAMD for dimensionality reduction, indicating that the data's complexity or quality might have influenced the ML performance rather than the features' dimensionality (Chen et al., 2021; Illarionov & Khudorozhkov, 2018). Clinical datasets often include complex datasets with many underlying factors affecting outcomes such as HAUTI. The weak performance of the ML models might reflect these intrinsic data challenges.

Overall, XGBoost consistently emerged as the best-performing algorithm across multiple imputations and datasets, with an average AUC higher than the others. This result is consistent with several other studies that found XGBoost to provide the most accurate outcome, outperform other algorithms, and provide detailed results regarding the factors associated with an outcome (Cava et al., 2019; Liu et al., 2021; Lv et al., 2021; Shooshani et al., 2023; Zhang et al., 2020). This can be attributed to XGBoost's ability to capture complex non-linear relationships between variables.

7.2.3 Third Objective

The third objective was to explore the key factors leading to HAUTI in the study's clinical context. This objective aims to answer the research question: what are the most important predicting variables of Healthcare-Associated Urinary Tract Infection in the participating organization? A closer look at the XGBoost models highlights that the algorithm best performed at a 30% missingness rate. I identified dimension one as the most influential in the XGBoost model, showing the highest gain, cut, and frequency, which indicates its critical role in model performance and HAUTI prediction. The variables contributing to dimension one, particularly those with high loading magnitudes, are primarily associated with the Braden Scale assessments and Glasgow Coma Scale scores. These include the Braden Skin Risk Assessment Score, Braden Scale risk level, sensory perception, mobility, GCS score, and Glasgow Coma Scale Verbal Response.

The Braden scale is commonly used to evaluate the risk of developing impaired skin integrity and predict pressure injuries (Pham et al., 2020). The assessment includes evaluating the patient's sensory function, moisture, activity, mobility, nutrition, shearing and friction (Pham et al., 2020). A higher score in each category reflects a worse clinical condition and, therefore, a higher score on the Braden scale.

The Glasgow Coma Scale is an assessment tool for the level of consciousness. The tool includes assessing the ability of the patient to open eyes, verbal response, and motor response (Reith et al., 2016). Like the Braden scale, a higher Glasgow Coma also reflects a worse clinical condition. This leads to a conclusion that, from a clinical perspective, the Braden Scale and Glasgow Coma Scale might act as proxies for overall patient frailty or acuity, with higher-risk scores reflecting greater vulnerability to a range of complications, including HAUTIs.

The relationship between these variables and HAUTI risk may also reflect the multifactorial nature of infection risk in hospital settings, where immobility, sensory perception, and skin moisture can influence a patient's susceptibility to infection. The data-driven emphasis on these variables suggests that, despite the complexity of HAUTI risk factors, specific patient assessments can provide valuable predictive insights. Highlighting the importance of comprehensive risk assessments in patient care management.

7.3 Study Strength

There are several strengths of this study. First, I used a systematic literature extensive that included a comprehensive forward and backward citation search. I also used a structured and duplicate approach to review and critically appraise all included studies.

Second, I have implemented an effective matching process in this study. The case and control groups were similar in many aspects, and the differences were not significant. The matching approach laid down the groundwork to support the study's reliability.

Another strength of this study is the breadth of data collection. I have included various nursing assessments and a comprehensive list of variables covering day-to-day nursing assessment and practice. This is important for developing a holistic understanding of patient needs and the effectiveness of nursing interventions.

I also used a comprehensive methodology to handle missing data. While the missingness rate was critical, the multi-approach I used in this study would mitigate the effect of missingness on study findings.

Finally, I used advance multiple imputation techniques, ran multiple ML methods and evaluated the models' performances using sensitivity analysis. These comprehensive methods provided a solid approach to data analysis.

7.4 Limitations

Like any other study, there are limitations associated with this study. Starting with the literature review, our review is limited by the number and heterogeneity of studies that met the inclusion criteria. The heterogeneity is likely because of different intervention designs, different SA requirements, and various clinical settings, which did not allow meta-analysis. Our review studies have a moderate to serious risk of bias, which decreases the trustworthiness of the results.

One of main limitation in this study is high missingness rate. The missing data posed a challenge to the reliability of the study findings. There is a significant missingness rate per variable and case; therefore, most values are imputed. While I used advanced techniques to handle data missingness, the effect of missingness on data quality and results cannot be excluded.

Another limitation is that the ML algorithms might accidentally fit a confounding variable in the predictive model to achieve the most accurate results (Kelly et al., 2019). A confounding variable might affect the model's generalizability to other datasets. To avoid this limitation, I used cross-validation, feature reduction, and sensitivity analysis to carefully examine the variables that the algorithm is learning during the training process.

A third limitation is the potential algorithmic bias. The algorithm may select the best model representing the majority of the population and not the minority subgroups (Kelly et al., 2019). The algorithm can also test different models using a dataset lacking data on these minorities (Kelly et al., 2019). While it is challenging to completely eradicate this risk, the effective matching process I used in this study would contribute to mitigating its effect on the results.

A fourth limitation is the potential limitation in external validation of the model beyond the participating site. As the plan is to prepare datasets using EHR, the system's differences might lead to limited generalizability. Other reasons for limited generalizability include different providers' practices and populations (Kelly et al., 2019). This limitation indicates the need to further test the findings of this study in a new dataset.

Finally, the imputation process was not entirely successful for all variables, leading to the exclusion of variables due to lack of variance or high missingness. It is difficult to estimate the effect of removed variables on calculating the risk of predicting HAUTI. This challenge suggests inheriting limitations in the available data for accurately estimating the values of some variables. This limitation points to the importance of considering the quality and completeness of data when designing studies and interpreting their results.

7.5 Knowledge Contribution

To the best of my knowledge, there are multiple ways through which I contributed to knowledge in this paper. The following explains this contribution.

Extending Endsley SA Model

As this study focuses on nurses' situation awareness, I used Endsley's SA model to promote the situated understanding of HAUTI data elements within the time and place dimensions (Chapter 3). However, the SA model alone does not examine the dynamics of provider-computer interactions within the healthcare domain. To this end, I extended the SA model by integrating it with the Activity Theory. The Activity Theory describes the healthcare environment and defines information technology systems as mediators between providers and patients. Combining the SA model and Activity Theory advances the understanding of the interaction between SA-oriented dashboards and providers in clinical settings.

Providing Up-to-Date Evidence on SA-Oriented Intervention

The systematic literature review in this study provided the most up-to-date evidence regarding SA interventions in clinical settings (Chapter 4). The review followed a comprehensive approach, provided detailed information about current SA interventions and laid out the gap in the literature. The review highlighted the necessity of incorporating the intervention design work with theory. The result of the review brought attention to the need to advance the work on designing SA-oriented interventions at the point of care.

Using ML to Improve Goal Directed Task Analysis

This study focused on preparing data elements required to improve nurses' SA on preventing HAUTI. As I explained in Section 5.3, Endsley described the GDTA as a methodology for defining the necessary information to support SA. GDTA uses interviews to extract expert opinions and discover variables contributing to SA. However, expert opinions represent the lowest level of evidence and do not necessarily confirm the probability of developing HAUTI. Without estimating the probability, it will be difficult to predict the infection accurately. To solve this challenge, I extended the GDTA by incorporating ML to discover the data element and using algorithms to project the probability of developing HAUTI.

Using Nursing Assessments and ML to Predict HAUTI

This study was the first to explore SA data elements using nursing assessments and ML. Since nurses constitute the largest workforce in the hospital setting and are often responsible for comprehensive patient assessments, incorporating nursing documentation is key in predicting adverse events like HAUTI. The use of nursing assessment as a data source is a unique aspect of this study.

Using a Novel Approach to Define Data Collection Cut-Off Date

As explained in Section 5.11, I employed a novel approach to defining the timeframe for collecting clinical data. This approach resulted from analyzing multiple methods for collecting data for infected and non-infected patients. The approach paves the way for future studies addressing ML and nosocomial infections in a hospital context.

Using Unsupervised Learning to Cluster Missing Data

While using unsupervised learning for data clustering is well-established, applying this method to cluster patterns of data missingness is an innovative approach (Section 5.12.1.4). I treated patterns of missingness as a variable and evaluated its contribution to the outcome variable. This approach offered insights into using unsupervised learning to evaluate how data characteristics might influence outcomes.

Managing Missing Data

As discussed in Chapter 5, I used a comprehensive approach to evaluate and manage data missingness in this study. This approach included data quantification, deletion, imputation, and sensitivity analysis to compare imputation results. The combination of all these approaches is a unique strength of this study.

Highlighting Variables to Predict HAUTI

The study highlighted the role of the Braden Scale assessments and Glasgow Coma Scale (GCS) scores in predicting HAUTI. The study suggests that these assessments can act as proxies for overall patient frailty, making them valuable tools in predicting HAUTI risk.

Publishing Multiple Papers

Finally, I have produced three papers out of this study. Two papers were published, and the third is in the process of being submitted for publication. The first published paper detailed the results of the literature reviews and presented up-to-date information related to SA-oriented interventions at the point of care (Alqarrain et al., 2024b). The second published paper illustrated the method I used to prepare the data for supervised learning algorithms and presented the challenges related to data missingness (Alqarrain et al., 2024a). The third paper will summarise the research study and report the results. All three papers add to the body of knowledge in nursing, situation awareness, and machine learning domains.

7.6 Future Research

There are several suggestions for future research. The first is that external validation of this study is necessary to evaluate the reliability of the study findings. The evaluation of the importance of variables in different contexts will validate the contribution of these variables to the development of HAUTI.

Another important future research topic is examining the reasons behind data missingness in electronic nursing documentation. Understanding these reasons can help establish strategies to minimize the missingness and, therefore, improve the utility of the data for secondary data use. This improvement can be related to the design of the electronic documentation to improve data quality and completeness.

A third suggestion is to evaluate the relationship between missing data in EHR and level of SA. Perception is the lowest level of SA. High data missingness would probably contribute to lower perception, which eventually affect all the subsequent levels of SA. This highlights the importance of quality data to support nurses' clinical work.

7.7 Ethics Approval

This study has Fraser Health Ethics board approval number H21-01398 (Appendix K) and authorization to conduct research number 2021137 (Appendix L). The researcher completed the require TCPS 2 CORE training (Appendix M).

Conclusion

The overall aim of this study was to discover the factors contributing to developing HAUTI and predicting the risk of acquiring the infection. If deemed valid, the original intention of discovering these variables was to pave the work for future use of these variables to design a SA-oriented dashboard. The dashboard would increase nurses' SA of HAUTI and therefore contribute to lowering down the risk of developing the infection.

This study included a comprehensive data collection approach covering various nursing assessment variables. It also involved implementing multiple methodologies to manage the datasets. While the significant data missingness posed a threat to the study's integrity, I employed multiple approaches, including data deletion, multiple imputation, multiple ML algorithms, and sensitivity analysis, to mitigate these challenges.

XGBoost emerged as the most effective model in predicting HAUTI and helped isolate factors such as improving skin integrity and mobility and monitoring neurological status as key strategies in reducing HAUTI rates. This finding aligns with clinical understandings of patient risk factors. However, these results should be carefully interpreted, given the high missingness rate in this study and poor data quality.

The high missingness rate in this study challenges the validity of using the discovered variables to design an SA-oriented dashboard. While these variables make sense clinically, further work is required to validate how they change HAUTI risk. This study's findings reinforce the necessity of high quality to support the interpretation of ML models. Moving forward, these insights can inform future studies' design and the development of strategies for improving data collection and electronic nursing documentation practices in healthcare organizations.

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Appendix A: Inclusion and Exclusion Criteria

Table 2. *Inclusion and Exclusion Criteria*

	exclusion criteria	**inclusion criteria**
First Screen	- Opinion papers, practice guidelines, letters to the editor, editorials, commentaries, annual reports, book chapters and book reviews, Self-publication, conference proceedings, and Thesis report. - Articles from non-healthcare domains, e.g., driving, military, logging, sport, and farming; or disaster and pandemic management. - Articles describing "awareness" from other perspectives, i.e., patient awareness of a disease or symptom, public awareness, self-awareness, and emotional awareness. - Articles that do not report results related to Situation Awareness or Situational Awareness.	- Peer-reviewed research article of any research design - At least one of the key terms, including Awareness or "Situation Awareness" or "Situational Awareness", is included anywhere in the article.
Secondary Screen	- Articles focusing on developing or validating a model, framework, theory, or tool. - Articles describing the implementation of projects related to Situation Awareness.	- Studies included the use of an intervention to improve "Situation Awareness" or "non-technical skills" or "Crew management resources" or "Crisis management resource.

	- Articles describing education intervention, i.e., classroom education, online education, and simulation education. - Studies with student research participants. - Articles that did not include Nurses (Registered Nurses, licensed practical nurses, or Nurse Practitioners) as study participants.	- Methodological literature reviews, e.g., systematic reviews and meta-analysis.

Appendix B: List of the Study Keywords

Database	CINAHL			
Platform	University of Victoria			
Date	April 6, 2020			
PICO	ID	Search Field	Search Term	Hits
Population	S1	TX	Nurs*	2,026,230
	S2	Subject	(MH "Nurses+") OR (MH "Nursing Models, Theoretical+") OR (MH "Nurse Administrators+") OR (MH "Education, Nursing, Diploma Programs") OR (MH "Students, Nursing, Associate") OR (MH "Students, Nursing, Male") OR (MH "Students, Nursing, Graduate+") OR (MH "Students, Nursing, Doctoral") OR (MH "Schools, Nursing") OR (MH "Nursing Staff, Hospital") OR (MH "Nursing Skills") OR (MH "Community Mental Health Nursing") OR (MH "Perioperative Nursing") OR (MH "Community Health Nursing+") OR (MH "Enterostomal Therapy Nursing") OR (MH "Students, Nursing, Masters") OR (MH "Students, Nursing, Baccalaureate+") OR (MH "Students, Nursing, Diploma Programs") OR (MH "Perianesthesia Nursing") OR (MH "Nursing Home Patients") OR (MH "Nursing Care Plans, Computerized") OR (MH "National Institute of Nursing Research (U.S.)") OR (MH "National Organization for Associate Degree Nursing") OR (MH "Hospice and Palliative Nursing") OR (MH "Ethics, Nursing") OR (MH "Emergency Nursing+") OR (MH "Education, Nursing, Associate") OR (MH "Nursing Shortage") OR (MH "American Society of Plastic Surgical Nurses") OR (MH "Nursing Leaders") OR (MH "Nursing Assistants") OR (MH "Students, Nursing+") OR (MH "Students, Pre-Nursing") OR (MH "Royal College of Nursing, Australia") OR (MH "Psychiatric Nursing+") OR (MH "Nursing Home Design and Construction") OR (MH "Esthetic Nursing") OR (MH "Nursing Organizations, International+") OR (MH "Otorhinolaryngology and Head-Neck Nursing") OR (MH "Hand Off (Patient Safety)+") OR (MH "Nursing Organizations+") OR (MH "State Nursing Organizations+") OR (MH "Student Nurses Organizations+") OR (MH "Orlando's Theory of the Deliberative Nursing Process") OR (MH "Neonatal Intensive Care Nursing") OR (MH	838,778

			"Practical Nursing") OR (MH "Pediatric Oncology Nursing") OR (MH "Pediatric Critical Care Nursing+") OR (MH "Nursing Units") OR (MH "Nursing Theory+") OR (MH "Nursing Protocols+") OR (MH "Nursing Practice, Evidence-Based+") OR (MH "Nursing Interventions") OR (MH "Nursing Outcomes") OR (MH "Nursing Information Systems+") OR (MH "Nursing Care Plans+") OR (MH "Nursing Audit") OR (MH "Maternal-Child Nursing+") OR (MH "Licensure, Nursing") OR (MH "Libraries, Nursing") OR (MH "Legislation, Nursing+") OR (MH "Iowa Nursing Outcomes Classification+") OR (MH "Insurance, Nursing Services") OR (MH "Gerontologic Nursing+") OR (MH "Education, Nursing, Practical") OR (MH "Education, Nursing, Masters") OR (MH "Education, Nursing, Doctoral") OR (MH "Correctional Health Nursing") OR (MH "Careers in Nursing") OR (MH "Association for Nursing Professional Development") OR (MH "American Nursing Informatics Association") OR (MH "Addictions Nursing") OR (MH "Advanced Nursing Practice+") OR (MH "Association of Women's Health, Obstetric, and Neonatal Nurses") OR (MH "Australian Nursing and Midwifery Federation") OR (MH "National Gerontological Nursing Association") OR (MH "British Nursing Index") OR (MH "Registries, Personnel") OR (MH "Surgical Nursing, Plastic+") OR (MH "State Boards of Nursing+") OR (MH "South African Nursing Council") OR (MH "Scope of Nursing Practice") OR (MH "Saba Clinical Care Nursing Interventions+") OR (MH "Saba Clinical Care Nursing Diagnoses+") OR (MH "Royal College of Nursing") OR (MH "Radiological Nursing") OR (MH "Perinatal Nursing") OR (MH "Parish Nursing") OR (MH "Oncology Nursing Society") OR (MH "Oncologic Nursing+") OR (MH "Occupational Health Nursing") OR (MH "Nursing Role") OR (MH "Nursing Practice+") OR (MH "Nursing Management+") OR (MH "Nursing Care Delivery Systems+") OR (MH "Nursing Administration Research") OR (MH "Neuroscience Nursing+") OR (MH "Holistic Nursing") OR (MH "HIV-AIDS Nursing") OR (MH "Gynecologic Nursing") OR (MH "Family Nursing") OR (MH "Education, Nursing, Theory-Based") OR (MH "Education, Nursing, Research-Based") OR (MH "Education, Nursing, Post-Doctoral") OR (MH "Education, Nursing, Graduate+") OR (MH "Education, Nursing, Continuing") OR (MH "Education, Nursing, Baccalaureate+") OR (MH "Critical Care Nursing+") OR (MH "Clinical Nursing Research") OR (MH "British Association for Nursing in Cardiovascular Care") OR (MH "Association of Community Health Nursing Educators") OR (MH "Association of Black Nursing Faculty") OR (MH "American Association of Colleges of Nursing") OR (MH "American Association for the History of Nursing") OR (MH "American Academy of Ambulatory Care Nursing") OR (MH "American Society of	

			PeriAnesthesia Nurses") OR (MH "Research, Nursing") OR (MH "College of Emergency Nursing Australasia Ltd.") OR (MH "Transcultural Nursing Society") OR (MH "Nursing Knowledge") OR (MH "Anesthesia Nursing") OR (MH "Wound, Ostomy and Continence Nursing+") OR (MH "Urologic Nursing") OR (MH "Spinal Cord Injury Nursing") OR (MH "Specialties, Nursing+") OR (MH "Society for Vascular Nursing") OR (MH "Skilled Nursing Facilities") OR (MH "Rural Health Nursing") OR (MH "Respiratory Nursing Society") OR (MH "Respiratory Nursing") OR (MH "National Association of Directors of Nursing Administration in Long Term Care") OR (MH "Radiation Oncology Nursing") OR (MH "Quality of Nursing Care") OR (MH "Primary Nursing") OR (MH "Philosophy, Nursing+") OR (MH "Pediatric Nursing+") OR (MH "Orthopedic Nursing") OR (MH "Office Nursing") OR (MH "Obstetric Nursing") OR (MH "Nursing Status Report (Saba CCC)") OR (MH "Nursing Service") OR (MH "Nursing Science") OR (MH "Nursing Records") OR (MH "Nursing Practice, Theory-Based") OR (MH "Nursing Practice, Research-Based") OR (MH "Nursing Literature") OR (MH "Nursing Indexes+") OR (MH "Nursing Homes+") OR (MH "Nursing Diagnosis") OR (MH "Nursing Costs") OR (MH "Nursing Contact (Saba CCC)+") OR (MH "Nursing Classification+") OR (MH "Nursing Care Coordination (Saba CCC)") OR (MH "Nursing Assessment") OR (MH "Nursing as an Art") OR (MH "Nursing as a Profession+") OR (MH "Nephrology Nursing") OR (MH "Neonatal Nursing+") OR (MH "NANDA Nursing Diagnoses+") OR (MH "Medical-Surgical Nursing+") OR (MH "Marker Nursing Model") OR (MH "Iowa Nursing Interventions Classification+") OR (MH "Intravenous Nursing") OR (MH "Home Nursing, Professional") OR (MH "History of Nursing") OR (MH "Geropsychiatric Nursing") OR (MH "Gastroenterology Nursing") OR (MH "Functional Nursing") OR (MH "Frontier Nursing Service") OR (MH "Faculty, Nursing") OR (MH "Education, Nursing+") OR (MH "Differentiated Nursing Practice") OR (MH "Democratic Nursing Organisation of South Africa") OR (MH "Cumulative Index to Nursing & Allied Health Literature Print Index") OR (MH "Burn Nursing") OR (MH "Australian Nursing and Midwifery Council") OR (MH "Ambulatory Care Nursing") OR (MH "Association for Radiologic and Imaging Nursing") OR (MH "Society of Trauma Nurses") OR (MH "Association of Rehabilitation Nurses") OR (MH "Nurse Editors") OR (MH "Infusion Nurses Society") OR (MH "Education, Nurse Anesthesia") OR (MH "American Society for Pain Management Nursing") OR (MH "Association of Nurses in AIDS Care") OR (MH "Unified Nursing Language System") OR (MH "Trauma Nursing") OR (MH "Total Patient Care Nursing") OR (MH "Team Nursing")	

			OR (MH "State, Provincial and Territorial Nursing Organizations+") OR (MH "Slater Nursing Competencies Rating Scale") OR (MH "Shared Governance, Nursing") OR (MH "School Health Nursing") OR (MH "Rehabilitation Nursing") OR (MH "Private Duty Nursing") OR (MH "Paterson and Zderad's Theory of Humanistic Nursing") OR (MH "Ophthalmic Nursing") OR (MH "Nursing Process+") OR (MH "Nursing Organizations Alliance") OR (MH "Nursing Minimum Data Set") OR (MH "Nursing Intensity") OR (MH "Nursing Informatics") OR (MH "Nursing Council of New Zealand") OR (MH "Nursing Care+") OR (MH "Nursing and Midwifery Council") OR (MH "Nursing Administration+") OR (MH "Nightingale's Nursing Theory") OR (MH "National League for Nursing") OR (MH "National Council of State Boards of Nursing") OR (MH "Modular Nursing") OR (MH "Military Nursing") OR (MH "International Nursing Association for Clinical Simulation and Learning") OR (MH "International Classification for Nursing Practice") OR (MH "Home Nursing") OR (MH "Henderson Nursing Model") OR (MH "Global Society for Nursing and Health") OR (MH "Genetics Nursing") OR (MH "Forensic Nursing") OR (MH "Flight Nursing") OR (MH "English National Board for Nursing, Midwifery and Health Visiting") OR (MH "Dermatology Nursing+") OR (MH "Cardiovascular Nursing+") OR (MH "Camp Nursing") OR (MH "Australian Council of Community Nursing Services") OR (MH "American Board of Nursing Specialties") OR (MH "American Assembly for Men in Nursing") OR (MH "American Academy of Nursing") OR (MH "Academy of Neonatal Nursing") OR (MH "NANDA International") OR (MH "Nurse Theorists") OR (MH "Emergency Nurses Association") OR (MH "Association of Pediatric Oncology Nurses") OR (MH "Queensland Nurses' Union") OR (MH "Nurse Practice Acts") OR (MH "American Psychiatric Nurses Association") OR (MH "American Nurses Association") OR (MH "Academy of Medical-Surgical Nurses") OR (MH "AORN") OR (MH "Nurse Ethicists") OR (MH "Impairment, Health Professional") OR (MH "Burnout, Professional+") OR (MH "Personnel Recruitment") OR (MH "Personnel Retention") OR (MH "Theses and Dissertations") OR (MH "Professional Regulation") OR (MH "Patient Rounds") OR (MH "Nursing Home Personnel") OR (MH "Students, Nursing, Practical") OR (MH "Nursing Manpower+") OR (MH "Nursing Care Studies") OR (MH "Nursing Orders") OR (MH "Coronary Care Nursing") OR (MH "International Nursing") OR (MH "Transcultural Nursing") OR (MH "National Nurses Society on Addictions") OR (MH "National Federation for Specialty Nursing Organizations")	

	S3		S1 OR S2	2,049,545
Intervention	N/A		N/A	
Comparison	N/A		N/A	
Outcome	S4	TX	(situation OR situational) N2 (awareness)	3,569
	S5	Subject	(MH "Cognition+")	69,008
	S6		S4 OR S5	72,229
	S7	TI	(situation OR situational) N2 (awareness)	333
	S8	AB	(situation OR situational) N2 (awareness)	835
	S9		S7 OR S8	946
	S10	AB	"non-technical skill" OR "non-technical skills" OR "nontechnical skill" OR "nontechnical skills" OR "crisis resource management" OR "crew resource management"	677
	S11	TX	"Team Emergency Assessment Measure" OR "Anesthetic NonTechnical Skills" OR ANTS OR "Nurse Anaesthetists' Non-Technical Skills" OR "N-ANTS" OR "Non-Technical Skills for Surgeons" OR NOTSS OR NOTSSdk OR "Non-Technical Skills" OR "Oxford non-technical skills" OR NOTECHS OR "Situation Awareness Global Assessment Technique" OR SAGAT OR "Team Situation Awareness Global Assessment Technique" OR TSAGAT OR "The Clinical Teamwork Scale" OR CTS	43,335

			OR "Disruptions in Surgery Index" OR DiSI OR "Behavioural Rating System for Scrub Practitioners Non-Technical Skills" OR SPLINTS OR "Wondrous Original Method for Battle Airmanship Testing in Complex Systems" OR WOMBAT-CS OR "Observational Teamwork Assessment for Surgery" OR OTAS OR "Imperial Military Personnel Assessment Tool" OR "Observational Teamwork Assessment for Surgery" OR OTAS-D OR "TeamSTEPPS" OR "emergency nurses' non-technical skills" OR EENTS OR "human factors rating scale-modified for nurses" OR HFRS-MN OR "anesthetic nontechnical skills for anesthetic practitioner" OR ANTS-AP OR "Ottawa crisis resource management global rating scale" OR "Ottawa GRS" OR "Situation Awareness Rating Technique" OR SART	
	S12		S10 OR S11	43,643
	S13		S6 AND S12	985
	S14		S9 OR S13	1,761
	S15		S3 AND S14	811
			Restricted to English studies	797

Database	PsycInfo			
Platform	University of Victoria			
Date	April 6, 2020			
PICO	ID	Search Field	Search Term	Hits
Population	S1	TX	Nurs*	169,006
	S2	Subject	DE "Nurses" OR DE "Psychiatric Nurses" OR DE "Public Health Service Nurses" OR DE "School Nurses" OR DE "Nursing"	45,516
	S3		S1 OR S2	169,006
Intervention	N/A		N/A	
Comparison	N/A		N/A	
Outcome	S4	TX	(situation OR situational) N2 (awareness)	1,549
	S5	Subject	DE "Awareness" OR DE "Attention" OR DE "Body Awareness" OR DE "Phonological Awareness"	99,356
	S6		S4 OR S5	100,247
	S7	TI	(situation OR situational) N2 (awareness)	452
	S8	AB	(situation OR situational) N2 (awareness)	1,366
	S9		S7 OR S8	1,400

	S10	AB	"non-technical skill" OR "non-technical skills" OR "nontechnical skill" OR "nontechnical skills" OR "crisis resource management" OR "crew resource management"	265
	S11	TX	"Team Emergency Assessment Measure" OR "Anesthetic NonTechnical Skills" OR ANTS OR "Nurse Anaesthetists' Non-Technical Skills" OR "N-ANTS" OR "Non-Technical Skills for Surgeons" OR NOTSS OR NOTSSdk OR "Non-Technical Skills" OR "Oxford non-technical skills" OR NOTECHS OR "Situation Awareness Global Assessment Technique" OR SAGAT OR "Team Situation Awareness Global Assessment Technique" OR TSAGAT OR "The Clinical Teamwork Scale" OR CTS OR "Disruptions in Surgery Index" OR DiSI OR "Behavioural Rating System for Scrub Practitioners Non-Technical Skills" OR SPLINTS OR "Wondrous Original Method for Battle Airmanship Testing in Complex Systems" OR WOMBAT-CS OR "Observational Teamwork Assessment for Surgery" OR OTAS OR "Imperial Military Personnel Assessment Tool" OR "Observational Teamwork Assessment for Surgery" OR OTAS-D OR "TeamSTEPPS" OR "emergency nurses' non-technical skills" OR EENTS OR "human factors rating scale-modified for nurses" OR HFRS-MN OR "anesthetic nontechnical skills for anesthetic practitioner" OR ANTS-AP OR "Ottawa crisis resource management global rating scale" OR "Ottawa GRS"	6,576

			OR "Situation Awareness Rating Technique" OR SART	
	S12		S10 OR S11	6,756
	S13		S6 AND S12	562
	S14		S9 OR S13	1,841
	S15		S3 AND S14	93
			Restricted to English studies	93

Database	Web of Science			
Platform	University of Victoria			
Date	April 6, 2020			
PICO	ID	Search Field	Search Term	Hits
Population	S1	ALL	Nurs*	652,083
Intervention	N/A		N/A	
Comparison	N/A		N/A	
Outcome	S2	ALL	Situation Awareness OR Situational Awareness	20,840
	S3	TI	(situation OR situational) NEAR/2 (awareness)	2,364
	S4	TS	(situation OR situational) NEAR/2 (awareness)	10,055
	S5		S3 OR S4	10,055
	S6	ALL	"non-technical skill" OR "non-technical skills" OR "nontechnical skill" OR "nontechnical skills" OR "crisis resource management" OR "crew resource management"	2,321
	S7	ALL	"Team Emergency Assessment Measure" OR "Anesthetic NonTechnical Skills" OR ANTS OR "Nurse Anaesthetists' Non-Technical Skills" OR "N-ANTS" OR "Non-Technical Skills for Surgeons" OR NOTSS OR NOTSSdk	108,689

			OR "Non-Technical Skills" OR "Oxford non-technical skills" OR NOTECHS OR "Situation Awareness Global Assessment Technique" OR SAGAT OR "Team Situation Awareness Global Assessment Technique" OR TSAGAT OR "The Clinical Teamwork Scale" OR CTS OR "Disruptions in Surgery Index" OR DiSI OR "Behavioural Rating System for Scrub Practitioners Non-Technical Skills" OR SPLINTS OR "Wondrous Original Method for Battle Airmanship Testing in Complex Systems" OR WOMBAT-CS OR "Observational Teamwork Assessment for Surgery" OR OTAS OR "Imperial Military Personnel Assessment Tool" OR "Observational Teamwork Assessment for Surgery" OR OTAS-D OR "TeamSTEPPS" OR "emergency nurses' non-technical skills" OR EENTS OR "human factors rating scale-modified for nurses" OR HFRS-MN OR "anesthetic nontechnical skills for anesthetic practitioner" OR ANTS-AP OR "Ottawa crisis resource management global rating scale" OR "Ottawa GRS" OR "Situation Awareness Rating Technique" OR SART	
	S8		S6 OR S7	110,053
	S9		S2 AND S8	456
	S10		S5 OR S9	10,087

	S12		S1 AND S10	313
			Restricted to English studies	308

Database	Medline Complete			
Platform	University of Victoria			
Date	April 6, 2020			
PICO	ID	Search Field	Search Term	Hits
Population	S1	TX	Nurs*	1,573,267
	S2	Subject	(MH "Nurses+") OR (MH "Postanesthesia Nursing") OR (MH "Nursing+") OR (MH "Cardiovascular Nursing") OR (MH "Nursing Assistants+") OR (MH "Oncology Nursing") OR (MH "Nursing Assessment+") OR (MH "Nephrology Nursing") OR (MH "Nursing Stations") OR (MH "Psychiatric Nursing") OR (MH "Parish Nursing") OR (MH "Family Nursing") OR (MH "Schools, Nursing") OR (MH "Rural Nursing") OR (MH "Primary Nursing") OR (MH "Perioperative Nursing+") OR (MH "Students, Nursing") OR (MH "Obstetric Nursing") OR (MH "Military Nursing") OR (MH "Specialties, Nursing+") OR (MH "Societies, Nursing+") OR (MH "Philosophy, Nursing+") OR (MH "Nursing Theory") OR (MH "Nursing Staff+") OR (MH "Nursing Services+") OR (MH "Nursing Records") OR (MH "Nursing Process+") OR (MH "Nursing Homes+") OR (MH "Nursing Diagnosis") OR (MH "Nursing Care+") OR (MH "Nursing Audit") OR (MH "Neuroscience Nursing") OR (MH "Neonatal Nursing") OR (MH "Models, Nursing+") OR (MH "Licensure, Nursing") OR (MH "Libraries, Nursing") OR (MH "Legislation, Nursing") OR (MH "History of Nursing") OR (MH "Faculty, Nursing") OR (MH "Ethics, Nursing") OR (MH "Emergency Nursing") OR (MH "Education, Nursing+") OR (MH "Economics, Nursing") OR (MH "Nursing, Supervisory") OR (MH "School Nursing") OR (MH "Rehabilitation Nursing") OR (MH "Pediatric Nursing+") OR (MH "Office Nursing") OR (MH "Nursing, Practical") OR (MH "Geriatric Nursing") OR (MH "Forensic Nursing") OR (MH "Travel Nursing") OR (MH "Transcultural Nursing") OR (MH "Orthopedic Nursing") OR (MH "Nursing, Team") OR (MH "Nursing Research+") OR (MH "Nursing Informatics") OR (MH "Home	534,680

			Nursing+") OR (MH "Holistic Nursing") OR (MH "Standardized Nursing Terminology") OR (MH "Nursing Evaluation Research") OR (MH "Education, Nursing, Continuing") OR (MH "Nursing Education Research") OR (MH "Nursing Administration Research") OR (MH "Education, Nursing, Graduate") OR (MH "Education, Nursing, Baccalaureate") OR (MH "Education, Nursing, Associate") OR (MH "Clinical Nursing Research") OR (MH "Occupational Health Nursing") OR (MH "Skilled Nursing Facilities") OR (MH "Nursing Staff, Hospital+") OR (MH "Nursing Service, Hospital") OR (MH "Nursing Faculty Practice") OR (MH "Maternal-Child Nursing+") OR (MH "Insurance, Nursing Services") OR (MH "Nursing Methodology Research") OR (MH "Radiologic and Imaging Nursing") OR (MH "Nursing, Private Duty") OR (MH "Medical-Surgical Nursing") OR (MH "Evidence-Based Nursing") OR (MH "Critical Care Nursing") OR (MH "Primary Care Nursing") OR (MH "Home Health Nursing") OR (MH "Advanced Practice Nursing") OR (MH "Shared Governance, Nursing") OR (MH "Public Health Nursing") OR (MH "Operating Room Nursing") OR (MH "Community Health Nursing+") OR (MH "Education, Nursing, Diploma Programs") OR (MH "Hospice and Palliative Care Nursing") OR (MH "National Institute of Nursing Research (U.S.)") OR (MH "Patient Handoff")	
	S3		S1 OR S2	1,591,790
Intervention	N/A		N/A	
Comparison	N/A		N/A	
Outcome	S4	TX	(situation OR situational) N2 (awareness)	4,364
	S5	Subject	(MH "Awareness")	19,849
	S6		S4 OR S5	23,771
	S7	TI	(situation OR situational) N2 (awareness)	310
	S8	AB	(situation OR situational) N2 (awareness)	1,350

	S9		S7 OR S8	1,418
	S10	AB	"non-technical skill" OR "non-technical skills" OR "nontechnical skill" OR "nontechnical skills" OR "crisis resource management" OR "crew resource management"	1,276
	S11	Subject	(MH "Crew Resource Management, Healthcare")	34
	S12	TX	"Team Emergency Assessment Measure" OR "Anesthetic NonTechnical Skills" OR ANTS OR "Nurse Anaesthetists’ Non-Technical Skills" OR "N-ANTS" OR "Non-Technical Skills for Surgeons" OR NOTSS OR NOTSSdk OR "Non-Technical Skills" OR "Oxford non-technical skills" OR NOTECHS OR "Situation Awareness Global Assessment Technique" OR SAGAT OR "Team Situation Awareness Global Assessment Technique" OR TSAGAT OR "The Clinical Teamwork Scale" OR CTS OR "Disruptions in Surgery Index" OR DiSI OR "Behavioural Rating System for Scrub Practitioners Non-Technical Skills" OR SPLINTS OR "Wondrous Original Method for Battle Airmanship Testing in Complex Systems" OR WOMBAT-CS OR "Observational Teamwork Assessment for Surgery" OR OTAS OR "Imperial Military Personnel Assessment Tool" OR "Observational Teamwork Assessment for Surgery" OR OTAS-D OR "TeamSTEPPS" OR "emergency nurses’ non-technical skills" OR EENTS OR "human factors rating scale-modified for nurses" OR HFRS-MN	198,337

			OR "anesthetic nontechnical skills for anesthetic practitioner" OR ANTS-AP OR "Ottawa crisis resource management global rating scale" OR "Ottawa GRS" OR "Situation Awareness Rating Technique" OR SART	
	S13		S10 OR S11 OR S12	198,920
	S14		S6 AND S13	922
	S15		S9 OR S14	2,092
	S16		S3 AND S15	745
			Restricted to English studies	739

Appendix C: Data Collection Forms

Category	Data Items	Comments
Eligibility criteria	- Study eligibility for the literature review	
Study methods	- Study design	
	- Single or multicentre study (if multicentre, number of recruiting centres)	
	- Recruitment and sampling procedures used	
	- Explanation of any sampling interim analyses and stopping guidelines	
	- Enrolment start and end dates; length of participant follow-up	
	- Details of random sequence generation, allocation sequence concealment, and masking for randomized trials, and methods used to prevent and control for confounding, selection biases, and information biases for non-randomized studies	
	- Who generated the random allocation sequence, who enrolled participants, and who assigned participants to interventions.	
	- Description of the similarity of interventions	

	- Methods used to prevent and address missing data	
	- Unit of analysis (e.g., individual participant, clinic, village, body part)	
	- Statistical methods	
	- Likelihood of reporting and other biases	
	- Source(s) of funding or other material support for the study	
	- Authors' financial relationship and other potential conflicts of interest	
Participants	- Setting	
	- Region(s) and country/countries from which study participants were recruited	
	- Study eligibility criteria, including diagnostic criteria	
	- Characteristics of participants at the beginning (or baseline) of the study (e.g., age, sex, comorbidity, socioeconomic status)	
Intervention	- Rational of the Intervention	
	- Components, routes of delivery, doses, timing, frequency, intervention protocols, length of intervention	
	- Factors relevant to the implementation	
	- Integrity of interventions	

	- Any strategies used to ensure or assess fidelity or adherence to the intervention and the extent to which the intervention was delivered as planned.	
	- Reference standard (comparison)	
	- Description of co-interventions	
	- Definition of 'control' groups	
	- Components, dose, timing, frequency	
	- For observational studies: description of how intervention status was assessed; length of exposure, cumulative exposure	
	- Documentation that instructs the recipient on the intervention	
	- Who provides the intervention (including their skill level), how (e.g., face to face, web-based), and in what setting (e.g., home, school, or hospital)	
Outcomes	- Evidence of assessing the outcome	
	- Measurement tool or instrument	
	- Specific metric	
	- Method of aggregation	
	- Timing of outcome measurements	
	- Any changes to outcomes	
	- Adverse outcomes	

Results	- Participants numbers	
	- Summary data for each group	
	- Between-group estimates	
	- If subgroup analysis is planned	
Limitation	- Study limitation	
Generalisability	- Study generalizability	
Conclusion	- Study conclusion	

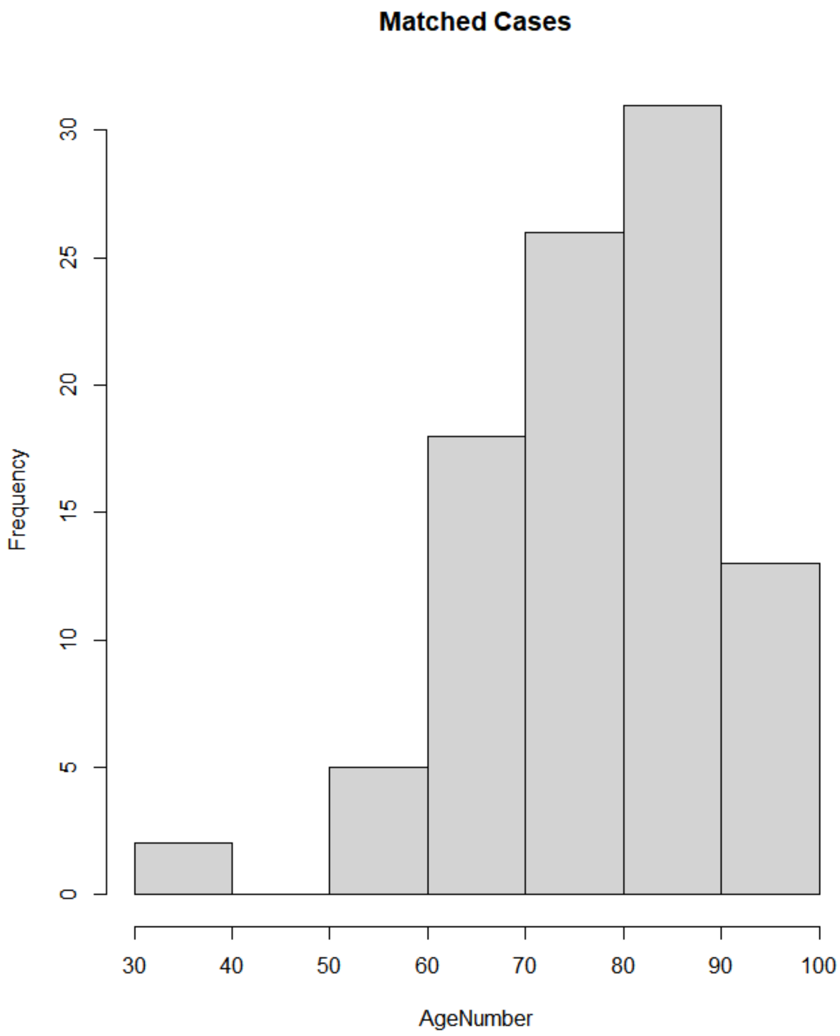
Appendix D: Summary of Narrative Synthesis

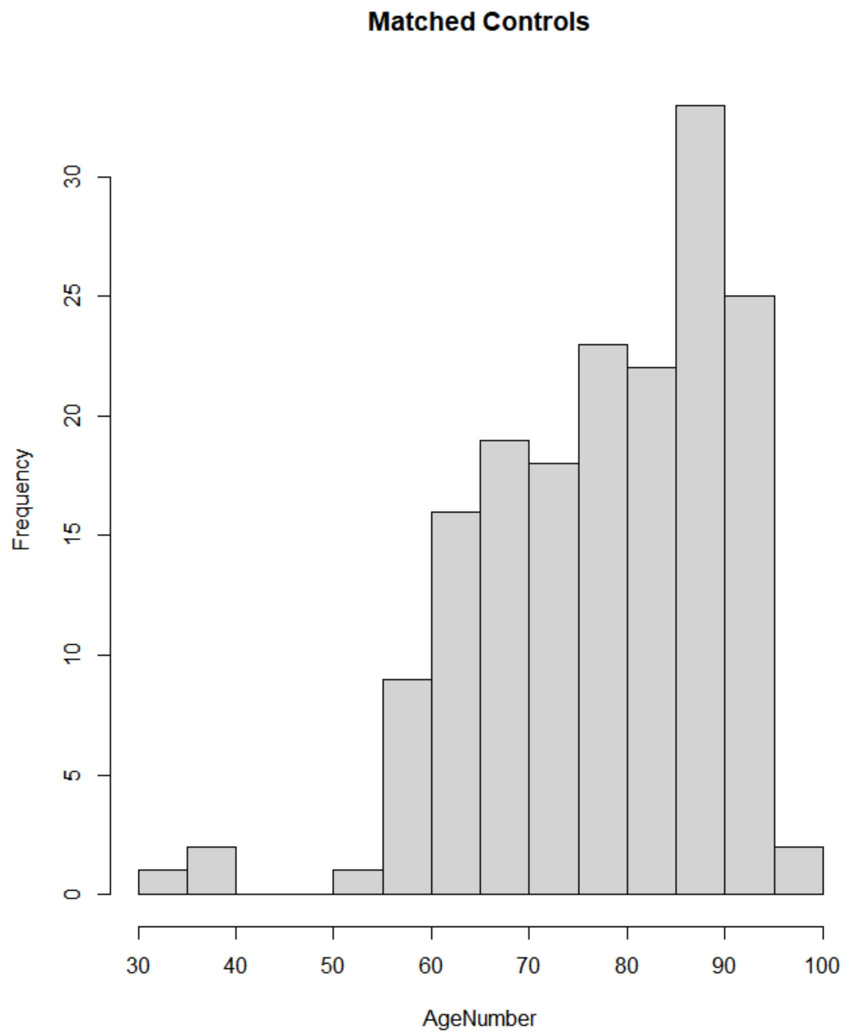
Reference	Research design	Sample size/type	Setting	Patient Condition	Intervention	SA Type	Intervention Design Method	Results
(Koch et al., 2013)	Quantitative- repeated- measures design	12 nurses	Burn Trauma ICU	Not specific - ICU Patients	Integrated Information display	Individual SA	Iterative, user-centered approach.	The use of integrated display is associated with higher SA with accuracy of 85.3% (compared to 61.8% for traditional display) and odds ratio of 3.61 (p < .001, 95% CI = 2.34-5.57).
(Cornell et al., 2014)	Quantitative- observational	960 multidisciplinary patient reviews	Medical-Surgical wards	Patient report	IDR and SBAR	Shared SA	IDR and SBAR development Not explained	Compared to baseline, the review time is shorter for IDR and SBAR with a significant analysis of variance on patient review times (F = 17.25, p < .001).
(McGeorge et al., 2015)	Quantitative- two-group posttest	32 nurses and physicians	ED	Simulated ED cases	ED Information Displays	Team SA	Cognitive systems engineering ecological interface design, and	No significant difference in situation awareness between display conditions.

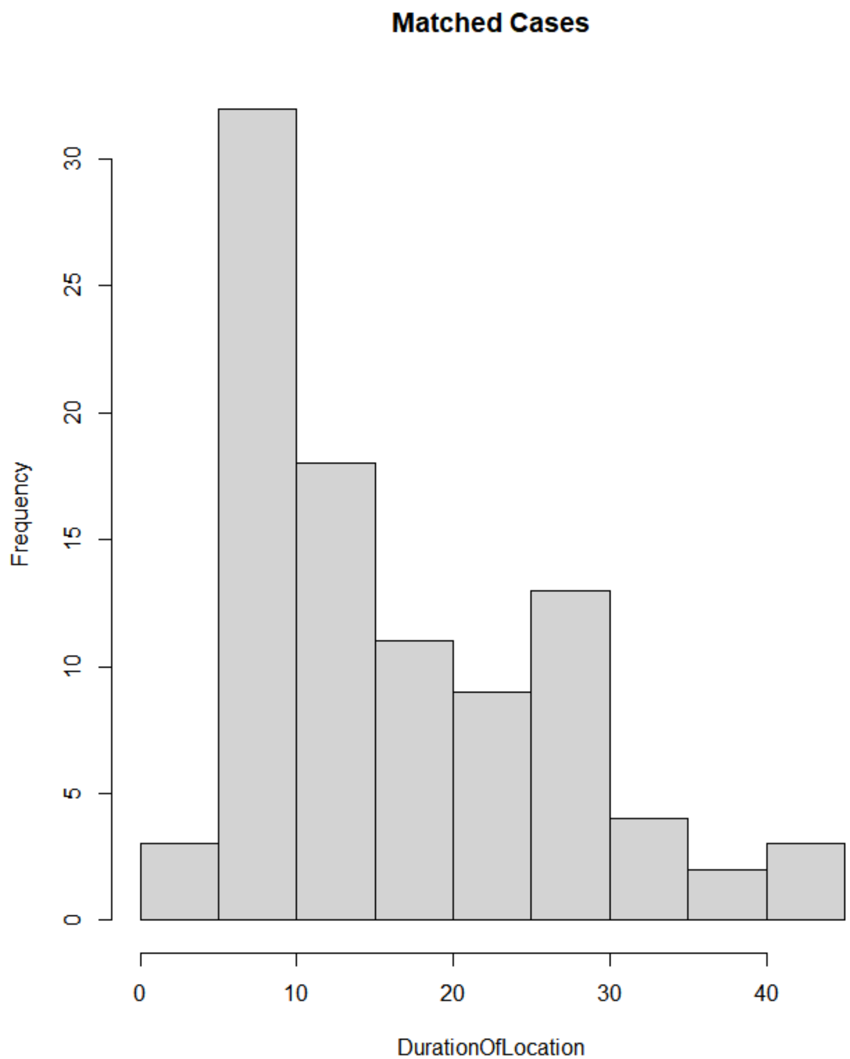
							user-centered design methods	
(Munroe et al., 2016)	Quantitative- Pre-post design	38 nurses with < 3 yrs of experience	ED	Not specific - ED Patients (Abdominal pain and shortness of breath)	Nursing assessment framework (HIRAID)	Individu al SA	Evidence-based assessment	The mean SA score significantly improved after the intervention from 4.68 ($SD = 1.77$) to 5.58 ($SD = 2.11$) ($p < < .01$).
(de Vries et al., 2017)	Qualitative- cross-sectional observational study	16 nurses and other professions	Pediatri c wards	Recognition of clinical deterioration	PEWS and PRESS	Team SA	PEWS and PRESS development Not explained	Combining PEWS with PRESS has an added value to SA compared to PEWS alone.
(Kettelhu t et al., 2017)	Quantitative- quasi-experimental survey with pre and post design	19 healthcare providers, including nurses and non-unit consultants.	Medica l-surgical wards	Infection control (antibiotic-resistant infection transmission and risk of exposure)	Health data visualizatio n (VIZ)	Team SA	The conceptual model of antibiotic-resistant infection transmission.	The median total SA scores significantly increased for each group after using the VIZ (2.57 vs. 4.36, $p = .011$ for unit staff and 1.29 vs. 4.86, $p = .008$ for non-unit staff)
(Parush et al., 2017)	Quantitative - repeated measures	13 physicians, nurses, and respiratory therapists	ED	Patient resuscitation	Situation display	Team SA	User-centered design approach	There were no overall clear and consistent differences in situation awareness scores, as measured by the SAGAT

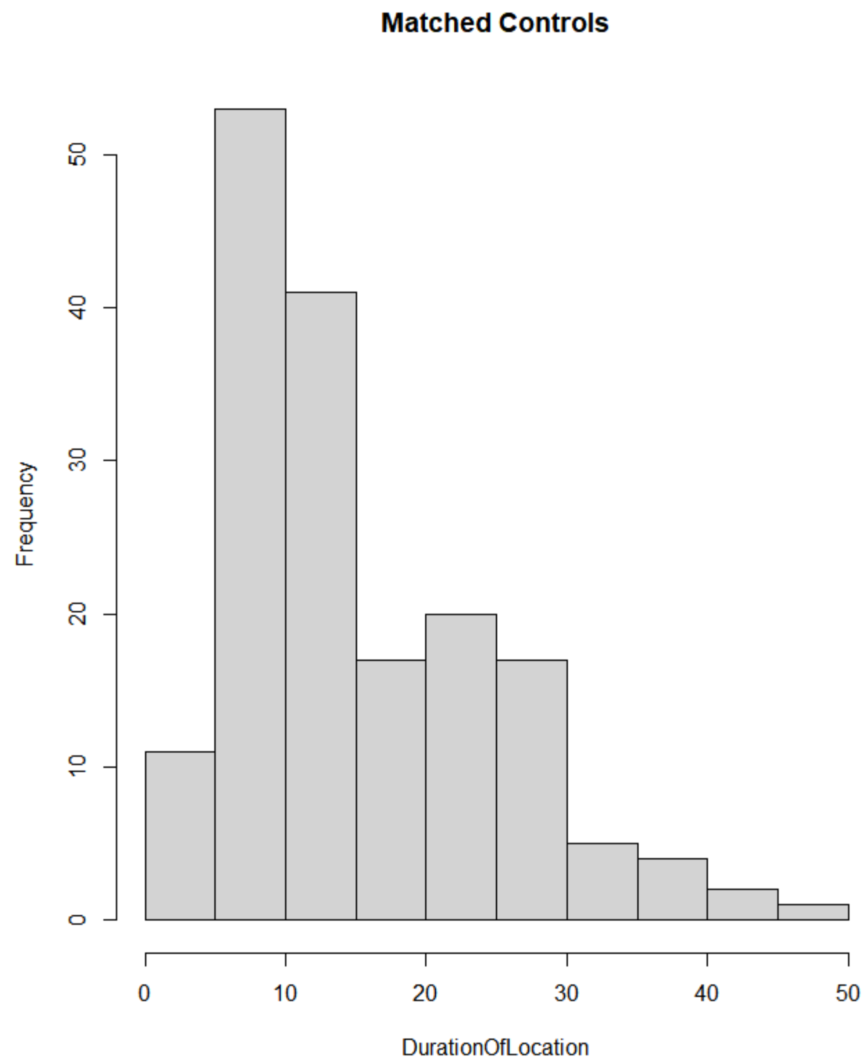
								probes, between the scenarios with and without the situation display.

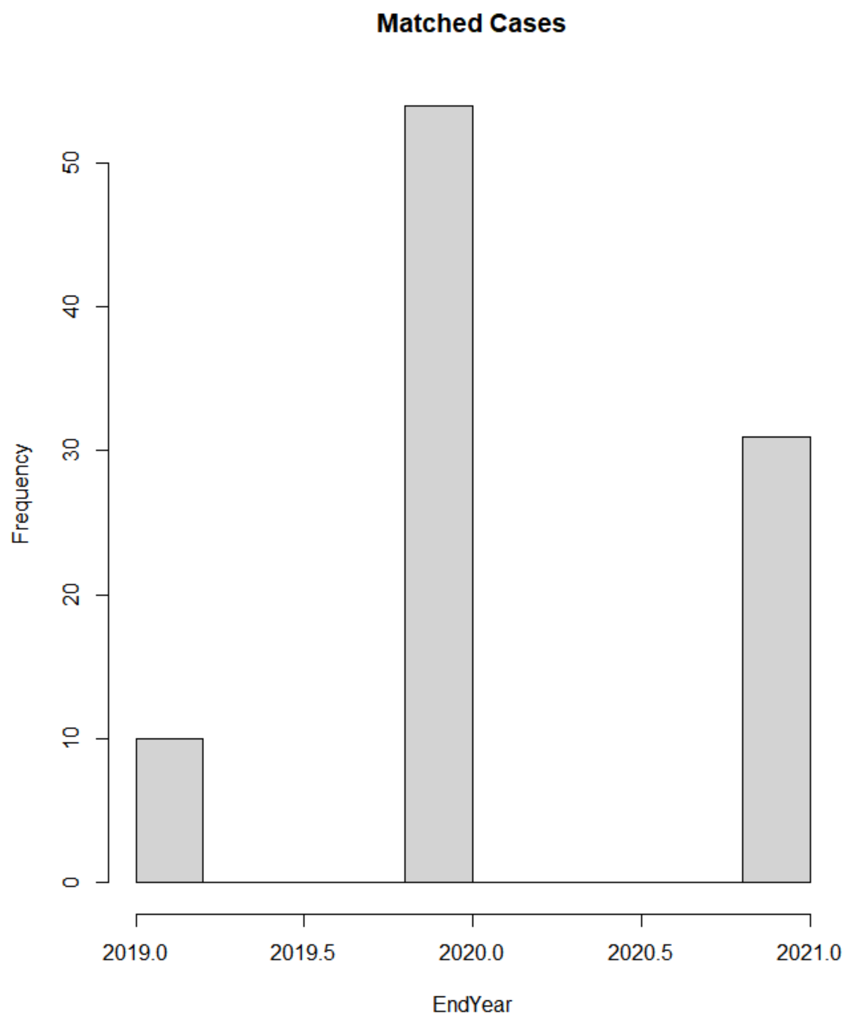
Appendix E Histograms for Matched Cases and Controls

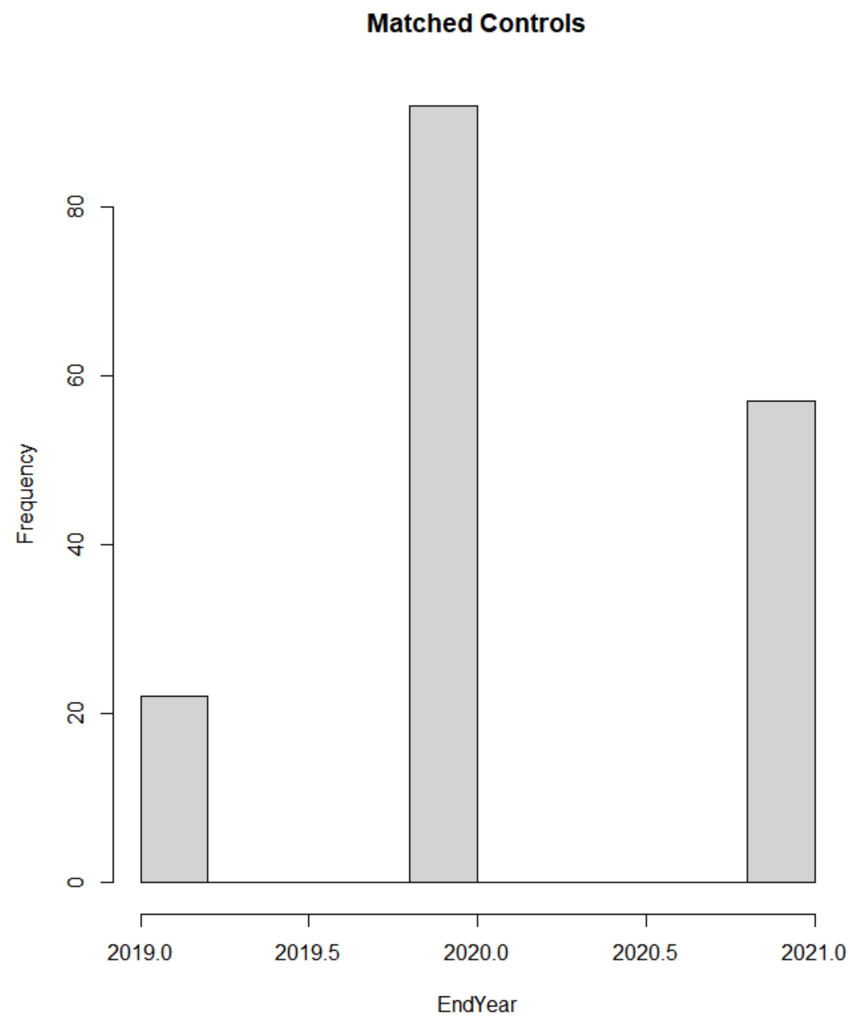


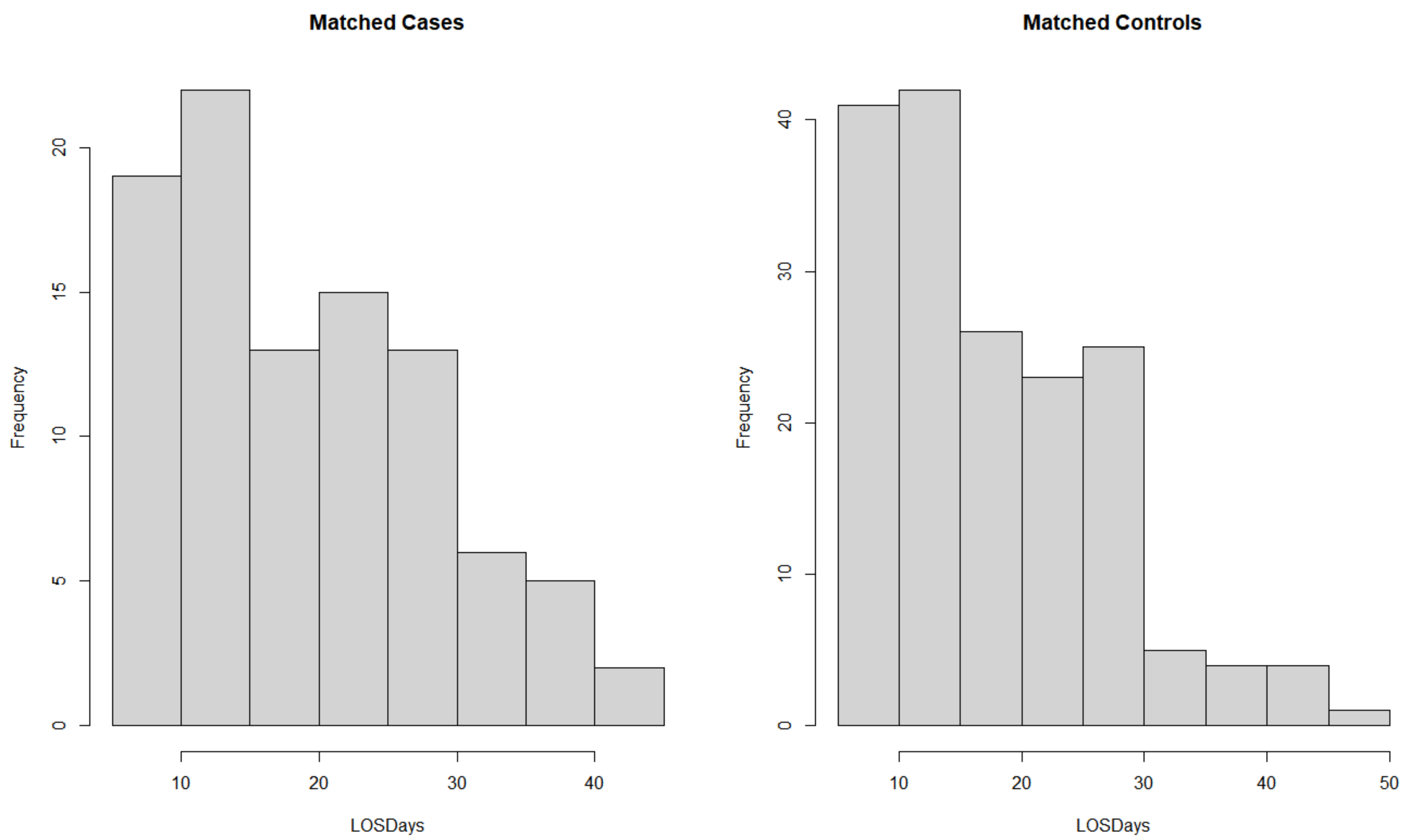



Matched Cases
Frequency
0
5
10
15
20
25
30
0
10
20
30
40
DurationOfLocation

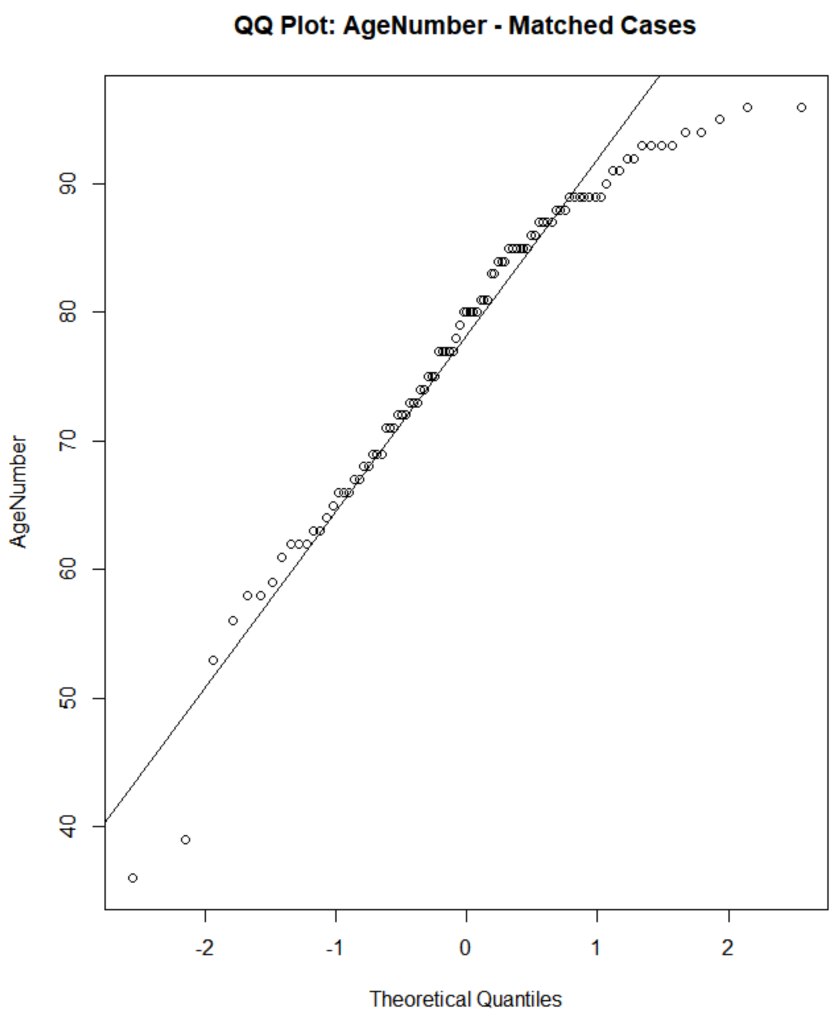

Matched Controls
Frequency
0
10
20
30
40
50
0
10
20
30
40
50
DurationOfLocation

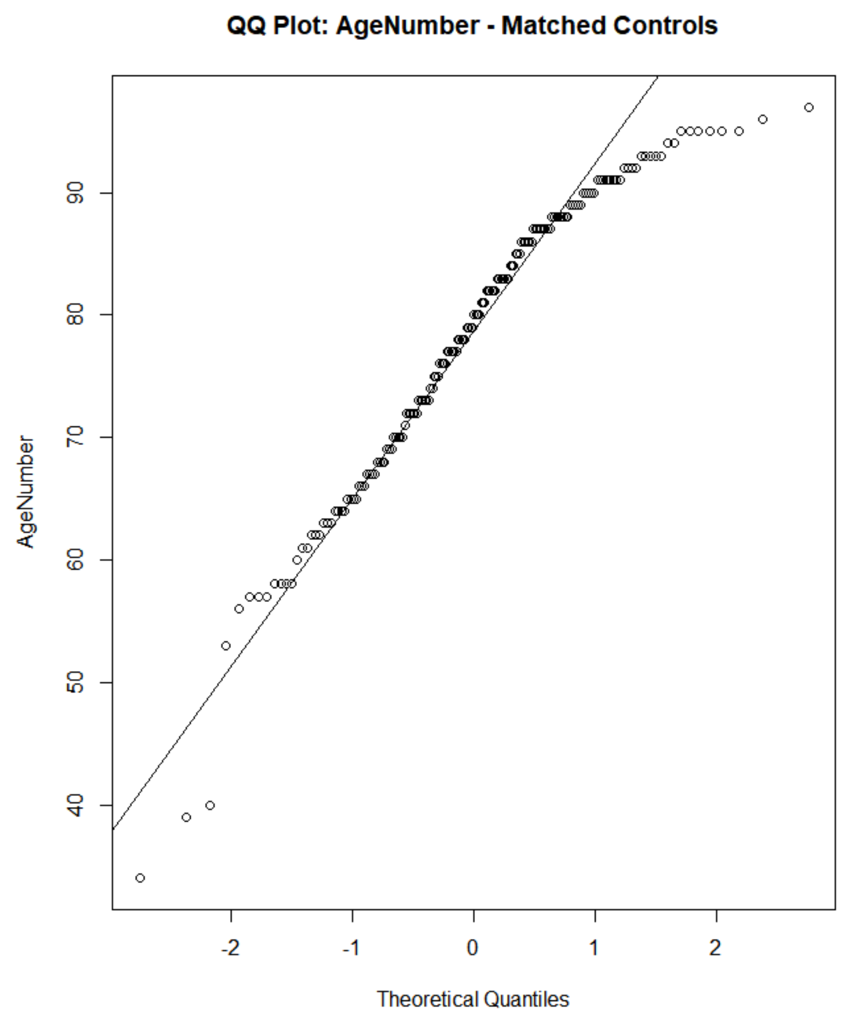

Matched Cases
Frequency
0
10
20
30
40
50
2019.0
2019.5
2020.0
2020.5
2021.0
EndYear

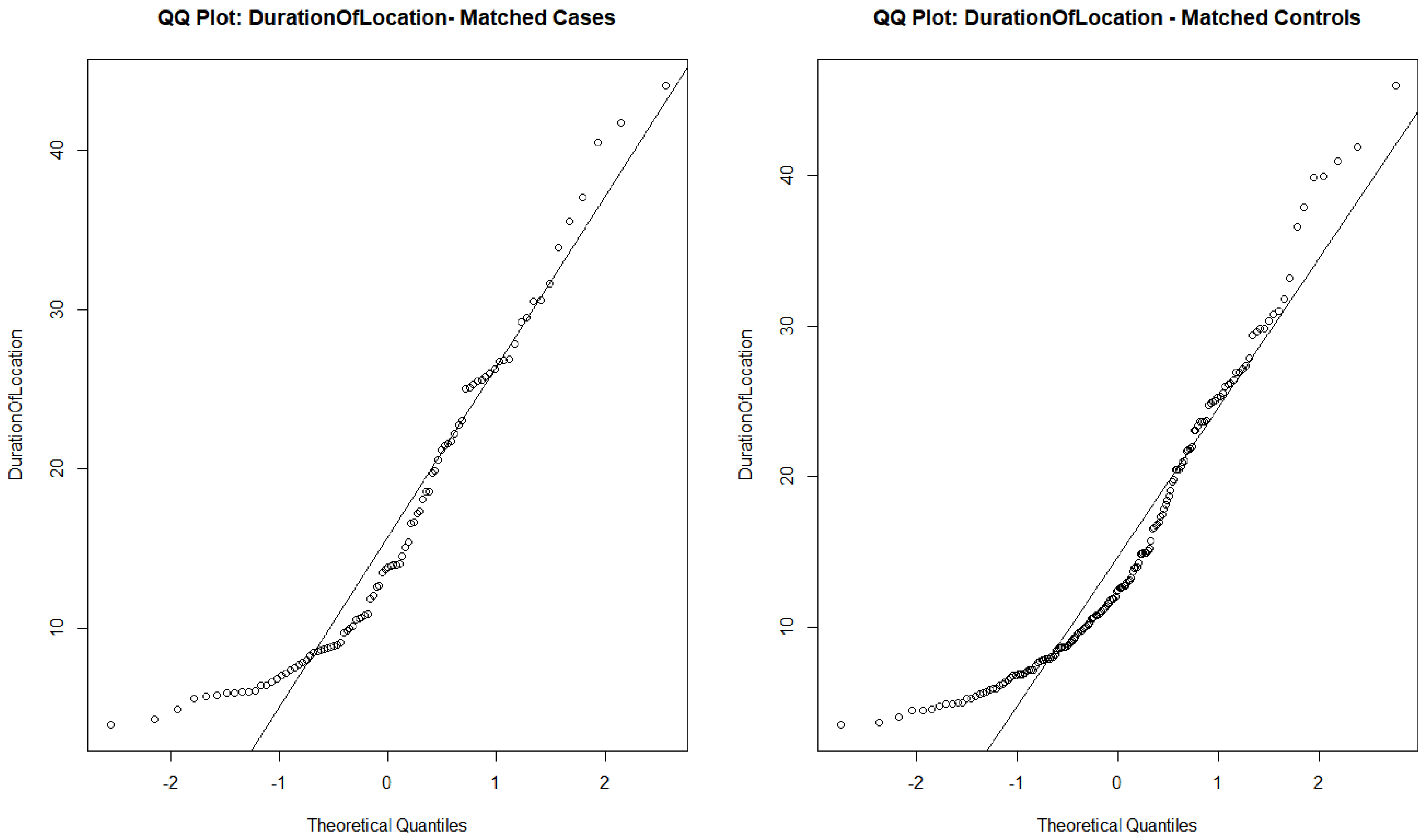

Matched Controls
Frequency
0
20
40
60
80
2019.0
2019.5
2020.0
2020.5
2021.0
EndYear

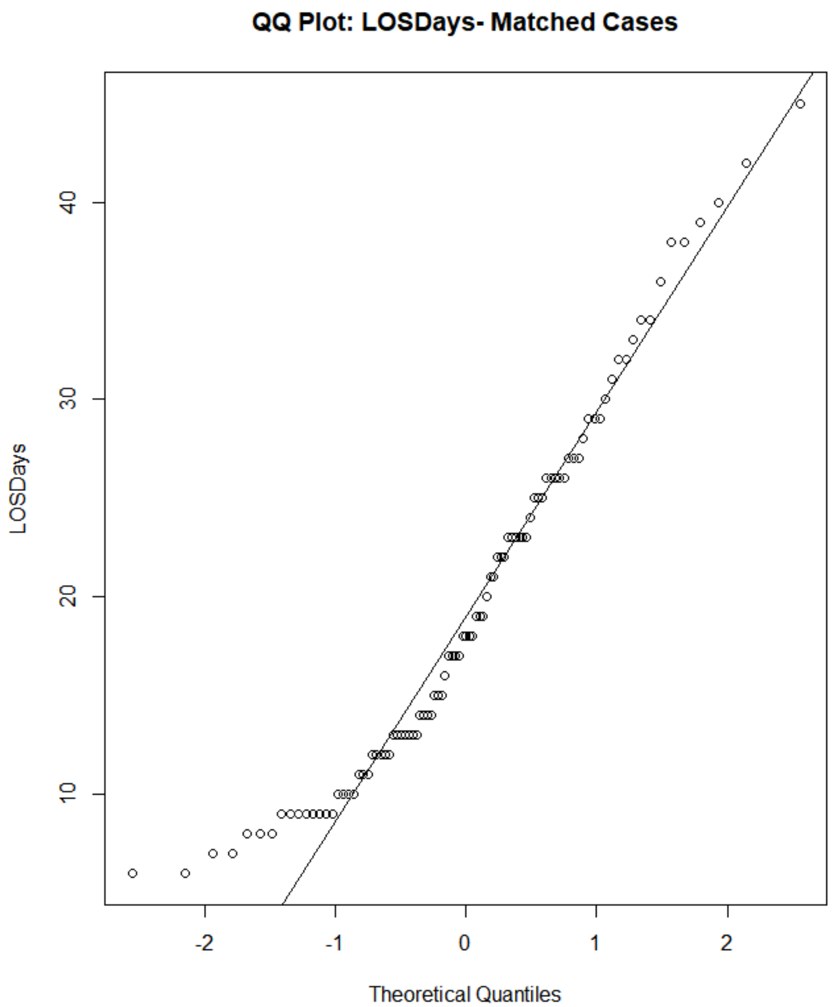

Matched Cases
Frequency
0
5
10
15
20
10
20
30
40
LOSDays
Matched Controls
Frequency
0
10
20
30
40
10
20
30
40
50
LOSDays

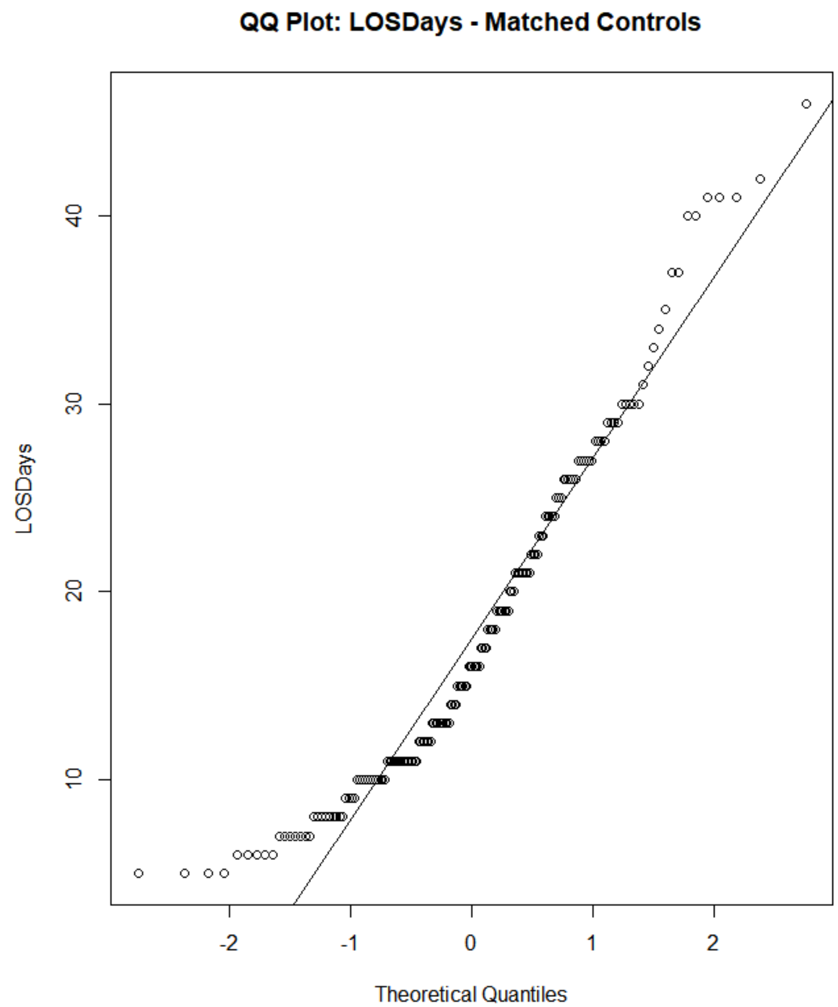
Appendix F: Quantile-Quantile Plots Matched Cases and Controls

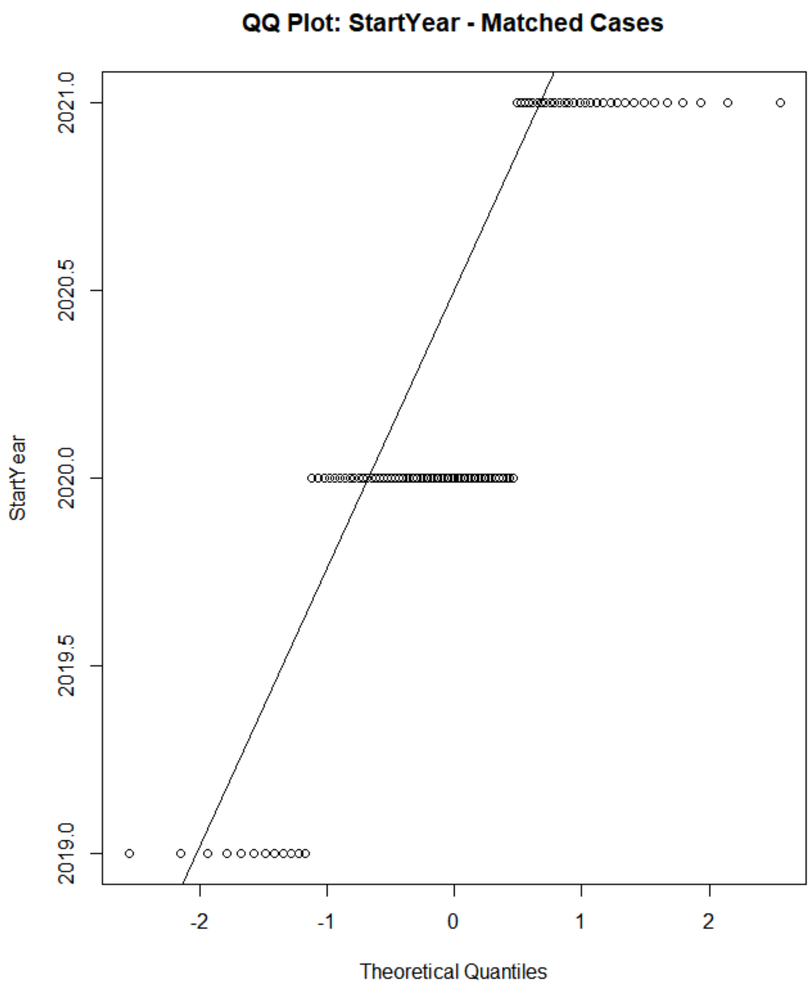


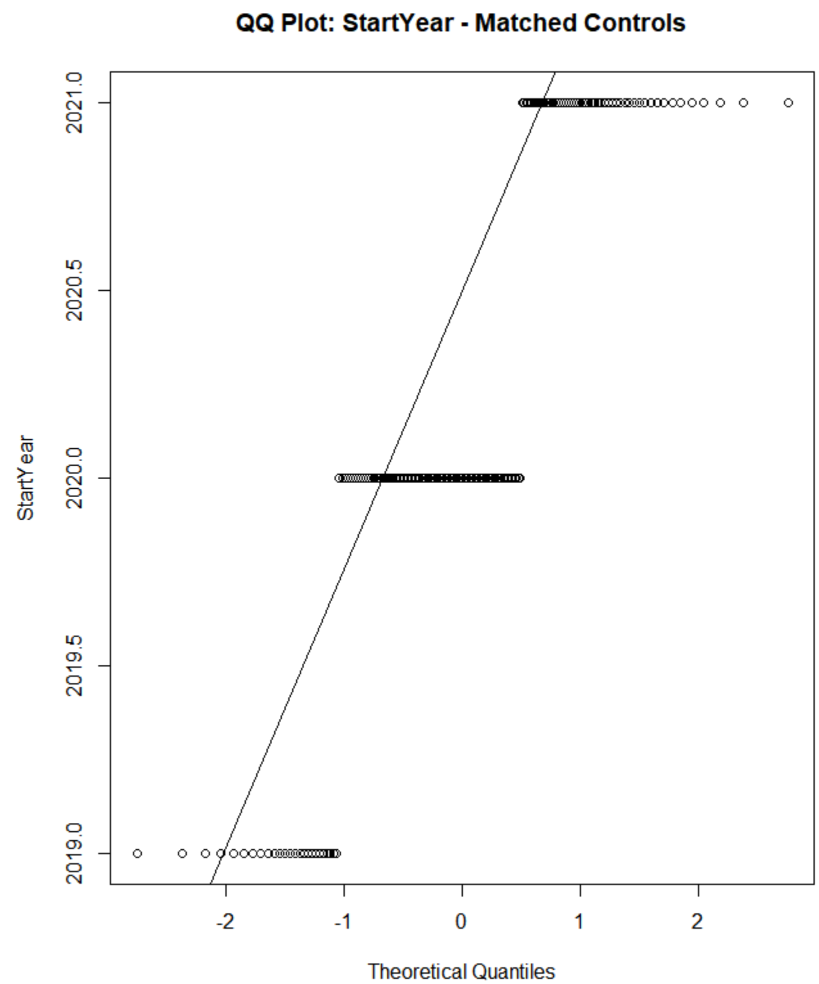


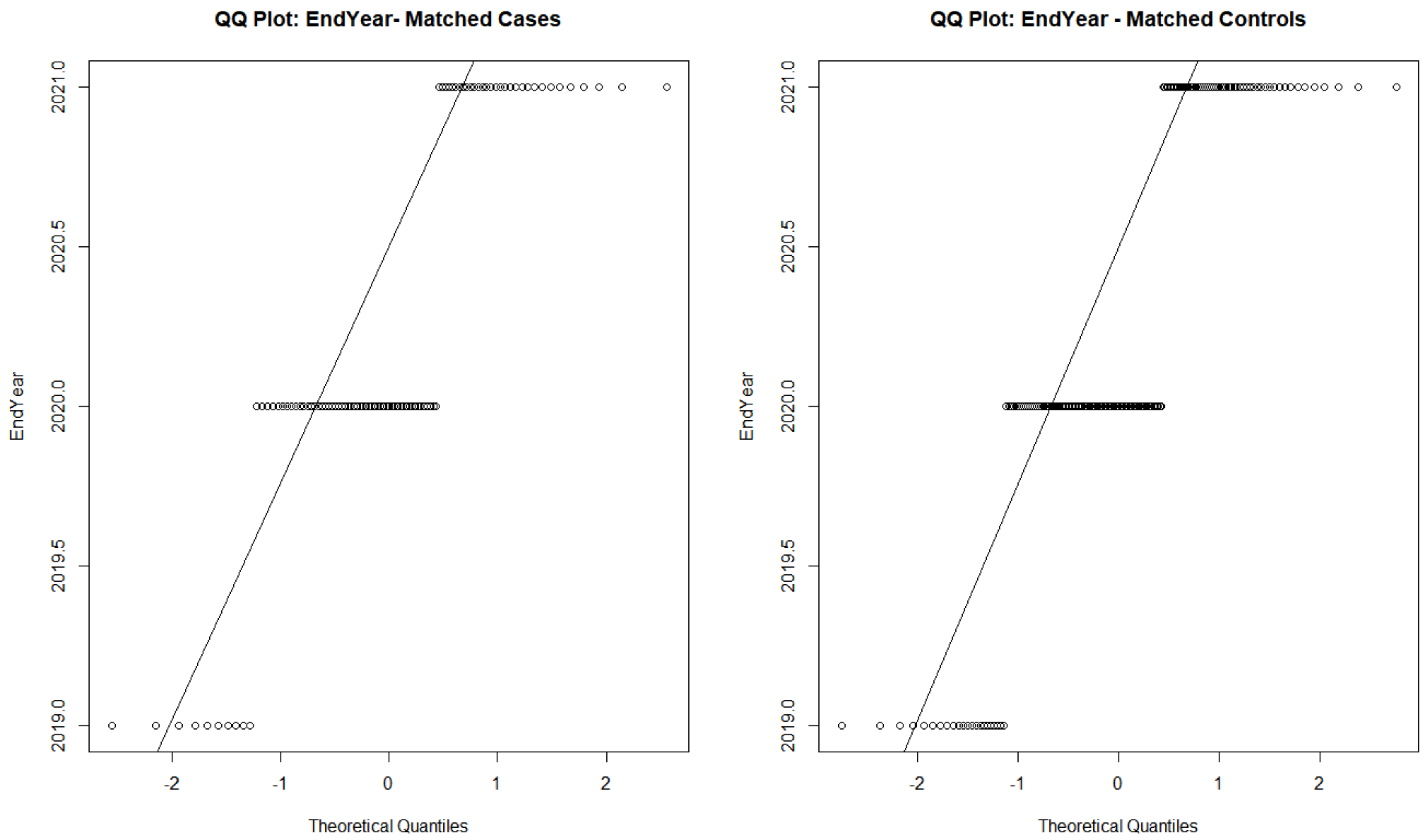

QQ Plot: DurationOfLocation- Matched Cases
DurationOfLocation
10
20
30
40
-2
-1
0
1
2
Theoretical Quantiles
QQ Plot: DurationOfLocation - Matched Controls
DurationOfLocation
10
20
30
40
-2
-1
0
1
2
Theoretical Quantiles


QQ Plot: LOSDays- Matched Cases
LOSDays
Theoretical Quantiles
10
20
30
40
-2
-1
0
1
2


QQ Plot: LOSDays - Matched Controls
LOSDays
Theoretical Quantiles
10
20
30
40
-2
-1
0
1
2


QQ Plot: StartYear - Matched Cases
StartYear
2019.0
2019.5
2020.0
2020.5
2021.0
-2
-1
0
1
2
Theoretical Quantiles


QQ Plot: StartYear - Matched Controls
StartYear
2019.0
2019.5
2020.0
2020.5
2021.0
-2
-1
0
1
2
Theoretical Quantiles


QQ Plot: EndYear- Matched Cases
EndYear
2021.0
2020.5
2020.0
2019.5
2019.0
-2
-1
0
1
2
Theoretical Quantiles
QQ Plot: EndYear - Matched Controls
EndYear
2021.0
2020.5
2020.0
2019.5
2019.0
-2
-1
0
1
2
Theoretical Quantiles

Appendix G: Percentage of Missing Data Per Variable

Variables	Variable Name	Missingness Percentage
Oxygentherapydeliverymethod	Oxygen therapy delivery method	1.13
Pulseoximetryoxygensaturation	Pulse oximetry oxygen saturation	1.13
Respiratoryrate	Respiratory rate	1.13
Temperature	Temperature	1.13
Temperaturesource	Temperature source	1.13
Probelocation	Probe location	1.88
Probelocationmodifier	Probelocationmodifier	3.76
BradenScaleactivity	Braden Scale activity	4.14
BradenScalemobility	Braden Scale mobility	4.14
BradenScalemoisture	Braden Scale moisture	4.14
BradenScalerisklevel	Braden Scale risk level	4.14
BradenScalesensoryperception	Braden Scale sensory perception	4.14
BradenSkinRiskAssessmentScore	Braden Skin Risk Assessment Score	4.14
Respiratorypattern	Respiratory pattern	5.26
Respiratorydepth	Respiratory depth	5.64
Nothingbymouth	Nothing by mouth	6.02
Skintemperature	Skin temperature	6.02

Skinmoisture	Skin moisture	6.39
Levelofconsciousness	Level of consciousness	7.89
Workofbreathing	Work of breathing	8.65
GCSscore	GCS score	9.77
GlasgowComaScaleEyeOpening	Glasgow Coma Scale Eye Opening	9.77
GlasgowComaScaleMotorResponse	Glasgow Coma Scale Motor Response	9.77
GlasgowComaScaleVerbalResponse	Glasgow Coma Scale Verbal Response	9.77
Edema	Edema	12.41
Capillaryrefillrightfoot	Capillary refill right foot	19.92
Capillaryrefillleftfoot	Capillary refill left foot	20.30
Urinecolour	Urine colour	21.05
Breakfastamountconsumed	Breakfast amount consumed	21.80
Capillaryrefilllefthand	Capillary refill left hand	24.81
Capillaryrefillrighthand	Capillary refill right hand	25.19
Urineoutputadequate	Urine output adequate	26.69
Lunchamountconsumed	Lunch amount consumed	27.07
Patientspositionduringbreakfast	Patients position during breakfast	30.45
VTEpreventionsequentialcompressiondeviceinuse	VTE prevention sequential compression device in use	30.45
Patientspositionduringlunch	Patients position during lunch	32.33

Handgripleft	Hand grip left	33.08
Clothingtype	Clothing type	33.83
Handgripright	Hand grip right	33.83
Dinneramountconsumed	Dinner amount consumed	34.21
Legstrengthright	Leg strength right	34.59
Transfersupportprovided	Transfer support provided	34.59
Washtypeperformed	Wash type performed	34.59
Armstrengthleft	Arm strength left	34.96
Armstrengthright	Arm strength right	34.96
Heartsoundsquality	Heart sounds quality	35.71
Legstrengthleft	Leg strength left	35.71
VTEpreventionantiembolicstockingsinuse	VTE prevention antiembolic stockings in use	39.10
Patientspositionduringdinner	Patients position during dinner	39.47
Bowelmovementamount	Bowel movement amount	40.23
Footweartype	Footwear type	42.11
Rightdorsalispedispulse	Right dorsalis pedis pulse	42.48
Leftdorsalispedispulse	Left dorsalis pedis pulse	43.23
Ambulationsupportprovided	Ambulation support provided	43.61
POSSscore	POSS score	45.11

BristolChartstoolconsistency	Bristol Chart stool consistency	46.24
Bathingsupportprovided	Bathing support provided	47.37
Painassessment	Pain assessment	48.12
Bowelsoundsactiveinallfourquadrants	Bowel sounds active in all four quadrants	50.75
Airentryadequatethroughout	Air entry adequate throughout	51.13
Breathsoundsclearthroughout	Breath sounds clear throughout	51.13
Dressingsupportprovided	Dressing support provided	53.01
PainassessmentMedSurguseonly	Pain assessment Med Surg use only	53.01
Tracheaposition	Trachea position	53.01
VTEpreventionanticoagulantordered	VTE prevention anticoagulant ordered	53.01
CardiovascularassessmentMedSurguseonly	Cardiovascular assessment Med Surg use only	53.38
GastrointestinalassessmentMedSurguseonly	Gastrointestinal assessment Med Surg use only	53.38
NeurologicalandcognitionassessmentMedSurguseonly	Neurological and cognition assessment Med Surg use only	53.38
Rightradialpulse	Right radial pulse	53.38
Skincolour	Skin colour	53.38
Ambulationlocation	Ambulation location	53.76
Bowelsoundsfrequency	Bowel sounds frequency	53.76
IntegumentaryassessmentMedSurguseonly	Integumentary assessment Med Surg use only	53.76

RespiratoryassessmentMedSurguseonly	Respiratory assessment Med Surg use only	53.76
Leftradialpulse	Left radial pulse	54.14
Toiletingassistance	Toileting assistance	54.14
PsychosocialandmoodassessmentMedSurguseonly	Psychosocial and mood assessment Med Surg use only	54.51
GenitourinaryassessmentMedSurguseonly	Genitourinary assessment Med Surg use only	54.89
Bedposition	Bed position	56.02
Patientexperiencingdiarrhea	Patient experiencing diarrhea	56.39
Patientexperiencingnauseavomiting	Patient experiencing nausea vomiting	56.39
Ambulationaid	Ambulation aid	56.77
Patientexperiencingconstipation	Patient experiencing constipation	56.77
Toiletingmethod	Toileting method	57.14
Rightposttibialpulse	Right post tibial pulse	57.52
Shortnessofbreath	Shortness of breath	57.52
Feedingassistance	Feeding assistance	57.89
Nauseafrequency	Nausea frequency	57.89
Patientposition	Patient position	57.89
Coughstrength	Cough strength	58.27
Bowelflatuspresent	Bowel flatus present	59.02
Armdrift	Arm drift	59.77

Cyanosis	Cyanosis	59.77
Transferequipment	Transfer equipment	60.53
Leftposttibialpulse	Left post tibial pulse	60.90
Bowelsoundslowerleftquadrant	Bowel sounds lower left quadrant	61.28
Bowelsoundslowerrightquadrant	Bowel sounds lower right quadrant	61.28
Bowelsoundsupperleftquadrant	Bowel sounds upper left quadrant	61.28
Bowelsoundsupperrightquadrant	Bowel sounds upper right quadrant	61.28
Oralcaresupportprovided	Oral care support provided	61.28
Heartsoundsmurmur	Heart sounds murmur	63.53
Bedmobilitysupportprovided	Bed mobility support provided	64.66
Currentfeedingsupportrequired	Current feeding support required	64.66
Bladderincontinence	Bladder incontinence	65.41
Outputurine	Output urine	65.41
Eyecare	Eyecare	66.17
Flatus	Flatus	67.29
Groomingsupportprovided	Grooming support provided	67.67
Heartsoundsrub	Heart sounds rub	68.05
Accompaniedwithchestdiscomfort	Accompanied with chest discomfort	68.42
Maintainingbaselinestoolpattern	Maintaining baseline stool pattern	68.80

Bowelmovementincontinence	Bowel movement incontinence	69.55
BradenScalefrictionandshear	Braden Scale friction and shear	70.30
BradenScalenutrition	Braden Scale nutrition	70.30
Transferaid	Transfer aid	70.30
Changeinbaselinevoidingpattern	Change in baseline voiding pattern	71.43
Coughproductive	Cough productive	72.18
Heartsoundsmechanicalvalveclick	Heart sounds mechanical valve click	72.18
Oxygentherapydeliveryrate	Oxygen therapy delivery rate	72.18
Toiletinghygieneability	Toileting hygiene ability	72.18
SleepaidPRNgiven	Sleep aid PRN given	72.93
Subcutaneousemphysema	Subcutaneousemphysema	73.31
Changeinbaselinebowelpatterncontinence	Change in baseline bowel pattern continence	74.44
Cornealreflexleft	Corneal reflex left	77.07
Cornealreflexright	Corneal reflex right	77.07
Neurovascularleftfoottemperature	Neurovascular left foot temperature	77.07
Urinarycatheterinsituandpatent	Urinary catheter in situ and patent	77.07
Leftlegpainwithpassivemotion	Left leg pain with passive motion	77.44
Leftlegprogressiveseverepain	Left leg progressive severe pain	77.44
Motorresponseleftleg	Motor response left leg	77.44

Motorresponserightleg	Motor response right leg	77.44
Neurovascularrightfoottemperature	Neurovascular right foot temperature	77.44
Rightlegpainwithpassivemotion	Right leg pain with passive motion	77.82
Rightlegprogressiveseverepain	Right leg progressive severe pain	77.82
Specialtyskinproductused	Specialty skin product used	78.95
Repositioningdeviceused	Repositioningdeviceused	79.32
Transferto	Transfer to	79.32
Assistancerequiredforrepositioninginbed	Assistance required for repositioning in bed	80.45
Urinarycatheterassessment	Urinary catheter assessment	80.83
Acuteonset	Acute onset	81.58
Alteredlevelsofconsciousness	Altered levels of consciousness	81.58
Bladderscanvolume	Bladder scan volume	81.58
CAMresult	CAMresult	81.58
Disorganizedthinking	Disorganized thinking	81.58
Fluctuatingcourse	Fluctuating course	81.58
Inattention	Inattention	81.58
Transferfrom	Transfer from	81.58
Coughreflex	Cough reflex	84.96
Washingassistance	Washing assistance	84.96

Urinarycathetersecurementdeviceinuse	Urinary catheter securement device in use	86.09
Gagreflex	Gag reflex	86.84
Mobilityinbedassistivedevices	Mobility in bed assistive devices	86.84
Heelpressurereliefmethod	Heel pressure relief method	88.72
Dressingassistance	Dressing assistance	89.85
Mouthcareassistance	Mouth care assistance	89.85
CurrentWeight	Current Weight	90.23
WeightCalculatedGrams	Weight Calculator Grams	90.23
Behaviouralconcerns	Behavioural concerns	91.35
ReasonforUndo	Reason for Undo	91.35
Canadianmalnutritionscreeningtoolhighnutritionalrisk	Canadian malnutrition screening tool high nutritional risk	91.73
Haveyoubeeneatinglessthanusualformorethanaweek	Have you been eating less than usual for more than a week	91.73
Haveyoulostwtinthepast6mowithouttryingtolosewt	Have you lost wt in the past 6 mo without trying to lose wt	91.73
Weightmeasurementmethod	Weight measurement method	91.73
Neurovascularrightarmtemperature	Neurovascular right arm temperature	92.48
Snackamountconsumed	Snack amount consumed	92.48
Informationsourceifreported	Information source if reported	92.86
Rightarmprogressivepain	Right arm progressive pain	92.86

Motorresponserightarm	Motor response right arm	93.23
Neurovascularleftarmtemperature	Neurovascular left arm temperature	93.23
Rightarmpainwithpassivemotion	Right arm pain with passive motion	93.23
Secretionsamount	Secretions amount	93.23
Motorresponseleftarm	Motor response left arm	93.61
Dialysistype	Dialysis type	93.98
Leftarmpainwithpassivemotion	Left arm pain with passive motion	93.98
Leftarmprogressiveseverepain	Left arm progressive severe pain	93.98
Durationoftimeupinchair	Duration of time up in chair	94.36
Shortnessofbreathonset	Shortness of breath on set	94.36
Immobilizationdeviceinuse	Immobilization device in use	94.74
Postvoidresidualvolume	Postvoid residual volume	94.74
Pulsesleftdorsalispedis	Pulses left dorsalis pedis	94.74
Pulsesrightdorsalispedis	Pulses right dorsalis pedis	94.74
Rightulnarpulse	Right ulnar pulse	94.74
Assistancegiven	Assistance given	95.11
Pulsesrightposttibial	Pulses right post tibial	95.11
Hairwashperformed	Hair wash performed	95.49
Leftpoplitealpulse	Left popliteal pulse	95.49

Pulsesleftposttibial	Pulses left post tibial	95.49
Mattresstype	Mattress type	95.86
Pulsesleftradial	Pulses left radial	95.86
Pulsesrightradial	Pulses right radial	95.86
Alteredlevelofconsciousness	Altered level of consciousness	96.24
CAMassessment	CAM assessment	96.24
Diagnosisofdeliriumsuggested	Diagnosis of delirium suggested	96.24
Difficultyfocusingattention	Difficulty focusing attention	96.24
Evidenceofacutechangeinmentalstatusfrombaseline	Evidence of acute change in mental status from baseline	96.24
Fluctuatingbehaviourduringthepastday	Fluctuating behaviour during the past day	96.24
InhalersNebulizersgiven	Inhalers Nebulizers given	96.24
IntakeOtherAmount	Intake Other Amount	96.24
Speechdisorganizedorincoherent	Speech disorganized or incoherent	96.24
Catheterdistaltipintactwithremoval	Catheter distal tip intact with removal	96.62
Nauseaseverity	Nausea severity	96.62
Ambulationability	Ambulation ability	96.99
Eatatriskorderinplace	Eat at risk order in place	96.99
Leftbrachialpulse	Left brachial pulse	96.99
Leftulnarpulse	Left ulnar pulse	96.99

Rightbrachialpulse	Right brachial pulse	96.99
Rightpoplitealpulse	Right popliteal pulse	96.99
Aidusedforindependentambulation	Aid used for independent ambulation	97.37
Assistancerequiredfortransfer	Assistance required for transfer	97.37
Emesisaccompaniedwithdiarrhea	Emesis accompanied with diarrhea	97.37
Secretionssource	Secretin source	97.37
Ambulation	Ambulation	97.74
IntakeOralAmount	Intake Oral Amount	97.74
Outputstool	Output tool	97.74
Rectaltubeinsitu	Rectal tube in situ	97.74
Shavegiven	Shave given	97.74
Arteriovenousfistulalocation	Arteriovenous fistula location	98.12
Assistancerequiredforambulation	Assistance required for ambulation	98.12
Leftfemoralpulse	Left femoral pulse	98.50
Mobilityaidusedfortransfertochair	Mobility aid used for transfer to chair	98.50
OutputGastricDrainageAmount	Output Gastric Drainage Amount	98.50
Rightfemoralpulse	Right femoral pulse	98.50
Secretionscolour	Secretions color	98.50
Abdominalbreaststumpandpelvicbinderinsitu	Abdominal breast stump and pelvic binder in situ	98.87

Bedexercisescompleted	Bed exercises completed	98.87
Educationformat	Education format	98.87
Glucometerbloodglucose	Glucometer blood glucose	98.87
Glycemicmanagementsamplesource	Glycemic management sample source	98.87
Mobilityaidusedforambulation	Mobility aid used for ambulation	98.87
Mobilizedtochair	Mobilized to chair	98.87
Proberepositioned	Probe repositioned	98.87
Arteriovenousfistulaassessment	Arteriovenous fistula assessment	99.25
Arteriovenousfistulabruitaudible	Arteriovenous fistula bruit audible	99.25
Arteriovenousfistulathrillpalpable	Arteriovenous fistula thrill palpable	99.25
Bloodintake	Blood intake	99.25
Evaluationforcontinuedrestraintuseassessedreassessed	Evaluation for continued restraint use assessed reassessed	99.25
Inbedmobilization	In bed mobilization	99.25
Interpreterutilized	Interpreter utilized	99.25
Positioningsiderailsbottom	Positioning side rails bottom	99.25
Positioningsiderailstop	Positioning side rail stop	99.25
Pulsesleftfemoral	Pulses left femoral	99.25
Skincondition	Skin condition	99.25
Enteralfeedingtubeconfirmedlength	Enteral feeding tube confirmed length	99.62

Enteralfeedingtubecurrentlength	Enteral feeding tube current length	99.62
Enteralfeedingtubesecurementdeviceintact	Enteral feeding tube securement device intact	99.62
Enteralnutritioncurrentrate	Enteral nutrition current rate	99.62
Enteralnutritiondeliveryschedule	Enteral nutrition delivery schedule	99.62
Feedingtubeinsertionsite	Feeding tube insertion site	99.62
Feedingtubetype	Feeding tube type	99.62
FractionofinspiredoxygenFiO	Fraction of inspired oxygen FiO	99.62
Insulininjectionsite	Insulin injection site	99.62
Insulinroute	Insulin route	99.62
IntakeFreeWaterAmount	Intake Free Water Amount	99.62
Intakeparenteralnutritionaminoacids	Intake parenteral nutrition amino acids	99.62
IntakeTubeFeedingAmount	Intake Tube Feeding Amount	99.62
Measuredbloodloss	Measured blood loss	99.62
Othermeasureoutput	Other measure output	99.62
Outputurinestoolmix	Output urine stool mix	99.62
Pulsesleftbrachial	Pulses left brachial	99.62
Pulsesrightbrachial	Pulses right brachial	99.62
Pulsesrightfemoral	Pulses right femoral	99.62
Pulsesrightulnar	Pulses right ulnar	99.62

Secretionsource	Secretion source	99.62
Shortactinginsulindose	Short acting insulin dose	99.62
Surroundingskinintact	Surrounding skin intact	99.62
Washmethod	Wash method	99.62

Appendix H: Modified Variables

Updated Variable	Variable Name	Variable used for the update	Variable Name
Toiletingassistance	Toileting assistance	Toiletinghygieneability	Toileting hygiene ability
Painassessment	Pain assessment	PainassessmentMedSurguseonly	Pain assessment Med Surg use only
Ambulationlocation	Ambulation location	Ambulation	Ambulation
Levelofconsciousness	Level of consciousness	Alteredlevelsofconsciousness	Altered levels of consciousness
Bathingsupportprovided	Bathing support provided	Washingassistance	Washing assistance
Currentfeedingsupportrequired	Current feeding support required	Feedingassistance	Feeding assistance
Dressingsupportprovided	Dressing support provided	Dressingassistance	Dressing assistance
Bowelflatuspresent	Bowel flatus present	Flatus	Flatus
Oralcaresupportprovided	Oral care support provided	Mouthcareassistance	Mouth care assistance
Bedmobilitysupportprovided	Bed mobility support provided	Assistancerequiredforrepositioninginbed	Assistance required for repositioning in bed

New Variable	Variable Name	Variables Used to Create New Variable	Variable Name
Ambulationdone	Ambulation done	Ambulation	Ambulation
		Ambulationlocation	Ambulation location
		Aidusedforindependentambulation	Aid used for independent ambulation
		Ambulationsupportprovided	Ambulation support provided
		Ambulationability	Ambulation ability
		Assistancerequiredforambulation	Assistance required for ambulation
		Mobilityaidusedforambulation	Mobility aid used for ambulation
		Ambulationaid	Ambulation aid
Foleyused	Foley used	Catheterdistaltipintactwithremoval	Catheter distal tip intact with removal
		Urinarycatheterassessment	Urinary catheter assessment
		Urinarycatheterinsituandpatent	Urinary catheter in situ and patent

		Urinarycathetersecurementdeviceinuse	Urinary catheter securement device in use
		Toiletingmethod	Toileting method
Bowelsoundpresent	Bowel sound present	Bowelsoundsactiveinallfourquadrants	Bowel sounds active in all four quadrants
		Bowelsoundsfrequency	Bowel sounds frequency
		Bowelsoundslowerleftquadrant	Bowel sound slower left quadrant
		Bowelsoundslowerrightquadrant	Bowel sounds lower right quadrant
		Bowelsoundsupperleftquadrant	Bowel sounds upper left quadrant
		Bowelsoundsupperrightquadrant	Bowel sounds upper right quadrant
Requiremobilityaid	Require mobility aid	Aidusedforindependentambulation	Aid used for independent ambulation
		Ambulationaid	Ambulation aid
		Ambulationability	Ambulation ability
		Ambulationsupportprovided	Ambulation support provided
		Assistancerequiredforambulation	Assistance required for ambulation
		Mobilityaidusedforambulation	Mobility aid used for ambulation
Bestarmstrength	Best arm strength	Armstrengthleft	Arm strength left
		Armstrengthright	Arm strength right
		Motorresponserightarm	Motor response right arm
		Motorresponseleftarm	Motor response left arm
		Handgripleft	Hand grip left
		Handgripright	Hand grip right
Bestlegstrength	Best leg strength	Legstrengthleft	Leg strength left
		Legstrengthright	Leg strength right
		Motorresponserightleg	Motor response right leg
		Motorresponseleftleg	Motor response left leg
Intaketotal	Intake total	IntakeFreeWaterAmount	Intake Free Water Amount
		IntakeOralAmount	Intake Oral Amount
		IntakeOtherAmount	Intake Other Amount
		IntakeTubeFeedingAmount	Intake Tube Feeding Amount
		Intakeparenteralnutritionaminoacids	Intake parenteral nutrition amino acids
Bestarmpulse	Best arm pulse	Pulsesleftbrachial	Pulses left brachial

		Pulsesrightbrachial	Pulses right brachial
		Pulsesleftradial	Pulses left radial
		Pulsesrightradial	Pulses right radial
		Pulsesrightulnar	Pulses right ulnar
		Leftradialpulse	Left radial pulse
		Rightradialpulse	Right radial pulse
		Leftulnarpulse	Left ulnar pulse
		Leftbrachialpulse	Left brachial pulse
Bestlegpulse	Best leg pulse	Pulsesleftdorsalispedis	Pulses left dorsalis pedis
		Pulsesleftfemoral	Pulses left femoral
		Pulsesleftposttibial	Pulses left post tibial
		Pulsesrightdorsalispedis	Pulses right dorsalis pedis
		Pulsesrightfemoral	Pulses right femoral
		Pulsesrightposttibial	Pulses right post tibial
		Leftpoplitealpulse	Left popliteal pulse
		Leftdorsalispedispulse	Left dorsalis pedis pulse
		Leftfemoralpulse	Left femoral pulse
		Rightposttibialpulse	Right post tibial pulse
		Rightdorsalispedispulse	Right dorsalis pedis pulse
		Leftposttibialpulse	Left post tibial pulse
Outputtotal	Output total	Othermeasureoutput	Other measure output
		OutputGastricDrainageAmount	Output Gastric Drainage Amount
		Outputstool	Output stool
		Outputurine	Output urine
		Outputurinestoolmix	Output urine stool mix
Bestcaprefill	Best cap refill	Capillaryrefillleftfoot	Capillary refill left foot
		Capillaryrefillrightfoot	Capillary refill right foot
		Capillaryrefilllefthand	Capillary refill left hand
		Capillaryrefillrighthand	Capillary refill right hand

Variables with One Level after Imputation	**Variable Name**
Bowelsoundpresent	Bowel sound present

Ambulationdone	Ambulation done
Cyanosis	Cyanosis
Tracheaposition	Trachea position
Accompaniedwithchestdiscomfort	Accompanied with chest discomfort
Heartsoundsrub	Heart sounds rub
Cornealreflexleft	Corneal reflex left
Cornealreflexright	Corneal reflex right
Heartsoundsmechanicalvalveclick	Heart sounds mechanical valve click
Leftlegprogressiveseverepain	Left leg progressive severe pain
Subcutaneousemphysema	Subcutaneousemphysema
Gagreflex	Gag reflex

Appendix I: Removed Variables with Reason

Variable	Variable Name	Reason of Removal
Accompaniedwithchestdiscomfort	Accompanied with chest discomfort	One Level
Aidusedforindependentambulation	Aid used for independent ambulation	Creation of new variables Ambulationdone and Requiremobilityaid
Alteredlevelsofconsciousness	Altered levels of consciousness	Combined with Levelofconsciousness
Ambulation	Ambulation	Combined with Ambulationlocation
Ambulationability	Ambulation ability	Creation of new variables Ambulationdone and Requiremobilityaid
Ambulationaid	Ambulation aid	Creation of new variables Ambulationdone and Requiremobilityaid
Ambulationdone	Ambulation done	One Level
Ambulationlocation	Ambulation location	Creation of new variable Ambulationdone

Ambulationsupportprovided	Ambulation support provided	Creation of new variables Ambulationdone and Requiremobilityaid
Armstrengthleft	Arm strength left	Creation of new variable Bestarmstrength
Armstrengthright	Arm strength right	Creation of new variable Bestarmstrength
Assistancerequiredforambulation	Assistance required for ambulation	Creation of new variables Ambulationdone and Requiremobilityaid
Assistancerequiredforrepositioninginbed	Assistance required for repositioning in bed	Combined with Bedmobilitysupportprovided
Bedposition	Bed position	No clinical significance
Bowelsoundpresent	Bowel sound present	One Level
Bowelsoundsactiveinallfourquadrants	Bowel sounds active in all four quadrants	Creation of new variable Bowelsoundpresent
Bowelsoundsfrequency	Bowel sounds frequency	Creation of new variable Bowelsoundpresent
Bowelsoundslowerleftquadrant	Bowel sounds lower left quadrant	Creation of new variable Bowelsoundpresent

Bowelsoundslowerrightquadrant	Bowel sounds lower right quadrant	Creation of new variable Bowelsoundpresent
Bowelsoundsupperleftquadrant	Bowel sounds upper left quadrant	Creation of new variable Bowelsoundpresent
Bowelsoundsupperrightquadrant	Bowel sounds upper right quadrant	Creation of new variable Bowelsoundpresent
Capillaryrefillleftfoot	Capillary refill left foot	Creation of new variable Bestcaprefill
Capillaryrefilllefthand	Capillary refill left hand	Creation of new variable Bestcaprefill
Capillaryrefillrightfoot	Capillary refill right foot	Creation of new variable Bestcaprefill
Capillaryrefillrighthand	Capillary refill right hand	Creation of new variable Bestcaprefill
CardiovascularassessmentMedSurguseonly	Cardiovascular assessment Med Surguse only	No clinical significance
Clothingtype	Clothing type	No clinical significance
Cornealreflexleft	Corneal reflex left	One Level

Cornealreflexright	Corneal reflex right	One Level
Cyanosis	Cyanosis	One Level
Dressingassistance	Dressing assistance	Combined with Dressingsupportprovided
Feedingassistance	Feeding assistance	Combined with Currentfeedingsupportrequired
Flatus	Flatus	Combined with Bowelflatuspresent
Footweartype	Footwear type	No clinical significance
Gagreflex	Gag reflex	One Level
GastrointestinalassessmentMedSurguseonly	Gastrointestinal assessment Med Surg use only	No clinical significance
GenitourinaryassessmentMedSurguseonly	Genitourinary assessment Med Surg use only	No clinical significance
Handgripleft	Hand grip left	Creation of new variable Bestarmstrength
Handgripright	Hand grip right	Creation of new variable Bestarmstrength

Heartsoundsmechanicalvalveclick	Heart sounds mechanical valve click	One Level
Heartsoundsrub	Heart sounds rub	One Level
Informationsourceifreported	Information source if reported	No clinical significance
IntegumentaryassessmentMedSurguseonly	Integumentary assessment Med Surg use only	No clinical significance
Interpreterutilized	Interpreter utilized	No clinical significance
Leftbrachialpulse	Left brachial pulse	Creation of new variable Bestarmpulse
Leftdorsalispedispulse	Left dorsalis pedis pulse	Creation of new variable Bestlegpulse
Leftfemoralpulse	Left femoral pulse	Creation of new variable Bestlegpulse
Leftlegprogressiveseverepain	Left leg progressive severe pain	One Level
Leftpoplitealpulse	Left popliteal pulse	Creation of new variable Bestlegpulse
Leftposttibialpulse	Left post tibial pulse	Creation of new variable Bestlegpulse

Leftradialpulse	Left radial pulse	Creation of new variable Bestarmpulse
Leftulnarpulse	Left ulnar pulse	Creation of new variable Bestarmpulse
Legstrengthleft	Leg strength left	Creation of new Bestlegstrength
Legstrengthright	Leg strength right	Creation of new Bestlegstrength
Mattresstype	Mattress type	No clinical significance
Mobilityaidusedforambulation	Mobility aid used for ambulation	Creation of new variables Ambulationdone and Requiremobilityaid
Mobilityinbedassistivedevices	Mobility in bed assistive devices	No clinical significance
Motorresponseleftarm	Motor response left arm	Creation of new variable Bestarmstrength
Motorresponseleftleg	Motor response left leg	Creation of new Bestlegstrength
Motorresponserightarm	Motor response right arm	Creation of new variable Bestarmstrength
Motorresponserightleg	Motor response right leg	Creation of new variable Bestlegstrength
Mouthcareassistance	Mouth care assistance	Combined with Oralcaresupportprovided

NeurologicalandcognitionassessmentMedSurguseonly	Neurological and cognition assessment Med Surg use only	Combined with Painassessment
PainassessmentMedSurguseonly	Pain assessment Med Surg use only	No clinical significance
Patientposition	Patient position	No clinical significance
Patientspositionduringbreakfast	Patients position during breakfast	No clinical significance
Patientspositionduringdinner	Patients position during dinner	No clinical significance
Patientspositionduringlunch	Patients position during lunch	No clinical significance
Positioningsiderailsbottom	Positioning side rails bottom	No clinical significance
Positioningsiderailstop	Positioning side rail stop	No clinical significance
Probelocation	Probe location	No clinical significance

Probelocationmodifier	Probe location modifier	No clinical significance
PsychosocialandmoodassessmentMedSurguseonly	Psychosocial and mood assessment Med Surg use only	No clinical significance
Pulsesleftbrachial	Pulses left brachial	Creation of new variable Bestarmpulse
Pulsesleftdorsalispedis	Pulses left dorsalis pedis	Creation of new variable Bestlegpulse
Pulsesleftfemoral	Pulses left femoral	Creation of new variable Bestlegpulse
Pulsesleftposttibial	Pulses left post tibial	Creation of new variable Bestlegpulse
Pulsesleftradial	Pulses left radial	Creation of new variable Bestarmpulse
Pulsesrightbrachial	Pulses right brachial	Creation of new variable Bestarmpulse
Pulsesrightdorsalispedis	Pulses right dorsalis pedis	Creation of new variable Bestlegpulse
Pulsesrightfemoral	Pulses right femoral	Creation of new variable Bestlegpulse
Pulsesrightposttibial	Pulses right post tibial	Creation of new variable Bestlegpulse
Pulsesrightradial	Pulses right radial	Creation of new variable Bestarmpulse
Pulsesrightulnar	Pulses right ulnar	Creation of new variable Bestarmpulse

ReasonforUndo	Reason for Undo	No clinical significance
Repositioningdeviceused	Repositioning device used	No clinical significance
RespiratoryassessmentMedSurguseonly	Respiratory assessment Med Surg use only	No clinical significance
Rightdorsalispedispulse	Right dorsalis pedis pulse	Creation of new variable Bestlegpulse
Rightposttibialpulse	Right post tibial pulse	Creation of new variable Bestlegpulse
Rightradialpulse	Right radial pulse	Creation of new variable Bestarmpulse
Shavegiven	Shave given	No clinical significance
Subcutaneousemphysema	Subcutaneous emphysema	One Level
Temperaturesource	Temperature source	No clinical significance
Toiletinghygieneability	Toileting hygiene ability	Combined with Toiletingassistance
Tracheaposition	Trachea position	One Level
Transferaid	Transfer aid	No clinical significance

Transferequipment	Transfer equipment	No clinical significance
Transferfrom	Transfer from	No clinical significance
Transferto	Transfer to	No clinical significance
Washingassistance	Washing assistance	Combined with Bathingsupportprovided

Appendix J: Final Variables for Each Dataset

Included Variables for each dataset	Variables Names	Datasets by percentage							
		20%	30%	40%	50%	60%	70%	80%	90%
BradenScaleactivity	Braden Scale activity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BradenScalemobility	Braden Scale mobility	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BradenScalemoisture	Braden Scale moisture	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BradenScalerisklevel	Braden Scale risk level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BradenScalesensoryperception	Braden Scale sensory perception	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BradenSkinRiskAssessmentScore	Braden Skin Risk Assessment Score	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Edema	Edema	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GCSscore	GCS score	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GlasgowComaScaleEyeOpening	Glasgow Coma Scale Eye Opening	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GlasgowComaScaleMotorResponse	Glasgow Coma Scale Motor Response	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GlasgowComaScaleVerbalResponse	Glasgow Coma Scale Verbal Response	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Levelofconsciousness	Level of consciousness	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nothingbymouth	Nothing by mouth	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Oxygentherapydeliverymethod	Oxygen therapy delivery method	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Painassessment	Pain assessment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pulseoximetryoxygensaturation	Pulse oximetry oxygen saturation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respiratorydepth	Respiratory depth	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respiratorypattern	Respiratory pattern	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respiratoryrate	Respiratory rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Skinmoisture	Skin moisture	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Skintemperature	Skin temperature	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temperature	Temperature	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Workofbreathing	Work of breathing	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bowelsoundpresent	Bowel sound present	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bestcaprefill	Best cap refill	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
infected	infected	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bowelflatuspresent	Bowel flatus present	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Breakfastamountconsumed	Breakfast amount consumed	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Currentfeedingsupportrequired	Current feeding support required	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lunchamountconsumed	Lunch amount consumed	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Toiletingassistance	Toileting assistance	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Urinecolour	Urine colour	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Urineoutputadequate	Urine output adequate	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bestlegstrength	Best leg strength	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bathingsupportprovided	Bathing support provided	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Dinneramountconsumed	Dinner amount consumed	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Heartsoundsquality	Heart sounds quality	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Transfersupportprovided	Transfer support provided	No	No	Yes	Yes	Yes	Yes	Yes	Yes
VTEpreventionantiembolicstockingsinuse	VTE prevention antiembolic stockings in use	No	No	Yes	Yes	Yes	Yes	Yes	Yes
VTEpreventionsequentialcompressiondeviceinuse	VTE prevention sequential compression device in use	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Washtypeperformed	Washtypeperformed	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Ambulationdone	Ambulation done	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Foleyused	Foley used	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Bestarmstrength	Best arm strength	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Bestlegpulse	Best leg pulse	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Bedmobilitysupportprovided	Bed mobility support provided	No	No	No	Yes	Yes	Yes	Yes	Yes
Bowelmovementamount	Bowel movement amount	No	No	No	Yes	Yes	Yes	Yes	Yes
BristolChartstoolconsistency	Bristol Chart stool consistency	No	No	No	Yes	Yes	Yes	Yes	Yes
Dressingsupportprovided	Dressing support provided	No	No	No	Yes	Yes	Yes	Yes	Yes
POSSscore	POS Sscore	No	No	No	Yes	Yes	Yes	Yes	Yes
Bestarmpulse	Best arm pulse	No	No	No	Yes	Yes	Yes	Yes	Yes
Airentryadequatethroughout	Air entry adequate throughout	No	No	No	No	Yes	Yes	Yes	Yes
Armdrift	Arm drift	No	No	No	No	Yes	Yes	Yes	Yes
Breathsoundsclearthroughout	Breath sounds clear throughout	No	No	No	No	Yes	Yes	Yes	Yes
Coughstrength	Cough strength	No	No	No	No	Yes	Yes	Yes	Yes
Cyanosis	Cyanosis	No	No	No	No	Yes	Yes	Yes	Yes
Nauseafrequency	Nausea frequency	No	No	No	No	Yes	Yes	Yes	Yes
Oralcaresupportprovided	Oral care support provided	No	No	No	No	Yes	Yes	Yes	Yes
Patientexperiencingconstipation	Patient experiencing constipation	No	No	No	No	Yes	Yes	Yes	Yes

Patientexperiencingdiarrhea	Patient experiencing diarrhea	No	No	No	No	Yes	Yes	Yes	Yes
Patientexperiencingnauseavomiting	Patient experiencing nausea vomiting	No	No	No	No	Yes	Yes	Yes	Yes
Shortnessofbreath	Shortness of breath	No	No	No	No	Yes	Yes	Yes	Yes
Skincolour	Skin colour	No	No	No	No	Yes	Yes	Yes	Yes
Toiletingmethod	Toileting method	No	No	No	No	Yes	Yes	Yes	Yes
Tracheaposition	Trachea position	No	No	No	No	Yes	Yes	Yes	Yes
VTEpreventionanticoagulantordered	VTE prevention anticoagulant ordered	No	No	No	No	Yes	Yes	Yes	Yes
Accompaniedwithchestdiscomfort	Accompanied with chest discomfort	No	No	No	No	No	Yes	Yes	Yes
Bladderincontinence	Bladder incontinence	No	No	No	No	No	Yes	Yes	Yes
Bowelmovementincontinence	Bowel movement incontinence	No	No	No	No	No	Yes	Yes	Yes
Eyecare	Eyecare	No	No	No	No	No	Yes	Yes	Yes
Groomingsupportprovided	Grooming support provided	No	No	No	No	No	Yes	Yes	Yes
Heartsoundsmurmur	Heart sounds murmur	No	No	No	No	No	Yes	Yes	Yes
Heartsoundsrub	Heart sounds rub	No	No	No	No	No	Yes	Yes	Yes
Maintainingbaselinestoolpattern	Maintaining baseline stool pattern	No	No	No	No	No	Yes	Yes	Yes

Outputurine	Output urine	No	No	No	No	No	Yes	Yes	Yes
Outputtotal	Output total	No	No	No	No	No	Yes	Yes	Yes
BradenScalefrictionandshear	Braden Scale friction and shear	No	No	No	No	No	No	Yes	Yes
BradenScalenutrition	Braden Scale nutrition	No	No	No	No	No	No	Yes	Yes
Changeinbaselinebowelpatterncontinence	Change in baseline bowel pattern continence	No	No	No	No	No	No	Yes	Yes
Changeinbaselinevoidingpattern	Change in baseline voiding pattern	No	No	No	No	No	No	Yes	Yes
Cornealreflexleft	Corneal reflex left	No	No	No	No	No	No	Yes	Yes
Cornealreflexright	Corneal reflex right	No	No	No	No	No	No	Yes	Yes
Coughproductive	Cough productive	No	No	No	No	No	No	Yes	Yes
Heartsoundsmechanicalvalveclick	Heart sounds mechanical valve click	No	No	No	No	No	No	Yes	Yes
Leftlegpainwithpassivemotion	Left leg pain with passive motion	No	No	No	No	No	No	Yes	Yes
Leftlegprogressiveseverepain	Left leg progressive severe pain	No	No	No	No	No	No	Yes	Yes
Neurovascularleftfoottemperature	Neurovascular left foot temperature	No	No	No	No	No	No	Yes	Yes
Neurovascularrightfoottemperature	Neurovascular right foot temperature	No	No	No	No	No	No	Yes	Yes

Oxygentherapydeliveryrate	Oxygen therapy delivery rate	No	No	No	No	No	No	Yes	Yes
Rightlegpainwithpassivemotion	Right leg pain with passive motion	No	No	No	No	No	No	Yes	Yes
Rightlegprogressiveseverepain	Right leg progressive severe pain	No	No	No	No	No	No	Yes	Yes
SleepaidPRNgiven	Sleep aid PRN given	No	No	No	No	No	No	Yes	Yes
Specialtyskinproductused	Specialty skin product used	No	No	No	No	No	No	Yes	Yes
Subcutaneousemphysema	Subcutaneous emphysema	No	No	No	No	No	No	Yes	Yes
Urinarycatheterinsituandpatent	Urinary catheter in situ and patent	No	No	No	No	No	No	Yes	Yes
Acuteonset	Acute onset	No	No	No	No	No	No	No	Yes
Bladderscanvolume	Bladder scan volume	No	No	No	No	No	No	No	Yes
CAMresult	CAM result	No	No	No	No	No	No	No	Yes
Coughreflex	Cough reflex	No	No	No	No	No	No	No	Yes
Disorganizedthinking	Disorganized thinking	No	No	No	No	No	No	No	Yes
Fluctuatingcourse	Fluctuating course	No	No	No	No	No	No	No	Yes
Gagreflex	Gag reflex	No	No	No	No	No	No	No	Yes
Heelpressurereliefmethod	Heel pressure relief method	No	No	No	No	No	No	No	Yes

Inattention	Inattention	No	No	No	No	No	No	No	Yes
Urinarycatheterassessment	Urinary catheter assessment	No	No	No	No	No	No	No	Yes
Urinarycathetersecurementdeviceinuse	Urinary catheter securement device in use	No	No	No	No	No	No	No	Yes
Requiremobilityaid	Require mobility aid	No	No	No	No	No	No	No	Yes

Appendix L: Certificate of Ethical Approval for Harmonized Minimal Risk Clinical Study

Fraser Health

Certificate of Ethical Approval: Renewal for Harmonized Minimal Risk Clinical Study

Fraser Health Research Ethics Board
Suite 400
13450-102nd Avenue
Surrey, BC V3T 0H1

Also reviewed and approved by:

- **University of Victoria**

Principal Investigator:	**Primary Appointment:**	**Board of Record REB Number:**	**REB Number: H21-01398**
Abdul Roudsari			PAA #: H21-01398-A002

Study Title:
Improving Situation Awareness to Reduce Healthcare Acquired Urinary Tract Infections

Approval Date: November 14, 2023 **Expiry Date: November 14, 2024**

Research Team Members: Yaser Alqarrain

Sponsoring Agencies: N/A

Documents included in this approval: N/A

This ethics approval applies to research ethics issues only and does not include provision for any administrative approvals required from individual institutions before research activities can commence.

The Board of Record (as noted above) has reviewed and approved this study in accordance with the requirements of the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans (TCPS2, 2018).

The "Board of Record" is the Research Ethics Board delegated by the participating REBs involved in a harmonized study to facilitate the ethics review and approval process.

In respect of clinical trials:

1. The membership of this Research Ethics Board complies with the membership requirements for Research Ethics Boards defined in Part C Division 5 of the Food and Drug Regulations;
2. This Research Ethics Board carries out its functions in a manner consistent with Good Clinical Practices.
3. This Research Ethics Board has reviewed and approved the clinical trial protocol and informed consent form for the trial which is to be conducted by the qualified investigator named above at the specified clinical trial site. This approval and the views of this Research Ethics Board have been documented in writing.

This study has been approved either by the Board of Record's full REB or by an authorized delegated reviewer.

Appendix M: Letter of Authorization to Conduct Research

fraserhealth
Better health. Best in health care.

FRASER HEALTH LETTER OF AUTHORIZATION TO CONDUCT RESEARCH

File Number: 2021137 **RISe Number** (if applicable): H21-01398

Study Title: Improving Situation Awareness to Reduce Healthcare Acquired Urinary Tract Infections

Principal Investigator: Roudsari, Abdul

Primary Appointment: Non-Fraser Health

Funder/Sponsor: Unfunded

Research Type: Clinical

Institutional Approval Date: November 23, 2021
Certificate of Initial Ethical Approval Date: November 19, 2021

All necessary hospital program/resource approvals and institutional agreements/contracts are now in place This letter authorizes the principal investigator to begin research-related procedures in compliance with all Fraser Health research-related and privacy policies. The Letter of Authorization to Conduct Research will remain in effect as long as the Fraser Health Research Ethics Board (FHREB) approval is renewed annually and all amendments submitted are approved as required throughout the duration of this project. The The Letter of Authorization to Conduct Research will expire upon the FHREB receipt and acknowledgement of the study closure report.

Authorized by:

Kate Keetch, PhD
Director, Department of Evaluation and Research Services

Date of Signature: November 23, 2021

Appendix N: TCPS2 CORE Training


PANEL ON RESEARCH ETHICS
Navigating the ethics of human research

TCPS 2: CORE 2022

Certificate of Completion

This document certifies that

Yaser Alqarrain

successfully completed the Course on Research Ethics based on the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans (TCPS 2: CORE 2022)

Certificate # 0000443606 **23 July, 2024**