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Predicting the Risk of Falling with Artificial Intelligence

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Abstract

Background: Fall prevention is a huge patient safety concern among all healthcare organizations. The high prevalence of patient falls has grave consequences, including the cost of care, longer hospital stays, unintentional injuries, and decreased patient and staff satisfaction. Preventing a patient from falling is critical in maintaining a patient's quality of life and averting the high cost of healthcare expenses.

Local Problem: Two hospitals' healthcare system saw a significant increase in inpatient falls. The fall rate is one of the nursing quality indicators, and fall reduction is a key performance indicator of high-quality patient care.

Methods: This quality improvement evidence-based observational project compared the rate of fall (ROF) between the experimental and control unit. Pearson's chi-square and Fisher's exact test were used to analyze and compare results. Qualtrics surveys evaluated the nurses' perception of AI, and results were analyzed using the Mann-Whitney Rank Sum test.

Intervention. Implementing an artificial intelligence-assisted fall predictive analytics model that can timely and accurately predict fall risk can mitigate the increase in inpatient falls.

Results: The pilot unit (Pearson's chi-square = $p<0.028$; Fisher's exact test = $p<0.050$) showed a lower ROF and significant statistical difference from the control unit. There is a significant improvement in nurses' perception of AI post-implementation ($p<0.001$).

Conclusions: AI-assisted automatic fall predictive risk assessment produced a significant reduction if the number of falls, the ROF, and the use of fall countermeasures. Further, nurses' perception of AI improved after the introduction of FPAT and presentation.

Keywords: *Artificial intelligence, predictive analytics, falls, Qualtrics, quality-improvement*

Predicting the Risk of Falling with Artificial Intelligence

Introduction

Background

Patient falls are among the top components influencing patient outcomes in healthcare and are highly preventable among hospitalized patients. The Centers for Disease Control and Prevention (CDC) reported that in the United States, about thirty-six million adults 65 years and older report falling each year; thirty-seven percent of those who fall need medical attention because of injuries (Centers for Disease Control and Prevention, 2021). The high prevalence of patient falls has grave consequences, including increased cost of care, longer hospital stays, unintentional injuries, and decreased patient and staff satisfaction. Injurious falls cause extended hospitalization stays by six to twelve days and added costs from injuries ranging from $19,376 to $32,215 (Dykes et al., 2020). The United States government approximates fifty billion dollars of healthcare expenditures for treating patient falls, and seven hundred fifty-four million is spent on non-fatal falls each year (CDC, 2021)). The comorbidities and mortalities associated with patient fall impact hospitalized patients' quality of life. Fall preventive measures are critical in maintaining the patient's quality of life and averting the high cost of healthcare expenses (Yokota et al., 2017).

Nurses and other clinicians who use the electronic health record (EHR) produce the most information, generating billions of data points per year (Lytle et al., 2021). Information such as Braden Score, vital signs, and intravenous lines from nursing documentation can provide opportunities to recognize risk factors associated with iatrogenic conditions such as falls (Lucero et al., 2018). Iatrogenic conditions are circumstances induced by medical treatment, and falls in the hospital is the most commonly reported iatrogenic condition in medical-surgical units.

Traditionally validated fall risks assessment tools such as the Hendrich II Fall Risk Model (HIIFRM) and Morse Fall Scale (MFS) cannot identify factors that can contribute to falls, such as laboratory results, inadequate nutrition, central nervous system altering medications, and chronic conditions (Moskowitz et al., 2020). With the advancement in technology and the use of artificial intelligence (AI), there is an opportunity to utilize the EHR to identify patients at risk of falling without the added burden on clinicians (Cho et al., 2021). However, the use of AI has been slower for nurses than for physicians and advanced practitioners, which can hinder the creation of a comprehensive individualized risk assessment tool (Lytle et al., 2021). One possible ground for this phenomenon is the potential of AI to disrupt the relationship between healthcare professionals and patient care (Kerasidou, 2019). There is a need to explore how AI complements the clinicians' predictive abilities in human-AI symbiosis (Lee. 2020). Such inquiry will support the Institute of Medicine's (IOM) goal of having 90% of clinical decisions supported by up-to-date clinical information and reflect the best available evidence for better health outcomes at a lower cost in 2020 (Lytle et al., 2021). Despite that, the documentation burden continues to be a significant challenge in nursing, and nurses need help to comply with all the documentation requirements. Nurses need to understand better the value of refining the accuracy and effectiveness of nurse-sensitive data to improve patient outcomes. An enhanced tool that can predict a patient's risk of falling using cognitive computing with AI has the potential to reduce documentation time and guide the nurses' decisions on fall prevention care plans and nursing interventions, thus improving patient outcomes is worth exploring.

Problem Description

In FY22, the two-hospitals health systems saw a significant increase in patient falls. The rate of falls went up from 1.455 in FY21 to 2.12 in FY22. Reducing hospital-acquired conditions

(HACs) became the quality goal for FY23. HACs are conditions a patient develops while hospitalized and could cause significant harm (Agency for Healthcare Research and Quality, 2023). The HAC index comprises five conditions: non-ventilated Hospital-acquired pneumonia, clostridium difficile, hospital-acquired pressure injury, surgical site infections, and falls.

As a Magnet-designated facility, the number of falls is benchmarked with other Magnet facilities and is submitted to the Nursing Database of Nursing Quality Indicators (NDNQI). While the health system performs better than other facilities, harm prevention is the top priority as the organization embarks on its journey to high reliability. Evidence-based fall prevention measures include visual monitors, purposeful hourly rounding, bed and chair alarms, and employee and patient education utilized by staff since 2016. However, falls continue to increase. Accurate prediction of the risk of harm is vital to improving care delivery and outcomes. The project addressed a significant gap in clinical practice and aspired to implement predictive analytics using AI to assess the patient's risk of falling more accurately and timely.

Setting

The setting for the Doctor of Nursing Practice (DNP) project is a Medical/Surgical/Oncology unit of a non-profit, community acute care hospital in Mountain View, California (El Camino Health, 2023). It is in an urban community with approximately three million residents and serves about 400,000 patients annually. The health system employs one thousand three hundred twenty registered nurses aware of the nursing professional shared-governance model. Each nursing unit has a partnership council working on process improvement using evidence-based practices. The Medical/Surgical/Oncology unit had seven falls out of the 6,668 total patient days in FY21 and eleven out of the 9,227 total patient days in FY22. Due to the increased incidence of falls, the Medical/Surgical/Oncology unit was chosen as the pilot unit for the DNP project.

Specific Aim

The primary aim of the DNP project is to use artificial intelligence to reduce the rate of falls in the pilot unit by implementing Epic's Fall Risk Cognitive Computing Risk Model, as evidenced by a lower rate of falls during the implementation phase in the pilot unit and comparing the scores between the pilot unit and a similar medical/surgical unit. Epic, an electronic health record system designed for hospitals and large system practices, uses an ordinal logistic regression program that categorizes patients into three levels of fall risks such as low, medium, or high (Epic, 2020). The Chief Nursing Officer supports the project and is the executive sponsor for implementing the predictive analytics tool (see Appendix A). The following objectives provided significant secondary outcomes.

- Improve the utilization of fall prevention interventions as evidenced by a decrease in the rate of fall (ROF) percentage. The ROF percentage was measured using deidentified patient information on the length of stay and a *yes* or *no* answer indicating a fall.
- Improve the nurses' perception of AI as a fall risk screening tool as measured by a 50% improvement in the pre-test and re-test evaluation on the nurses' knowledge of the fundamental principles of AI using a Mann-Whitney rank sum test. Nurses from the three shifts participate in a survey before and after education and implementation of the Fall Risk Cognitive Computing Model.
- Reduce the nursing documentation time by implementing the EHR-generated fall risk score, assuming one click equals one second. The number of clicks was calculated using the number of inpatient admissions and converted to nursing hours saved.

Available Knowledge

PICO(T) Question

The PICO(T) for this project and supported by the literature is: In medical/surgical/oncology adult inpatient unit, how does the implementation of a Predictive Analytic Fall Risk Tool compared to a nurse-driven Fall Risk Assessment Tool affect the rate of falls (ROF), improve the utilization of fall preventive measures, and improve nurses' perception on the use of artificial intelligence within four months of implementation?

Search Methodology

Based on the PICOT question, available evidence and literature searches were conducted in Cochrane Database for Systematic Reviews, Cumulative Index to Nursing and Health Literature (CINAHL) Complete, PubMed, Scopus, AHRQ Evidence Reports, and the Joint Commission and the CDC websites. Limiters such as year of publication (2017 to 2023), studies in English, and peer-reviewed articles were applied to all database searches for consistency of results and ease of eliminating duplicates. Boolean operators and Medical Subject Headings (MeSH) allowed mapping concepts and synonyms, yielding more valuable articles for review. The use of *search words* such as "fall prevention tool" AND "predictive analytics" in the Cochrane Database yielded fifteen articles. Using the advanced search box for PubMed, it produced 1,238 articles with the following search terms: fall prevention tool, hospitals, and fall screening. Upon adding the term "predictive analytics" and "artificial intelligence," the result went down to eighteen articles. The Scopus database displays articles that show every phase of the editorial process making it more user-friendly and saving much time when doing article reviews.

The year of publication is presented in an order showing the most recent to the top, making it easier to eliminate older articles that add no value to the literature search. Articles that included pediatric patients were automatically excluded since the project is focused on adult inpatients. Peer-reviewed articles with low sample sizes, systematic reviews that do not have the results, and studies that did not help answer the PICOT questions were excluded. The final yield was nineteen articles manually reviewed and appraised using the Johns Hopkins Nursing Evidence-Based Practice (JHNEBP) Research Appraisal tools.

Integrated Review of the Literature

The integrated review of evidence includes nineteen articles published between 2017 to 2021 (see Appendix B). Utilizing the JHNEBP tools, the studies were appraised and assigned levels of evidence (LOE) ranging from level I, good-quality, to level III, good-quality studies. Three themes emerged from these integrated reviews: (1) fall risk screenings, assessments, and interventions, (2) the use of technology and EHR as an enhancement in the traditional validated tool; and (3) nursing and clinicians' perception, attitudes, and understanding of AI.

Fall Risk Screenings, Assessments, and Interventions

Falls and related hospital injuries have been a safety and quality care concern for decades. Falls with injuries are considered a serious safety event in acute care settings and other healthcare facilities (Moskowitz et al., 2020). A quasi-experimental study conducted from January 1, 2012, to September 30, 2015, showed that an enhanced fall algorithm (EFA) tool is more accurate in identifying the patient's risk of falling (Moskowitz et al., 2020). The study looked at 171,515 hospital encounters and compared the rate of falls between the Morse Fall Scale (MFS) and the EFA tool. MFS identifies a patient's risk of falling using validated nursing assessment, including the following: fall history, secondary diagnosis, ambulatory assistive device, intravenous therapy or heparin lock, activity, and mental status. Each component included in the MFS is recorded and calculated daily and produces a score that determines the low, medium, and high risk of falling. The EFA included variables not used in the MFS tool, such as laboratory results, nursing assessments, medications, patient demographics, and Location. The result showed differences in the fall risk scores between MFS and EFA. The low-risk group increased from 52.8% to 66.5%, the medium-risk decreased from 19.2% to 17.4%, and the high-risk decreased from 28% to 16.2%. The model discrimination showed a concordance or c-statistics of 0.836 for EFA versus 0.688 for MFS. The result shows a statistically significant improvement in identifying the patient's risks more accurately using the EFA tool.

An observational case-control study looking at iatrogenic conditions mainly falls, and the variables that increase a patient's risk of falling was conducted from January 1 to October 31, 2013. Iatrogenic conditions are conditions induced by medical treatment and are preventable (Lucero et al., 2019). Fall risk assessment tools such as the STRATIFY scale, HIIFRM, and the MFS provide a risk score. However, the substantial variation in the variables used to calculate the risk makes predicting a fall challenging (Lucero et al., 2019). Medications, laboratory abnormalities, test preparations, and lack of activity contribute to falls. However, two of the factors commonly included in fall risk tools are the gender and age of patients, which are not alterable by any nursing intervention. Variables considered actionable factors, such as mobility and elimination patterns, are used less frequently in predictive analyses. After reviewing 814 samples, the study showed the significance of the following risk factors contributing to falls: age, gender, fall risk assessment, history of falling, mental status, mobility, and confusion. Additionally, a new set of risk factors, such as the number of fall-risk increasing drugs (FRIDs), hemoglobin level, physical initiation, Charlson Comorbid Index (otherwise known as severity of illness), nurse skill mix, and registered nurse staffing ratio. Lucero et al. (2019) concluded the significance of combining data-driven and practice-based approaches to identify more accurate fall risk factors.

Jung et al. (2019) conducted a study that evaluated the HIIFRM and looked at modifying fall risk interventions based on the patient's risk factors. A screening tool that can identify high-risk patients and the factors that can modify and mitigate such risk factors is crucial in fall prevention (Jung et al., 2019). One hundred sixty-five variables were extracted from the clinical practice guidelines for fall prevention from the following sites: World Health Organization (WHO), AHRQ, National Institute for Health and Clinical Excellence, Registered Nurses Association of Ontario, Australian Commission on Safety and Quality, Ministry of Health in Singapore, and the Hospital Association in Korea. Lower limb weakness was the most significant risk factor for falling because the ability of lower limb muscles to generate adequate force is a fundamental component in maintaining gait and balance (Jung et al., 2019). The prediction model for falls yielded greater predictive power than HIIFRM and was used to identify strategies focused primarily on patient education and modification of environmental hazards. The information from the study was used to create a clinical decision tree that predicts a patient's risks and provides evidence-based interventions based on the predicted risks and specific risk factors.

Hendrich et al. (2020) conducted a retrospective case-control study to validate the predictive ability of the HIIFRM and identify intrinsic factors that cause patient falls. HIIFRM consists of eight variables: mental status, symptomatic depression, altered elimination, dizziness/vertigo, two classes of medications (anti-epileptics and benzodiazepines), gender, and functional status. Intrinsic factors such as delirium, polypharmacy, dehydration, and decreased mobility cannot be captured by the HIIFRM but have shown promise for reducing falls (Hendrich et al., 2020). The result shows HIIFRM's specificity of 64.07%, a sensitivity of 78.72%, an area under the receiver operating characteristic curve (AUROC) of 0.765 with a standard error of 0.008, 95% confidence interval of 0.748, and $p<0.001$. The accuracy of the HIIFRM to predict falls is acceptable. However, the long-standing fall reduction goals caused the artificial reduction of AUROC, affecting the accuracy of results.

Pre-hospitalization information can be valuable in predicting a patient's risk of falling. Tago et al. (2020) conducted a retrospective cohort study from April 2012 to January 2015 to develop and validate an "easier to use" predictive model for falls. The study utilized public information from Japan's Ministry of Health, Labour and Welfare (MHLF) and included "bedriddenness" as a fall predictor. Two predictive models were created – one with seven factors and thirteen. Factors included were age, male, emergency admission, use of ambulance, referral letter, admission to internal medicine and neurosurgery, hypnotic medications, permanent disability from stroke, history of falls, visual impairment, independence of eating, and bedridden for Model 1. Age, use of ambulance, referral letter, admission to internal medicine, visual impairment, and permanent disability from stroke were excluded in Model 2. The two models had no significant difference in the predictability of risk for falls. Model 2 was the more user-friendly tool because of its simplicity and ease of use.

While most studies looked at the validity, predictability, and dependability of fall risk screening tools, Jellette et al. (2020) investigated the impact of removing a fall screening tool on the number of falls, injuries, and completion rate of all fall activities by staff. The Peninsula Health Fall Risk Assessment Tool (PHFRAT) is a tool that combines screening, assessment, and intervention. The fall risk screening tool requires staff to complete four sections: (1) fall history,

(2) medications, (3) psychological, and (4) cognitive status of the patient. Patients screened as medium or high risk go through an entire risk factor assessment, after which staff selects intervention focusing on behavior management, mobility, continence, environment, and medical concerns. The goal of removing the risk screening is to decrease resource utilization by 8% and redirect the time spent screening for the implementation of fall prevention strategies. The result showed an incidence rate ratio (IRR) of 0.84, 95% CI of 0.67 to 1.05, $p=.14$, which shows a favorable result. Similarly, the fall rate with serious injury resulted in an IRR of 0.90, 95% CI of 0.26 to 3.09, $p=.87$. There was also a thirty-six-second reduction in time to complete fall prevention paperwork.

Tricco et al. (2017) demonstrated that no one intervention could prevent a patient fall. In a study to identify fall prevention programs that may effectively reduce falls with injuries in older adults, 238 randomized control trials (RCTs) and 54 network meta-analyses were reviewed. Previous RCTs and systematic reviews looked at selective fall prevention programs limiting the understanding of fall prevention interventions. Interventions coded in broad categories were: basic fall risk assessment, calcium and vitamin D supplementations, cognitive behavioral therapy, devices, diet modification, electromagnetic field therapy with whole body vibration, environmental assessment and modification, exercise, floor modifications, multifactorial assessment and treatment, osteoporosis medications, podiatry assessment and treatment, social engagement, surgery, and vision assessment. The result of the meta-analysis proposed that combining interventions help prevent falls. The four interventions were: (1) exercise, odds ratio (OR) of 0.51, CI of 0.33 to 0.79, (2) combined exercise, and vision assessment and treatment, OR of 0.17, 95% CI of 0.07 to 0.38, (3) combined exercise, vision assessment and treatment, and environmental assessment and modification, OR of 0.30, 95% CI of 0.13 to 0.70, and (4) combined clinic-level quality improvement strategies, multifactorial assessment, and treatments, OR of 0.12, 95% CI of 0.03 to 0.55. The study showed that each group of combined interventions was associated with better outcomes and a significant reduction in the rate of injurious falls.

The Fall Tailoring Interventions for Patient Safety (TIPS) toolkit is a nurse-led, evidence-based intervention that individualizes care depending on specific risk factors. A nonrandomized controlled trial using a stepped-wedge design study on combining non-technology and high-technology approaches as a fall prevention toolkit showed that this approach resulted in a significant reduction in the rate of falls and a 34%reduction in the rate of injurious falls (Dykes et al., 2020). The non-technological approach included laminated Fall TIPS posters displayed at the bedside. In contrast, the high-technology approach involved the color-coded clinical decision support linked to the MFS and the appropriate preventive interventions. Both approaches allowed continuous patient and family engagement in the fall prevention program.

Use of Technology and EHR as an enhancement in the traditional validated tool

Lytle et al. (2021) conducted a consensus-based, qualitative, descriptive, retrospective observational study and reviewed twenty-seven million patient encounters in sixty-seven hospitals and four clinics. Its purpose is to define the process of standardizing EHR flowsheet documentation for better information exchange, quality enhancement, and expansive data exploration. The metadata produced from the nursing flowsheet and discreet data from periodic and repeated documentation is labor-intensive, yet nurses find little value in the information (Lytle et al., 2021). Complex workflows, accreditation requirements, and regulatory mandates added to the documentation burden. Further, nursing hours are bundled with room charges, so there are no incentives to appraise nursing documentation contributions to patient outcomes.

Using FloMap software, mapping and grouping EHR data into concepts form the information model (IM) that helped create content format and standard documentation workflow to support clinical and financial decision-making. A fall prevention IM, which includes nursing assessment, interventions, and outcomes, became available for data comparison across organizations. This concept showed the significant contribution of nursing documentation in identifying the patient's risk factors and improving patient outcomes.

EHR has been adopted in healthcare organizations, making large quantities of clinical data available for research and advanced clinical practice (Cho et al., 2019). Utilizing nursing records to create a predictive model to assess a patient's risk for falling was the focus of the retrospective cohort study conducted in two tertiary hospitals with different EHR systems and risk assessment tools. The Predictive Bayesian Model was compared with HIIFRM and STRATIFY tools. The predictive model showed an error rate of 11.7% and c-statistics of 0.96, superior performance compared to HIIFRM and STRATIFY. This study showed that a risk prediction model could improve the identification of patients likely to incur a fall (Cho et al., 2019).

A follow-up study by Cho et al. (2021) reviewed the impact of an electronic analytic tool for predicting falls and the nurses' response to patients' risks. The study was done in twelve medical-surgical units. Six units assessed the patients using the electronic tool (Intervention group = IG), and the other six used STRATIFY (Control group = CG). The project implemented at the IG was called Intelligent Nursing @ Safety Improvement Guide of Health Technology Systems (IN@SIGHTS). Of the 42,476 admissions, 707 patients incurred a fall, and 134 of those who fell had injuries. There was an increase in the mean fall rate in the CG from 1.95 to 2.11 and a decrease in the IG from 1.92 to 1.72. The mean fall rate decrease revealed that the analytic tool could lower falls and increase staff awareness of the patient's risk of falling, leading to positive changes in the nursing intervention (Cho et al., 2021).

Studies on the effects of pharmacology as a fall risk contributor are limited (Choi et al., 2018). Fall risk-increasing drugs (FRIDs) must be examined for their effects on the overall risk so clinicians can make the necessary adjustments in medication administration and therapeutic dosing. Choi et al. (2018) constructed a dynamic EHR-based fall risk prediction model for hospitalized patients given FRIDs in the first five days of admission. The AHRQ Fall Prevention Toolkit, the American Geriatric Society Beers Criteria, and expert opinion were referenced in high-risk FRIDs and low-risk FRIDs (See Evidence Table in Appendix A). The predictive model was compared to MFS, which included six MFS items, FRIDs, comorbidity, laboratory results, demographic, visual, and gait impairment. The study showed an unbiased c-statistics of 0.69 versus 0.62, demonstrating improvement in the model's predictive validity using FRIDs compared to MFS. The clinical implications of this study prove the need for evaluation and dose adjustments of FRIDs to lower the patient's risk for falling. Additionally, automation and accuracy of risk screening proved worth exploring.

The timing of risk evaluation and re-evaluation is crucial as the patient's condition changes (Yokota et al., 2017). Most risk assessments are done on admission and when a patient's status changes. Performing a re-evaluation entails clinicians searching for previous assessments and observing patient behavior and responses, which adds to the documentation burden on the nurses. The Find Fall Risk of Inpatients from Nursing Data (FiND), a discriminant model, was constructed to evaluate if a patient fall could be prevented using data from the previous day's nurse note. The FiND includes patient status, treatments from the previous day, and patient attributes for the day. The model showed a sensitivity of 64.9% and a specificity of 69.9%, which meant the model provided an objective evaluation without adding to the nurses' workload.

There were concerns about the accuracy of the represented values for patients at various times and sources in predicting the patient's risk for falling because assessments are done on admission, and values frequently change (Jung et al., 2019). Using logistic regression, Cox PH regression, and a decision tree, a risk prediction model was created with EHR data documented at the point of care and at different times and sources. The prediction model was compared to the HIIFRM and showed that 52 of the 158 features were statistically significant at $P<.05$, showing that the EHR data could accurately provide the patients' risk status.

Nursing and Clinicians' Perception, Attitudes, and Understanding of AI

The emergence of AI, the advancement of healthcare informatics, and the ability of AI to transform clinical care have received permeating attention, particularly over the last decade (Abdullah & Fakieh, 2020). A non-experimental survey using a revised Likert Scale questionnaire explored healthcare employees' perceptions and attitudes toward implementing AI in Saudi Arabia. Nurses were the majority of the participants, ages 20 to 40, with almost half of the respondents having a bachelor's degree. The results show that healthcare workers in Saudi Arabia moderately accept AI. The responses indicated concerns that AI would eliminate the nurses' jobs. While AI can process data and information quickly, accurately, and efficiently, 65% of respondents did not trust that AI can deliver clinically relevant and high-quality data in real-time (Abdullah & Fakieh, 2020). Training on AI's advantages, challenges, and potential to improve healthcare processes and efficiencies could improve healthcare employees' acceptance and appreciation of AI. Further, the government and universities' role is crucial in promoting and advancing the use of AI.

Teng et al. (2022) performed a non-experimental cohort study in eighteen universities across Canada to explore and identify knowledge gaps in the knowledge of Canadian students regarding AI, how healthcare students differ in perspective on AI, and recognize how to incorporate AI into the healthcare curriculum. Using the 11-point Likert scale, slider, and narrative questions, 78.77% of students responded that AI would affect their careers, and 74.5% reported a favorable outlook toward AI. Students suggested incorporating basic AI into the curricula.

Akbar et al. (2021) conducted a systematic review of twenty-eight articles to understand the different decision support systems (DSS) involving two nursing care plans (NCP) steps: the assessment and the intervention. The review result showed that 82% of the nursing assessment utilized a DSS, and 86% of the interventions benefited from the DSS. The systematic review demonstrated increased use of DSS in the clinical setting. However, the awareness of the benefits of DSS automation is understudied (Akbar et al., 2021). One implication of this systematic review is to involve the nurses in designing and implementing DSS. Additionally, understanding the readiness of the clinical staff in the use of technology and AI is a significant step in DSS automation.

Summary/Synthesis of the Evidence

Nineteen articles were reviewed, evaluated, and included in the literature reviews (see Appendix B). The themes that emerged were (1) fall risk assessments, screenings, and interventions, (2) the use of predictive analytics, AI, and EHR, and (3) the clinicians' perception, attitude, and understanding of AI. All articles were pertinent in answering the PICOT question. While not all articles were appraised as high quality, they provided relevance and context to the project.

The use of technology in predicting the patient's risk for falling is promising. Embedded information from clinician documentation could help create clinical decision support to assist in an individualized approach to fall prevention. The timing of the fall risk screening and assessment also proved critical, and re-evaluating the patient's risk using nursing documentation at the point of care can prove beneficial as the patient's condition changes.

Evidence shows that simple strategies such as laminated sheets, visual cues, and audits effectively reduce falls. Multiple fall prevention interventions and patient and family involvement lower the relative risk of injurious falls. Additionally, other risk factors such as laboratory results, medications, vision, and patient activities documented in EHR can enhance fall prediction using computer technology.

Removing the fall risk screening tool had no adverse effect on the rate of falls. Redirecting nursing hours to completing risk factor assessment and providing fall prevention interventions proved beneficial, as shown in decreased nursing documentation time and lower fall incidences. While this study result does not answer the PICOT question, it supports the importance of accurate risk factor assessment, appropriate fall interventions, and decreased nursing documentation time.

The Institute of Medicine Roundtable on Evidence-based Medicine aims to have 90% of clinical decisions supported by accurate, timely, and up-to-date clinical information by 2020. This goal made the interoperability of nurse-driven data a priority because healthcare organizations are incentivized for meaningful use of EHRs. Standardizing the EHR flowsheet documentation improves data exchange and supports quality and research. It provides metadata and helps in the creation of several fall risks screening and assessment models such as the Falls TIPS, Enhanced Fall Algorithm tool, Peninsula Health Fall Risk Assessment Tool, Predictive

Bayesian Model, Intelligent Nursing @Safety Improvement Guide of Health Information Technology Systems, and the Fall Risk of Inpatients From Nursing Data. AI made intrinsic fall risk variables such as fall risk-inducing drugs (FRIDs) and laboratory results readily available.

The use of AI in healthcare continues to be a subject in recent studies. Nurses have shown reluctance to AI's use in healthcare in previous studies. Nurses' perception and acceptance of the applicability and reliability of AI in the clinical setting need to be understood better. There is an opportunity for the government and universities to include AI in the curricula to improve clinicians' understanding of the significance of AI in improving clinical outcomes.

The concept of enhancing fall risk screening tools has been discussed in the last ten years, yet little evidence has been shared. Evidence proved that new risk factors enhances validated tools using AI. Technology can bridge the gap between clinical presentation and documentation—standardization, documentation reporting, and data sharing promise to improve care delivery.

Rationale

Two theories are combined to form the conceptual framework that guided this evidence-based, practice change, quality improvement project – Locsin's Theory of Technological Competency as Caring in Nursing (TCCN) and Lewin's Change Theory. Nursing practice centers on caring for patients and involves the dynamic nurse-patient relationship requiring nurses to focus on patient needs through observation and interaction. This concept helps formulate a framework for patient safety (Locsion, 2016). This process describes nurse-patient communication. Today, nurse-patient communication integrates complex and constantly changing patient needs with technology. While caring is primarily associated with human relationships, Locsin's theory of TCCN demonstrates that *knowing the person* is a *multidimensional process* that can *utilize technology* in caring for individuals. Further, the theory describes that technology provides an opportunity for interaction and allows nurses to know the patient better using information previously collected and documented in the EHR.

Nursing documentation was computerized over a decade ago, and nurses' responses to these changes vary (Bozak, 2003). Using technology for bar code administration, bedside documentation, and EHR to create a clinical decision support (CDS) system guides the nurses in providing the best care pathways for patients. With AI, fall predictive models and CDS are created. Introducing a change in practice using technology would shift the nursing workflow from manually inputting fall risk screening to using the fall predictive analytics tool. For this change to occur successfully, the project leader must know the factors that encourage or impede change. Strategies must be in place for nurses to accept the change.

The Three-Step Change Theory demonstrated Lewin's interest in social and organizational change (Burnes, 2020). This theory was later used to understand group dynamics and how it shapes the behavior of team members. Burnes (2020) explained that Lewin's approach is due to the construct that action depends on perceptions; therefore, fact-finding or investigation is crucial to understanding a situation. Nurses' perceptions and readiness for change must be understood before introducing a change in current practice.

Lewin's Change Theory provided the structure for understanding the organizational culture, particularly the nurses' attitudes before, during, and after the project. Lewin's Change Theory has three distinct and essential stages: unfreezing, change or movement, and refreezing. The theory is often used in planned organizational change and is one of the most robust change management theories (Burnes, 2020).

The first stage of the Change Theory is the *unfreezing stage.* In this stage, the need for change could involve discomfort, apprehension, and disagreement among the team (Bozak, 2003). The organization's goal of reducing falls was presented, and it was at this stage team members agreed to change current practice and let go of the old way of doing. It is crucial to acknowledge that driving forces could move positively, and the restraining factors must be eliminated.

In the unfreezing stage, AI and predictive analytics were shared with stakeholders, the Fall Prevention Committee, the Direct Care Informatics Committee, the Quality Department, and the pilot unit. The Medical/Surgical/Oncology unit was chosen as the pilot unit and was instructed to use the Fall Predictive Analytics Tool (FPAT) instead of the HIIFRM.

The second stage is *changing* or *moving to a new level.* In this stage, the pilot unit staff understands the need to switch to the PFAT model. The PFAT model became the primary tool for assessing the patient's fall risk, and nurses were not required to complete the HIIFRM. The risk scores produced by FPAT guided the staff nurses' clinical decisions on activating the different fall prevention strategies.

The third and final stage, *refreezing,* must be achieved after implementing the new process. New habits will become the norm or part of the nurses' standard work in this stage. It is vital to ensure that refreezing is achieved to prevent backsliding into the old ways. Once the desired results are achieved, FPAT becomes the fall risk screening tool. The rate of falls will be monitored and reported in the organization's quality dashboard. It is crucial to ensure that nurses receive ongoing support, reward departments with low fall risk rates, and monitor the overall fall risk rate of the organization.

Predictive analytics is assumed to improve the accuracy of the patient's risk for falling based on the literature and evidence presented in the studies by Jung et al. (2019), Yokota et al. (2017), Choi et al. (2018), Cho et al. (2021), and Lytle et al. (2021). This DNP project measured the effect of FPAT (independent variable) on the rate of falls (dependent variable), the nurses' perception of predictive analytics, and the nursing compliance with using fall prevention strategies to prevent falls based on the FPAT score. The overall outcomes of the studies were positive and worth replicating.

Methods

Context

The DNP project is an initiative that aligns with the organization's strategic goals to achieve zero preventable harm. The project site in a health system consists of two acute care hospitals and several primary care, multi-specialty, and urgent care clinics across Santa Clara County in California. Patient falls in hospitals are considered preventable, and AI can potentially identify at-risk patients timelier and more accurately. The increase in the number of falls and the significant injuries that resulted from the fall warranted a higher focus on fall prevention. Further, being a four-time designated Magnet facility, it is essential to focus on nurse-sensitive quality care indicators, fall being one of the indicators. Additionally, leveraging technology for fall prediction supported the recognition received by the organization from the College of Healthcare Information Management Executives (CHIME) as one of the 2021 and 2022 Digital Health Most Wired Organizations worldwide (El Camino Health, 2023).

Numerous stakeholders support the DNP project. The Chief Nursing Officer, Chief Information Officer, and Chief Informatics Medical Officer approved the project implementation. Additionally, the Fall Prevention Committee, the Nursing Informatics Team

(IT), and Direct Care Informatics Committee (DCIC) supported the implementation of the FPAT. The DCIC, whose members are direct care staff, provided feedback on how best to implement the tool in the pilot unit. The Nursing IT and clinical documentation team provided support in the back end and ensured the predictive model was behaving as designed.

The number of falls per unit is discussed in the Fall Prevention Committee's monthly meetings and displayed in Tableau and the unit's visual management board. Fall occurrences are reported daily at the Enterprise huddle, where learnings and opportunities to prevent falls are shared. The daily discussions of harm-related events, particularly that of falls, created a heightened awareness of the need for a practice change: using FPAT for fall screening to lower the number of falls.

Intervention(s)

Epic's Fall Predictive Analytics is a tool that uses AI to scope, learn, and cognitively compute the patient's fall risk score based on multiple variables known to contribute to falls. The FPAT was implemented in the medical/surgical/oncology unit, and the rate of falls was measured and compared between two periods: (1) four months prior to FPAT implementation and (2) four months using FPAT. The purpose of the FPAT implementation is to measure if there is a significant reduction between the two periods and an improvement in the use of fall prevention strategies. Evaluating if there is a reduction in documentation time can provide valuable information on the positive influence of using AI. It is also necessary to measure the nurses' perception of using AI as an adjunct to clinical assessment and help support clinical decisions in patient harm prevention.

The project site is a thirty-two-bed medical/surgical/oncology unit that reported a fall rate of 1.455 in FY21 to 2.12 in FY22. After reviewing, evaluating, and testing by the clinical analysts and Nursing IT, the DCIC, and Fall Prevention Committee supported the project implementation. The project was then presented to the Internal Review Board of the health system and received the approval to implement the quality improvement, evidence-based project (see Appendix C). All nurses from the pilot unit participated in the pre-implementation survey, after which all nurses received information through an in-person presentation from the project lead about the FPAT. A follow-up survey was completed by the nurses who were part of the pre-implementation survey group. After the predictive model activation, the unit charge and break nurses audited compliance with the fall prevention strategies. During the plan-do-study-act (PDSA) iterations, nurses provided feedback adjustments in the model's calculation timing and modifications in the audit tool. Additionally, in the second month of implementation, nurses discovered that supplies were low on the fall risk armband and the yellow socks. Nurses also reported that the tool is not calculating a risk score on postoperative patients in the post-anesthesia care unit.

The PDSA cycle brought about several discoveries and changes in the current nursing workflow to fall prevention. First, the FPAT was set to calculate and update the score every four hours, and nursing staff modified and adjusted the fall prevention strategies based on the updated scores. The workflow's second iteration focuses on the postoperative patients recovering from anesthesia by performing hourly rounding and activating fall prevention strategies as soon as FPAT generates a risk score. Lastly, fall prevention supplies, such as armbands and yellow socks, are monitored to ensure sufficient supplies.

Gap Analysis

A gap analysis was performed to review the organization's current rate of falls in two fiscal years. The rate of falls significantly increased from FY21 to FY22 (see Appendix D), and reviewing a risk assessment tool using AI is warranted.

In the current state, HIIFRM is the tool used to identify a patient's risk of falling, and a fall risk assessment is performed every twelve hours. Gaps identified with HIIFRM include (1) no triggers to alert the nurses when a patient's condition changes, and (2) the tool does not include intrinsic factors such as laboratory results, vital signs, FRIDs, patient's length of stay, and admitting diagnosis.

There is no information regarding the nursing staff's perceptions of using AI and the effects of using the FPAT in the nursing documentation time. This lack of baseline information may be considered a discovery instead of a gap analysis. The project also aimed to see a correlation between using the FPAT and compliance with fall prevention strategies.

Gantt Chart

The Gantt chart shows the significant tasks completed throughout the project phases. It is helpful in monitoring, adjusting, and redirecting efforts to evaluate the milestones of the project (American Society for Quality, 2022). It also described the progress and dependency of project activities on the timelines.

The project's Gantt chart has six phases: assessment, planning, implementation, evaluation, project completion, and write-up and reporting (see Appendix E). The overwhelming support from the executives is a critical milestone in the planning phase. However, challenges in meeting some of the target dates due to the restrictions imposed by the increasing COVID cases necessitate meeting cancelations. The Gantt chart for this project was adjusted due to IRB approval delays and key team members' resignations. As a result, the Gantt chart had two iterations to reflect the changes in completion dates since project kick-off depended on IRB approval and reassignment of Epic analyst.

Work Breakdown Structure

The work breakdown structure (WBS) is one of the essential project management documents. It represents a collaborative approach between the project leader and team members, with the completion of the project as the ultimate goal (see Appendix F). It consists of three levels, with the project title in the zero position and level one describing key project components. Each box represents a task for completion in the level two work components. Literature reviews, gap analysis, and the conceptual framework guided the development of this WBS.

Level one includes gap analysis, organizational commitment, education, project implementation, finance, and evaluation. Reconciling the literature and the organization's current process is one of the deliverables and helped with gap analysis. The stakeholders' approval of the project, the establishment of a core team, and attendance in planning meetings demonstrated organizational commitment and support. Two critical components in level two are the IRB approval and the establishment of the project team. While several unforeseen events, such as IRB approval delay and team member resignations, happened prior to the project implementation, there was no need to adjust the WBS.

Several PDSAs were completed during the implementation phase, creating workflow and audit tool changes. In this phase, the regular meeting cadence with the project lead, pilot unit nurses, and the informatics team led to the discovery and correction of the frequency of risk score generation from every hour to four hours and created a more stable scoring cadence. The fall risk icon was changed from a yellow triangle to a falling man's image, providing a better visual representation of a person at risk for falling. The pre/post-test and the review of the audits on the staff compliance with the fall prevention strategy based on the risk scores provided an excellent tool for the project evaluation.

The project design and interventions were to be similar to that of the original pilot project. The evaluation phase started after all audit data, pre/post-test results, and the rate of falls in the pilot unit and the "like" medical/surgical inpatient units were reviewed. Because the monthly fall incidence rates are reported monthly at the Fall Prevention Committee meeting showing the pilot unit's significant decrease in the number of falls since the start of the project, the project was expanded to the medical/surgical/telemetry unit in the DNP project site's other hospital beginning mid-February of 2023.

The measure of project completion was the final paper report with the following results:

- Rate of falls and number of falls with injury in the pilot unit compared to the other medical/surgical inpatient unit
- The perception of nurses on the use of AI for clinical decision support
- Compliance of nursing staff on the use of fall prevention strategies based on the FPAT score
- Potential number of clicks saved or reduction in the nursing documentation time from switching to FPAT

Responsibility/Communication Matrix

The responsibility and communication plan matrix clarifies the participation and expectations of the various stakeholders in assuring deliverables and task completion. This matrix ensured that all stakeholders received communications throughout the project (see Appendix G). The responsibility and communication for the project included the objective, timeline, methods of communication, and the person in charge of each task.

The project lead, the DNP student, holds most of the communication and responsibility to ensure that each member receives essential information about the project's development, challenges, and needed support. In-person or Zoom meetings were the primary communication method, and emails went out regularly as a reminder of each team member's tasks and follow-up action items. The project lead reported the progress at the Fall Prevention Committee, the Nursing IT, and DCIC monthly and quarterly at the Patient and Employee Safety Committee meeting. Having the responsibility and communication matrix prevented redundancy of tasks and role confusion, enabling the efficiency and timely execution of the project.

SWOT Analysis

The strengths, weaknesses, opportunities, and threats (SWOT) Analysis is the strategic technique employed by the DNP student which helped identify fact-based and data-driven identification of a current problematic situation (see Appendix H). Three of the identified project strengths can positively impact its success. The first one is the organization's overwhelming support to fall reduction as it aligns with the high-reliability journey. Secondly, Epic has a built-in AI tool that can cognitively calculate a risk score to predict a patient's risk of falling. Lastly, executives are fully committed to seeing through the implementation of this AI model as the organization strives to remain one of the most wired hospitals in the world.

The nurses' reluctance and lack of trust in AI, conflicting multiple priorities, and resource limitations as nurses continue to move across the health system and some leaving the bedside are weaknesses and threats that could affect the success of the project implementation. Integrating technology in providing nurses with the most recent and accurate information to guide them in care planning for fall prevention is exciting and promising.

Comprehensive Financial Analysis

Implementing the AI-assisted Fall Predictive Analytics Tool offers the organization cost-benefit, cost-avoidance, and cost savings. The tool is estimated to produce a cost savings of $120, 227 in three years from the estimated reduction in nursing documentation time and cost-avoidance of $948,828.68 from the reduction of injurious falls (see Appendix I). This innovative quality improvement project would yield an ROI of 5.34 and has a high potential for improving the quality of care with a possible 43.75% reduction in falls and injuries. Demonstrating the potential yearly decline in falls and injuries is a strategy to show the project's cost-effectiveness. It helps build a successful business case for this innovative, quality improvement project.

Preventing patients from falling in the hospital is a persistent challenge. On average, each patient who falls and sustains will stay an additional 6.3 days in the hospital (TJC, 2022). Hospital-adjusted expenses per inpatient day for non-profit hospitals in California is around $4,098 (Kaiser Family Foundation, 2022). The Joint Commission (TJC) worked with seven hospitals on a Robust Process Improvement (RPI) to identify and develop solutions to prevent falls. In aggregate, there was a 62% reduction in the overall falls with injury rate (TJC, 2022). Northwestern Memorial Hospital implemented Epic's Fall Predictive Analytics Tool (FPAT) in Fall 2020 and saw a 43.75% reduction in injurious falls.

The implementation of FPAT in the pilot unit has projected a return on investment (ROI) of 5.35 three years after implementation (see Appendix J). The total expense at the start of the project is primarily from the team's salary of $25,704.08. The unit champions are clinical nurse IIIs in the higher salary bracket than clinical nurse IIs. One hour is allocated for staff training and will cost around $128, 019.3. A four percent inflation for yearly contractual increases and the 10% contingency allowance for newly hired staff are included in the budget consideration. The

AI software cost was separate from the budget and financial analysis because it was purchased in 2015. In years two and three, expenses were minimal at $15, 492.84 and $16, 112.24 respectively.

The project is estimated to produce savings and cost avoidance of $505, 781 from an estimated 43.75% reduction of injurious falls (19 fewer falls), mirroring Northwestern Memorial Hospital's reduction rate multiplied by $25,817.4 (6.3 days x $4,098) per patient in the first year, followed by $159,972.87 or 5.96 less for year two. The cost savings from eliminating HIIFRM documentation is assumed to be $36,978.13 in year one, $39,994.42 in year two, and $43,255.06 in year three. This amount was calculated by multiplying the total number of inpatient encounters by sixteen clicks (the number of clicks needed to document the eight sections of the HIIFRM multiplied by two since fall risk screening is required every twelve hours per hospital policy). The savings from the reduction in nursing documentation time totaled $120,227.61.

Study of the Intervention(s)

Utilizing quantitative data provided a more objective way to assess the project's impact. Implementing an automated fall risk model within the EHR to accurately predict the risk of falling is a tool that can mitigate hospital falls. This study's primary data source is the hospital's quality dashboard and EHR. The hospital's quality dashboard collects and tracks the number of falls and calculates the rate of falls for each unit and the cumulative rate for the enterprise, with the experimental unit using the FPAT and the control unit using HIIFRM. Using descriptive statistics, the Fisher's Exact test, it will show if there is a significant difference in the ROF between the two units. The staff compliance with fall prevention strategies based on the FPAT score will be measured and analyzed based on data from the audit tool utilized by the experimental group. Finally, a pre/post electronic survey was developed using Qualtrics, a web-based survey tool, and provided information on the nurses' perception of using AI as a clinical decision tool for fall prevention.

The Qualtrics survey comprised five questions, and nurses responded to questions 1 thru 4 amongst ranked choices: No = 0, Maybe = 1, and Yes = 2 (see Appendix J). The pre/post-survey results were presented in graph charts to illustrate the distribution of the responses. The responses were analyzed using Mann-Whitney Rank Sum Test. The fifth question was open with a free text response style to collect comments. The comments provided qualitative data that helped augment the evaluation of the FPAT.

Outcome Measures

The number of falls in the pilot unit pre-and post-implementation is the key performance indicator for this project. There were three falls out of the 3,206 (0.94 fall rate) patients admitted in the pilot unit from May 1 to August 31, 2022 (pre-implementation phase), and only one fall out of the 3,299 patients (0.30 fall rate) from September 1 to December 31, 2022 (implementation phase). In contrast, the control unit only had two falls out of the 3,529 patients (0.57 fall rate) from May 1 to August 31, 2022, and nine falls out of the 3,658 patients (2.46 fall rate) from September 1 to December 31, 2022.

The rate of fall (ROF) is vital in conducting an observational project comparing the performance of the experimental and control groups and assessing the effect of FPAT on the number of fall occurrences. Using de-identified EHR data, ROF was calculated using the following patient information: encounter, admission date, length of stay, and fall incidence. Two statistical significance tests, Pearson's Chi-square and Fisher's exact test were utilized in the analysis of the ROF. Both tests help evaluate the two sets of categorical data (Kim & Mallory, 2017). During the pre-implementation phase, there was no difference between the two units

(Pearson's chi-square: *p*-value = 0.510 and Fisher's Exact Test: *p*-value = 0.413). In the implementation phase, the pilot unit using FPAT showed a lower ROF and a significant statistical difference between the pilot unit and the control unit (Pearson's chi-square = *p*-value = 0.028 and Fisher's Exact Test: *p*-value = 0.050). The graphic representation of this result is shown in Appendix K.

The fall prevention strategies utilized based on the FPAT risk scores were audited every shift in the pilot unit using a paper tool. Fall prevention strategies include bed alarm, call light within patient reach, bed at its lowest position, fall risk signage outside patient's door, whiteboard signage, yellow socks, and armbands. The audit tool aims to see if nurses use FPAT to guide their strategies to prevent patient falls. Upon analysis of the audit results, bed alarm activation on the day shift was only 16% in low-risk and 26% in moderate to high-risk patients. Nurses verbalized that bed alarms cause too much noise because patients are constantly in and out of bed due to multiple therapy sessions and other activities. However, bed alarms were activated in the evening (91% in low-risk patients; 83% in high-risk) and night shifts (100% in low-risk patients; 95% in the high-risk group). The low supply of yellow socks and armbands due to supply chain global issues resulted in lower compliance. There is an observable difference in the usage of fall prevention strategies between the patient groups classified by FPAT as low risk and moderate to high risk. While there is better compliance overall on the use of fall prevention strategies, a statistical comparison between the two groups is susceptible to sample size bias due to the difference in their sample sizes.

The DNP student organization intends to implement FPAT in all inpatient units in FY24. This goal influenced the IRB's decision to send the pre/post surveys to all nurses in the pilot unit to have higher participation without making it mandatory. The surveys were sent to nurses via a

QR or quick response code, which helped with the respondents' anonymity. The pre-implementation survey began on August 15, 2022, and was closed on August 30, 2022. Nurses who completed the pre-survey were instructed to complete the post-survey after hearing the AI tool presentation. There were forty-three responses received for the pre-survey and forty-two for the post-survey. The survey had four questions answerable by no, maybe, and yes, and one question with a free text response. The limited answer options made using paired t-tests challenging. An equivalent test, the Mann-Whitney Rank Sum test, was used to show data distribution other than a normal distribution curve. The result showed that all four responses showed a statistically significant difference with a $p<0.001$.

CQI Method and Data Collection Tools

Several continuous quality improvement methods and data collection tools were used for this project. Fall occurrences are reported in the project site's iSafe Reporting system and exported to a dashboard called Tableau. This dashboard helps track each unit's fall rate. In the pilot unit, an audit tool was created to measure nursing compliance with fall prevention strategies based on the FPAT score. The PDSA process helped identify barriers and guided the team's actions to successful project implementation. The pre/post surveys provided an understanding of staff readiness in using AI in their daily work. Using the Qualtrics survey, quantitative information was collected and analyzed from the dichotomous type questions answerable by no (0), maybe (1), or yes (2). This tool helped gauge the nurses' perceptions and attitudes toward AI.

Analysis

This intervention was evaluated by comparing the fall rate in the pilot and control units. Using Pearson's chi-square and Fisher's exact tests, the ROF was calculated and yielded a statistical improvement in the pilot unit compared to the control units. Nursing staff compliance on the use of fall prevention strategies for medium and high fall-risk patients audit results was represented in graphs to show the noticeable improvement.

A pre-and post-assessment of the nurses' perception of AI was measured using a dichotomous survey, and results were interpreted using the Mann-Whitney Rank Sum test. This type of survey question served as a way to create baseline information since this was the first survey to measure the nurses' attitudes and perceptions about this tool before this project. The nature in which the survey was distributed using a QR code made it easier for the participants to answer the survey truthfully. The survey result showed a statistically significant difference in the post-survey showing a considerable improvement in the nurses' perception of the predictive analytics tool.

The objective of documentation time reduction is to give time back to nurses for more meaningful patient interactions. While there is no test to measure the nurses' documentation time reduction, an approximation of time saved from removing sixteen clicks in 24 hours was calculated based on the number of patient encounters. An assumption that one click equals one second demonstrated thousands of hours of nursing documentation time saved.

Ethical considerations

Implementing an AI-assisted fall predictive model is a quality improvement, an evidence-based project designed to accurately identify a patient's fall risk. It is a project approved for implementation by the IRB and the quality department. The goal of this project is to assist in the reduction of falls and falls with injuries. This project's results can also be replicated to help other organizations interested in implementing an AI-assisted fall predictive model to aid in fall reduction.

The American Nurses Association (ANA) Code of Ethics guides the nursing profession and provides a framework for ethical practice and decision-making (ANA, 2015). Nurses in all roles and settings must follow the code and use nursing competencies to protect patients, families, communities, and the public with the utmost respect for the profession and the law. The ANA Provision 4 of the Code of Ethics describes nursing as a professional body with the authority, accountability, and responsibility to make decisions and take actions to promote health and deliver optimal care. DNP-prepared leaders have to supervise direct care staff to ensure that the highest quality of care is always provided to patients. Nurse leaders must ensure nurses have the tools to assess and evaluate their patient's needs and develop the best clinical decisions to protect patients from harm. Eliminating barriers to providing the best care by exploring options to redirect the focus on care provision instead of documentation is responsible leadership. With AI, clinical decision support can be formulated to aid in better patient outcomes.

Jesuit values guided the project's relevance. One of the values states *"the freedom and the responsibility to pursue truth and follow the evidence to its conclusion*" (Gunn et al., 2016). The body of evidence encourages the use of AI in assisting nurses in providing appropriate patient care by accurately identifying risk factors to harm. The hallmark of nursing is its commitment to using the body of knowledge to deliver effective and high-quality service. Putting knowledge into practice through a quality improvement project is applying the pursuit of the truth and using it to prevent patient harm.

Technology added another layer of complexity and functionality to care delivery. Knowing is caring, and the co-existence of caring and technology proved helpful in healthcare (Locsin, 2016). With the widespread adaption of technology in healthcare, nurses must take advantage of this interactive relationship. This project supported Locsin's theory and heeded the Jesuit's call to follow the evidence.

Results

Fall Reduction and Rate of Fall (ROF)

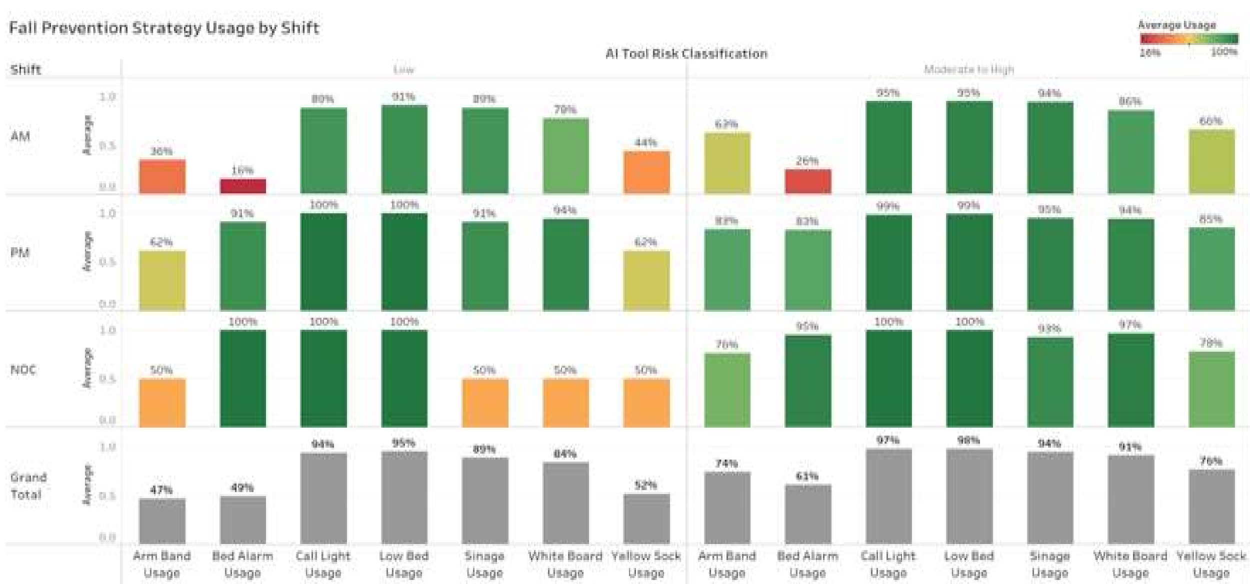
There were eighteen falls in the Medical/Surgical/Oncology unit in FY21 and FY22. The AI-assisted Fall Predictive Analytics tool was implemented from September 1, 2022, until December 31, 2022. Three falls were reported pre-implementation (May 1 through August 31, 2022), while only one was reported during the implementation phase. The reduction of falls was evident pre-and-post FPAT implementation.

The rate of fall (ROF) was calculated using the following data: encounter, admission date, length of stay, and fall incidence. Pearson's chi-square and Fisher's exact tests showed no statistical difference in the ROF between the pilot/experimental and control units' pre-FPAT implementation. However, with the implementation of FPAT, it showed a lower ROF and a statistically significant difference in the ROF between the experimental and control units. This result is represented in Appendix K.

AI-assisted Clinical Decision in Using Fall Prevention Strategies

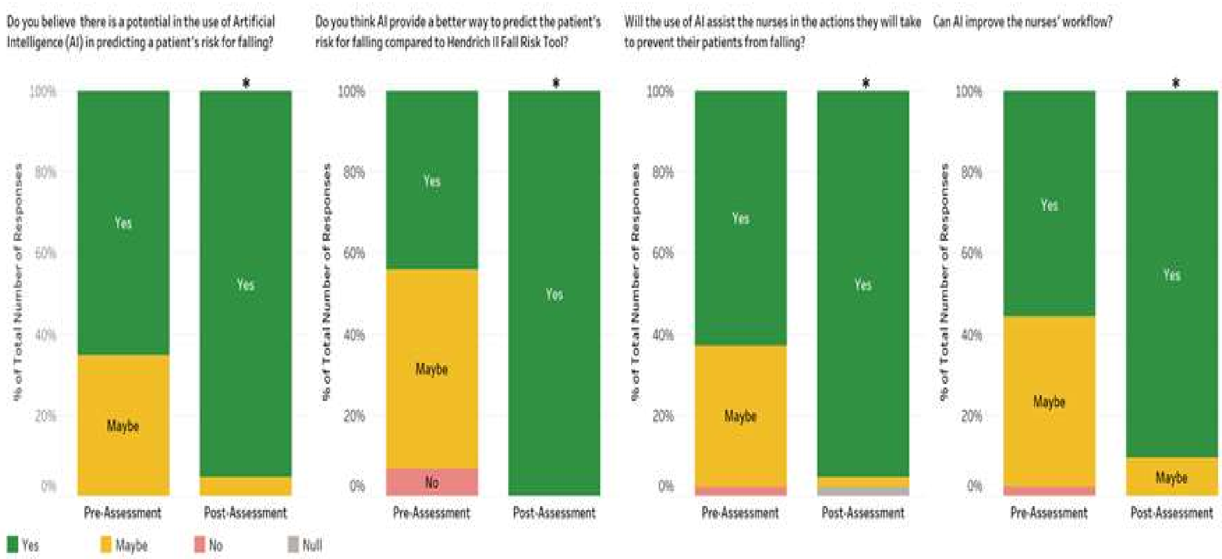
The analysis of fall prevention strategies based on the FPAT risk scores was completed using an audit tool. The audits were conducted in the pilot unit from September 1 to December 31, 2022. During the implementation phase, two significant nursing operational changes took place in the pilot unit; one was a 30% nursing turnover brought about the outpatient Cancer Center nursing vacancies, and the switch from 8-hours to 12-hour shifts in October 2022 to mitigate the short staffing. As a result, the audits were completed every 12 hours instead of every 8 hours. These changes did not affect the audit results.

There is an observable difference in the usage of fall prevention strategies between the patient groups classified by the FPAT as low-risk and the medium-to-high-risk patients. Overall, compliance with using fall prevention strategies with the use of FPAT. However, a statistical comparison between the two groups would be susceptible to sample size bias because of the number of patients categorized in the low-risk and medium to high-risk categories.



Nursing Perception of AI

A presentation about the literature reviews, functionality of the FPAT, variables included in the cognitive computing, and the visual representation of the risk scores were prepared before project implementation. This intervention significantly improved the nurses' positive perception of using AI to help identify fall-risk patients ($p<0.001$). The graph illustrates the distribution of responses as percentages of total responses. Differences in the results are expressed as numerical values and analyzed using the Mann-Whitney Rank Sum test. The responses to all four questions showed an increased value greater than would be expected by chance.



Discussion

Summary

Fall prevention is a priority for safety. Validated fall risk tools such as the Hendrich II Fall Risk Model are user subjectivity and do not have the functionality of pulling information already embedded in the EHR. Based on literature reviews and the promise of technology, the implementation of AI-assisted Fall Predictive Analytics was implemented. This algorithmic model performs data mining of discreet information within the EHR to automatically produce a fall risk score based on variables known to cause a fall.

The implementation of the AI-assisted fall predictive model, FPAT, yielded significant results showing the following:

- There are fewer falls in the pilot unit compared to the control unit and the rest of the inpatient Medical/Surgical units
- The rate of fall (ROF) was significantly lower in the pilot unit compared to the control unit.
- There was a significant improvement in the nurses' perception of using AI to guide them in their clinical decision-making.
- There is potential to decrease nursing documentation burnout by reducing nursing documentation time with automated fall risk prediction.

Interpretation

The finding of this quality improvement project could support a nursing practice change in the nursing workflow from manually entering a risk score using HIIFRM to relying on an AI-assisted cognitively computed predictive analytics model. With a strong interest in the nursing field to lower the nursing documentation burden and increase the nursing time spent on patient interaction, implementing FPAT is timely and warranted.

Two studies conducted by Cho et al. in 2019 and 2021 showed that the risk prediction model could improve the identification of patients likely to fall. In addition, risk assessment timing is crucial to the fall prevention strategies implemented as the patient's condition changes (Yokota et al., 2017). Based on this current knowledge, it is prudent to conduct a quality improvement project to understand the correlation of having a fall predictive tool that can assist in targeted interventions that can be used to mitigate the increasing number of falls in the hospital setting.

One area of concern raised by the Quality and Risk department of the project site is the risk of variability in the fall prevention strategies or countermeasures against the patient's fall risk status. With the automation and the need for more interaction in the risk assessment flowsheet, a concern was raised about what score is considered for the fall prevention strategies utilized by the nurses. Nurses must enter the FPAT score in the fall prevention flowsheet row as required documentation. The strategy mitigated the risk and satisfied the requirement of the Quality and Risk Department.

The American Medical Informatics Association (AMIA) EHR-2020 Taskforce recommended reducing the documentation burden by lowering data entry (2015). Automating risk scores and assessments could improve the efficiency and accuracy of a patient's risk to harm. With the significant improvement in the falls and ROF in the pilot unit, FPAT will be implemented in all the nursing units in the two-hospital health system.

Limitations

The analysis of this observational quality improvement project was conducted retrospectively and could lead to bias. All patients in the pilot unit received an automated FPAT score, which was displayed differently than the HIIFRM. FPAT scores are classified as low, medium, and high with matching color codes. Green for low, yellow for medium, and red for high-risk – this color coding provided a much more intuitive visual reminder to all care team members. Additionally, the image of a man falling gave a better interpretation of a patient's risk than HIIFRM's yellow triangle with an exclamation point in the center. The knowledge of the higher risk score could have influenced the care provided and fall strategies implemented.

The risk score generated by the HIIFRM and the FPAT for each encounter were not compared due to the time limitation to complete the project and the high number of admitted patients in the pilot and control units. Hence, the ROF comparison between the two units was measured instead.

The audit analysis on fall prevention compliance showed an observable difference in the higher utilization of countermeasures. The difference in the number of patients in the low and medium-to-high-risk categories by FPAT made it susceptible to sample size bias. For this reason, a statistical analysis cannot be performed.

The success of the FPAT implementation depends on the nursing attitude toward this tool. While this project improved the pilot unit's perception of the tool, the result does not measure the organizational climate on using FPAT in fall risk prediction. Future studies are needed to understand the organizational appetite for AI-assisted risk assessment tools.

Conclusions

The DNP evidence-based quality improvement project showed an improvement in reducing falls and implementing fall countermeasures. The next phase of this project is to implement the FPAT in all nursing inpatient units in the enterprise and monitor the continuous quality improvement activities in refining the process and adaptation of the tool.

Automating the fall risk tool needs to be quantified better to show the nursing documentation time saved. It is essential to show the correlation between nursing documentation time reduction and the documentation burden. Future studies are necessary to create knowledge on preventing nursing burnout from documentation fatigue.

This project is worth replicating to validate its results. A detailed review of the predictive model and a thorough configuration of the model to the current workflow must be considered for organizations looking to implement an automated fall risk tool. The results of this quality improvement project add to the evidence to support the care transition from manually inputted data to a more automated process.

Funding

There was no funding received for this quality improvement DNP project. This project is implemented to help reduce falls and falls with injury. The project will be implemented in all inpatient units as a valuable mitigating strategy in fall prevention.

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Appendices

Appendix A

Letter of Support from Agency

El Camino Health

2500 Grant Road
Mountain View, CA 94040
650-940-7000

815 Pollard Road
Los Gatos, CA 95032
408-378-6131

August 18, 2021

University of San Francisco
School of Nursing and Health Professions
2130 Fulton Street
San Francisco, CA 94117 -1080

To Whom It May Concern,

This letter is to express my support of Ann Aquino, MSN, RN, NEA-BC, CMSRN, to implement her Doctor of Nursing Practice (DNP) Project at El Camino Health. Ann's project is to implement a Fall Predictive Analytics tool from Epic's Cognitive Computing Artificial Intelligence function, to enhance the accuracy of the fall risk screening and decrease the rate of injurious falls in the Mountain View and Los Gatos campuses.

We give her the permission to use the name of our health system in her DNP project and future publications and presentations. This letter verifies that El Camino Health has an existing contract with University of San Francisco's School of Nursing and Health Professions.

Warm Regards,

Cheryl Reinking, DNP, RN, NEA-BC
Chief Nursing Officer
2500 Grant Road, Mountain View, CA 94040
650-940-7121 (Direct Line)
Cheryl_reinking@elcaminohealth.org

Appendix B

Evaluation Tables

Purpose of article or review	Design / Method / Conceptual framework	Sample/setting	Major variables studied with definitions	Measurement of major variables	Data analysis	Study findings	Level of evidence (critical appraisal score) / Worth to practice / Strengths and weaknesses / Feasibility / Conclusion(s) / Recommendation(s) /
APA reference: Abdullah, R. & Fakieh, B. (2020). Health care employees' perception of the use of artificial intelligence applications: Survey study. *Journal of Medical Internet Research, 22(5):* e17620. https://doi.org/10.2196/17620							
To explore healthcare employee perceptions and attitudes toward implementing artificial intelligence technologies in healthcare institutions in Saudi Arabia.	**Design:** Non-experimental survey study **Methods:** -Descriptive analytical method -quantitative approach to collecting primary data -snowball sampling -questionnaire was adapted from a previous study with revision from multiple choice to the Likert scale. -test and re-test method **Conceptual framework:** none	**Setting:** -4 largest hospitals in Riyadh, Saudi Arabia **Sample:** -doctors, nurses, pharmacists, and support staff -250 employees	**IV:** Artificial intelligence **DV:** Healthcare employees' perception	-tables and analysis -questionnaire	-Cohen's formula -data collected using Microsoft Excel -analyzed using Statistical Package for the Social Sciences (IBM Corporation) -ANOVA tested the significant differences between demographic variables.	-74.8% of the sample were female -the majority of samples were nurses -between 20 to 40 y/o (74.8%) -respondents had a bachelor's degree (55.2%). -the result of ANOVA showed no statistical difference by gender, age, or educational attainment -significant differences by job type (*P*=.007) with significance defined as .05.	**LOE: III-C** **WTP:** The adoption of AI in health care needs to be understood. Understanding healthcare employees' perceptions is warranted and worth exploring. **Strength:** The study provided a baseline understanding of the staff's perceptions of AI. The study lacks rigor, but the design, methodology, and results were well reported. **Weakness:** The sample size is small and cannot be generalized across all healthcare disciplines. **Feasibility:** The study design can be easily replicated, providing baseline knowledge for future studies. **Conclusion:** The study's result showed a need to include the benefits of artificial intelligence to guide clinicians in their care delivery pathway. **Recommendation:** Based on the result of this study, nursing leaders and educators must consider incorporating AI in the training and education of the nursing workforce to correct misconceptions about the negative implications of artificial intelligence.

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APA reference: Akbar, S., Lyell, D. & Magrabi, F. (2021). Automation in nursing decision support systems: A systematic review of effects on decision making, care delivery, and patient outcomes. *Journal of the American Medical Association, 28(11):*2502-2513. https://doi.org/10.1093/jamia/ocab123							
To summarize research literature on nursing decision support systems (DSSs), understand which DSSs support the nursing care process (NCP) steps, and analyze the effects of automated information processing on decision-making, care delivery, and patient outcomes.	**Design:** Systematic review **Methods:** -Systematic review using PRISMA statement -2 reviewers screened articles. **Conceptual framework:** DSSs were examined using a previously published framework that described the automation of human information processing into 4 distinct stages. 1. Information acquisition 2. Information analysis 3. Decision selection 4. Action implementation	**Setting:** -articles about electronic DSS exclusively used by nurses. -long-term care facilities (community, home health care, nursing homes) and short-term care (inpatient wards, critical care units, emergency or urgent care, outpatient clinics, ambulance, and remote consultation) **Sample:** -28 articles -searched PubMed, CINAHL, Cochrane, Embase, Scopus, and Web of Science from	**IV:** Automation of DSS **DV1:** Decision-making **DV2:** Care delivery **DV3:** Patient care outcomes	-tables and analysis -the quality of studies was assessed using the Cochrane risk-of-bias tool for RCTs and Joanna Briggs Institute's checklist for non-RCTs	-Used information value chain two reviewers inter reliability using Cohen's k.	-28 studies reported 56 outcome measures. -22 measures related to decision-making -11 linked to care delivery -12 related to patient outcomes. DSS positively affected nurses' decision-making in 18 of the 22 outcome measures.	**LOE: II-B** **WTP:** AI can advance problem automation and enhance decision support for nurses. **Strength:** Colossal sample size (28 RCTs and non-RCTs). Results are generalizable and provide opportunities for future studies & research. **Weakness:** Risk of bias for concealing allocation sequence. Missing participant data. Unclear methodology (quasi-experimental vs. observational). They have limited statistical analysis. Confounding factors were not addressed. **Feasibility:** The findings of this study can be used for future quality improvement studies and research. DSS alone cannot prevent patient harm; it is an essential component of the NCP, but a fall-prevention toolkit, staff, and patient education must be included to keep patients safe. **Conclusion:** Current nursing DSS does not adequately support the NCP and has limited automation. **Recommendation:** Advancement in artificial intelligence has proven effective in disease diagnosis, which suggests that it is possible to automate problem identification on quantifiable data from EHR. Using these data can help make

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		January 2014 to April 2020. -focused on DSSs used exclusively by nurses and their effects. -information about the stages of automation, NCP, and effects was assessed.					decisions to reduce errors and improve the quality of care. Additionally, it is vital to identify which step in the NCP to automate and focus on workflow analysis to make the process more meaningful for the nurses. Nurses must be involved in the design and implementation process.

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APA reference: Cho, I., Boo, E., Chung, E., Bates, D.W. & Dykes, P. (2019). Novel approach to Inpatient Fall Risk Prediction and its cross-site validation using time-variant data. *Journal of Medical Internet Research, 21(2):*e11505. https://doi.org.10.2196/11505							
To investigate whether readily available longitudinal EMR data, including nursing records, could be utilized to compute the risk of inpatient falls and to assess their accuracy compared with existing fall risk assessment tools.	**Design:** A retrospective cohort study **Methods:** Two study cohorts (DC & VC) were divided from the clinical repository data of 2 institutions. The 2 study sites have different EMRs with two terminology standards and two fall risk assessment tools. **Conceptual framework:** none but used model concepts adopted fall prevention guidelines from the following: -Korean Hospital Nurses Association -The Joint Commission -AHRQ -ECRI Institute	**Setting:** South Korea Tertiary hospitals for both development and validation cohort Both hospitals have approximately 1000 beds and have used EMR for over ten years **Sample:** <u>DC</u> -18 y/o and older -admitted to the cardiovascular, hematology-oncology, and neurology medical departments for at least 24 hours. -14,307 admissions <u>VC</u>	**IV:** Predictive Bayesian network structure for falls. **DV:** Inpatient risk for falling	The predictive Bayesian model's performance was assessed using 10-fold cross-validation. The model was compared with Hendrich II and STRATIFY using ROC and calibration curves. Each cohort was compared using the chi-square test or t-test to quantify the differences in the population characteristics. Data collected were deidentified.	Statistical analysis was performed using R software version 3.3 for population profiles' descriptive statistics. Netica modeling software version 3.2 was used to analyze the degree of variations in the reliability of the probability predictions.	In the DC, the 11.7% error rate of the predictive model. The predictive model and Hendrich II showed two probability ranges: high probability underestimated and low probability overestimated. The probability model showed almost perfect prediction at 0.96 for at-risk and no risk for falling, while Hendrich II was only 0.69. In the VC, the proportion of the observed fall increased steadily, with the projected risk reaching 84.8% in the	**LOE: II-B** **WTP:** Longitudinal EMR data could create a prediction model to identify patients at risk and not at risk for falling. The result of the study implied that relevant and time-variant elements from the EMR can be a reliable guide for fall risk assessment tools. **Strength:** The study was conducted in 2 sites with two different EMRs and fall risk assessment tools, which showed that the predictive model was applicable and portable to different EMRs. The study used many variable sets and took advantage of the available information in the EMR. Another strength of the study is nursing process data in the prediction model that previous studies did not include in their predictive model. **Weakness:** There were differences in the characteristics of the population cohorts. The patients in the DC had longer LOS and had secondary diseases, while in the VC, the patients were older. Another weakness of the study is the underestimated rate of injury falls as

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	-Institute from Clinical Systems Improvement -Institute from Healthcare Improvement -The Joint Commission Center for Transforming Healthcare -Veterans Affairs for patient safety	-18 y/o and older -same eligibility criteria as DC -21,172 admissions Data collection on both sites was done from June 1, 2014, to May 31, 2016				highest-risk decile, while the curve for the STRATIFY did not exhibit a consistent increase.	data for this calculation came from the Incident reporting system, and some incidents could be under-reported. **Feasibility:** Developing a predictive model is not part of the DNP student's proposed project. The predictive analytics tool is already embedded in the EMR system. **Conclusion:** The prediction model for falls predicted patients at risk for falling better than Hendrich II and STRATIFY. **Recommendation:** The findings of this study support the goal of the DNP student's project to study the effect of using predictive analytics in reducing falls and falls with injury.

Purpose of article or review	Design / Method / Conceptual framework	Sample/setting	Major variables studied with definitions	Measurement of major variables	Data analysis	Study findings	Level of evidence (critical appraisal score) / Worth to practice / Strengths and weaknesses / Feasibility / Conclusion(s) / Recommendation(s) /
APA reference: Cho, I., Jin, I., Park, H. & Dykes, P. (2021). Clinical impact of an analytic tool for predicting the fall risk in inpatients: Controlled interrupted time series. *JMIR Medical Informatics, 9(11)*:e26456. https://doi.org/10.2196/26456							
To determine the impact of an electronic analytic tool for predicting fall risk on patient outcomes and nurses' responses.	**Design:** A nonrandomized controlled trial using an interrupted time series (ITS) design. Quasi-experimental study. **Methods:** Selected units were matched based on known fall rates and unit characteristics. The pre-intervention period was 16 months, and the post-intervention was 24 months. STRATIFY Fall risk assessment was replaced by the IN@SIGHT system Process metrics were analyzed every 6 months.	**Setting:** Seoul, Republic of Korea 900-bed public hospital 12 medical-surgical units = 6 units in the intervention group and 6 units in the control group **Sample:** -18 y/o and older -admitted in the selected units for over 1 day. -204 nurses -42,476 admissions of 40,345 unique patients corresponding to 362,805 patient days across both intervention and control groups.	**IV:** IN@SIGHT - **DV 1:** The overall rate of falls per 1000 patient days. **DV 2:** The overall rate of falls with injury and process metrics.	-Monthly fall rates from 16 months before the study from the quality assurance department to get a baseline rate. - the rate of falls with serious injury 1 month before the study served as a baseline - student test	-Poisson distribution was used to calculate the number of falls in the control group -Chi-square test categorical variables were used to compare participant characteristics, and t-test for continuous variables	-325 fall events in the intervention group -382 fall events in the control group -mean monthly rate decreased from 1.92 to 1.79 in the intervention group and increased from 1.95 to 2.11 in the control group. -29.73% rate of falls immediately post-intervention in the intervention group -non-significant reduction in the rate of falls of 16.58% in the control group. -non-significant increase in the rate ratio for	**LOE:** II-B **WTP:** The study showed that the electronic analytic predictive model could help nurses make informed clinical decisions. However, the study also showed that nurses are slow to adapt to that machine learning approach. It will be helpful for the DNP student to survey nurses' understanding of the analytic tool through cognitive computing using artificial intelligence. **Strength:** A previous study by the principal investigator in this study helped frame the study design. The familiarity of the investigator with the study site helped start this experiment. The sample size and the availability of comparables assisted in choosing the intervention and control groups. **Weakness:** One of the weaknesses of the study is the nurses' adaption to the new process. Like the original study, there were differences in the population between the intervention and control groups, such as the patient's age, length of hospital stay, and comorbidity. Such differences opened the potential for biases. Additionally, the length of time the

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	3 sessions of education before the start of the IN@SIGHT system Peer-to-peer education **Conceptual framework:** The nursing role effectiveness model was based on the structure-process-outcome design of the Donabedian quality care model.	Data were collected from May 1, 2017, to April 30, 2019.				both intervention and control groups for injury rate. -high rate of implementation of fall risk tools in both groups -the rate of communication and implementation was initially better in the control group, but on the fourth observational point, the intervention group showed better adherence.	study was conducted, which caused changes in staffing, could mean the result of the study cannot be generalizable. **Feasibility:** Introducing a new risk assessment tool proved challenging, as shown in this study. Previous studies showed that adopting machine learning through artificial intelligence in healthcare is slow even today. **Conclusion:** The adoption of predictive analytics to reduce falls is promising. However, thoughtful consideration of the nurses' perception of the use of technology must be studied further. The result of this study can be considered when developing survey questions before implementing the fall predictive analytics. **Recommendation:** An understanding of nurses' perception of artificial intelligence through surveys can help the adoption of predictive analytics.

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APA reference: Choi, Y., Staley, B., Henriksen, C., Xu, D., Lipori, G., Brumback, B. & Winterstein, A. (2018). A dynamic risk model for inpatient falls. *American Journal of Health-System Pharmacy, 75(17):* 1293-1303. https://doi.org/10.2146/ajhp180013							
To construct a dynamic electronic health record (EHR)-based fall risk prediction model specific to hospitalized patients who receive FRID during any of the first 5 days of hospital admission.	**Design:** A retrospective cohort of hospitalized patients using inpatient EHR data from the 2 largest University of Florida hospitals. **Methods:** -Data was extracted from 2 University of Florida (UF) Hospitals: UF Health Shands (852 beds) and UF Health Jacksonville (695 beds). -extracted fall occurrences from the hospital's automated incident reporting system. -used AHFS therapeutic drug classification system to classify FRIDs -Identified and stratified risk levels of FRID	**Setting:** University of Florida Hospitals -UF Health Shands (852 beds) -UF Health Jacksonville (695 beds) -Data from January 2012 to October 2013 (UF Health Shands) and from March 2013 to October 2013 (UF Health Jacksonville). **Sample:** -75,036 admissions -220,904 patient days -inpatients who were 18 years and older -received at least 1 FRID during any of the first 5 hospital days -excluded ventilated patients and	**IV:** Dynamic EHR-based fall prediction model **DV1:** Risk for falls	-incident reporting system - "look-back" 1 year to review inpatient and outpatient records	-univariate analyses to examine crude associations between risk factors and fall events. -used generalized estimating equations to generate ORs and 95% Cis -used multivariate logistics regression to model the relationship between risk factors. -discrimination and predictive performance of models were assessed using C-statistics analysis	-the 3 most common FRIDs are: oxycodone (given to 79,697 patients or 36.08%), morphine (53,427 or 23.73%) and hydromorphone (42,063 or 19.04%). -within the 90^{th} percentile of modeled risk scores, 30.9% were captured by the risk prediction model (unbiased C-statistic, 0.69) vs. 20.2% using the MFS model (unbiased C-statistic, 0.62). -strong predictors of inpatient falls include: • History of falling, OR 1.99, 95%CI 1.42 to 2.80 • Overestimation of ability to ambulate, OR 1.53, 95% CI 1.12	**LOE: III-B** **WTP:** The result of the study identified 3 widespread pain medications administered in the inpatient population. MFS and Hendrich II Fall risk tool do not consider these medications in assessing the risk for falling. It is worth exploring whether these FRIDs contributed to the fall incidents in the DNP student hospital. **Strength:** The EHR provided data used in the prediction model and was easily accessed for this study. The investigators utilized discreet data that could easily be analyzed and interpreted. **Weakness:** Some variables, one of which is other models that have used urinary incontinence for fall risk assessment, were not included. Natural language processing, such as nursing notes, is not part of discreet data and, therefore, is not included in the model development. Information under clinician notes may contain valuable information that can help predict, hence, prevent a fall. **Feasibility:**

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	using AHRQ Fall Prevention Toolkit, the American Geriatric Society's Beers criteria, and expert opinion. **Conceptual framework:** none	continuous immobilizing sedative agents. -466 fall events				to 2.09 • Comorbidity predisposition, OR 1.60, 95% CI 1.30 to 1.97	Epic's fall predictive analytics model captures most of the variables included in the prediction model. Because the DNP student is not building the prediction model, there is no opportunity to modify Epic's fall predictive analytic function. However, utilizing technology to capture information in EHR will be explored for the DNP project. **Conclusion:** The proposed risk model for inpatient falls achieved superior predictive performance than the MFS model. **Recommendation:** Artificial intelligence improves the clinician's ability to use the best care plan to prevent falls.

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APA reference: Dykes, P., Burns, Z., Adelman, J., Benneyan, J., Bogaisky, M., Carter, E., Ergai, A., Lindros, M., Lipsitz, S., Scanlan, M. Shaykevich, S. & Bates, D. (2020). Evaluation of a patient-centered fall-prevention took kit to reduce falls and injuries: A nonrandomized controlled trial. *Journal of the American Medical Association, 3*(11*)*. https://doi.org/10.1001/jamanetworkopen.2020.25889							
To assess whether a fall-prevention tool kit that engages patients and families in the fall prevention process throughout hospitalization is associated with reduced falls and injurious falls.	**Design:** -Non-randomized controlled trial using stepped wedge design **Methods:** -Analyzed & reviewed the 3-step fall prevention process -Interrupted time series - created a toolkit that included low-tech & high-tech Fall TIPS modalities -Start dates vary depending on the Fall TIPS modality selected -Descriptive statistics shown	**Setting:** -Adult inpatients -37,231 patients -14 medical units **Sample:** -3 academic medical centers (Boston, Massachusetts, Bronx, New York, New York, New York) -21 months pre-intervention & 21 months post-intervention	**IV:** A nurse-led fall-prevention tool kit linking evidence-based preventive interventions to patient-specific fall risk factors and designed to integrate continuous patient and family engagement in the fall-prevention process **DV1:** # of Falls	Fall TIPS (IV) Focus groups - interviews -workflow observations -patient-activation survey - compliance audits DV -reviewed Incident reporting system at all participating hospitals to find the total # of falls and falls with injury	-Poisson Regression Model to calculate the rates (pre and post-intervention) - Charlson Comorbidity Index Score (0.1 0r ≥2.) for patient characteristics -SAS statistical software, version 9.4 -Statistical significance was set at P<.05 using the 2-sided test.	*Fall rate/with injury -2.92 falls per 1000 pt days before implementation of Fall Tips -2.49 post-implementation For injurious fall rate: 0.73 before implementation 0.48 after implementation *TIPS compliance -Site 1: 86% -Site 2 & 3 = mean compliance rate of 95%	**LOE: III-B** **WTP:** The study suggests that there are tools to support patient engagement in preventing falls, which may be associated with reducing falls and fall-related injuries. Furthermore, high-tech and low-tech tools facilitate patient engagement in fall-prevention plans. Patients can carry out interventions recommended by their care providers. DNP students must explore how to influence more hospitals to adopt such tools to decrease their fall rates and improve outcomes. **Strength:** - The study was conducted in 3 big medical centers, and different populations enhance the generalizability of the Fall TIPS toolkit. There is formal and non-formal leaders' buy-in on 3 medical centers. - colossal sample size and demographic is well-balanced -patient participation was good. **Weaknesses:** The number of samples is so huge that it can be challenging because it cannot be fully controlled. -go-live dates for the EHR integration were delayed; therefore, the modality

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APA reference: Dykes, P., Burns, Z., Adelman, J., Benneyan, J., Bogaisky, M., Carter, E., Ergai, A., Lindros, M., Lipsitz, S., Scanlan, M. Shaykevich, S. & Bates, D. (2020). Evaluation of a patient-centered fall-prevention took kit to reduce falls and injuries: A nonrandomized controlled trial. *Journal of the American Medical Association, 3*(11). https://doi.org/10.1001/jamanetworkopen.2020.25889							
	in graphs **Conceptual framework:** None **Implementation framework:** RE-AIM						could not be randomized. **Feasibility:** The Fall TIPS kit and its 3 modalities can be replicated in any facility. Toolkit integration in EHR can help design the project. **Conclusion:** Implementation of a fall-prevention toolkit was associated with a statistically significant 16% reduction in overall inpatient falls and a 34% reduction in injurious falls. **Recommendation:** **-**this article talks about tailoring fall prevention nurse-led intervention, and the result showed a significant reduction in fall and fall with injuries. It may not be directly related to the project, but it helps understand why falls happen and why one standard way of fall prevention has not lowered falls in the hospital.

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APA reference: Hendrich, A. L., Bufalino, A. & Groves, C. (2020). Validation of the Hendrich II Fall Risk Model: The imperative to reduce modifiable risk factors. *Applied Nursing Research, 53*. https://doi.org/10.1016/j.apnr.2020.151243							
To validate the psychometrics of the Hendrich II Fall Risk Model (HIIFRM) and identify the prevalence of intrinsic fall risk factors in a diverse, multisite population.	**Design:** Retrospective Case-control study **Methods:** - retrospective analysis from EHR **Conceptual framework:** none	**Setting:** -9 hospitals that are part of Ascension Health -Bed numbers at the included sites ranged from 25 to 474 **Sample:** -adult inpatients, pediatric patients excluded -214,358 patients -January 2016 through December 2018	**IV:** HIIRFM **DV1:** # of Falls	- data abstracted from HER -incident report	-ROC was used to check the diagnostic ability of the model -a graphical plot of the true positive rate (sensitivity) against the false positive rate (1-sensitivity). -SSPS Statistics v22. -Microsoft Excel -Pearson's chi-squared test (measured categorical variables) and two-tailed t-test (continuous variables).	-Overall fall rate was 0.29%. -standard threshold of HIIFRM score ≥5,492 falls and 76,800 non-falls. -HIIFRM specificity 64.07%, sensitivity 78.71%), AUROC was 0.765, -standard error 0.008, 95% c=CI 0.748, 0.781; $p < 0.001$. -moderate accuracy of HIIFRM to predict falls. -an additional 74 falls could have been identified, with an improvement in sensitivity (90.56%) and reduction in specificity (44.43%)	**LOE: II-B** **WTP:** This study proved that HIIFRM could lower the model's threshold to consider ≥4 as high risk and could have identified more patients at risk for falling. **Strength:** The study examined a considerable sample size from a health system. This study discussed a new theme not previously included; patients admitted from the ED represent a higher proportion of those who fell. **Weaknesses:** A vast sample size made analysis challenging and hard to control. **Feasibility:** The HIIFRM can inform an individualized care plan to prevent the patient from falling. **Conclusion:** The study result showed that HIIFRM gas has solid psychometric characteristics. **Recommendation:** Hospitals that are not in the process of automating their fall risk screening will benefit from the result of this study. It is worth exploring lowering the high fall risks from ≥5 to ≥4.

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APA reference: Jellett, J., Williams, C., Clayton, D., Plummer, V. & Haines, T. (2020). Fall risk score removal does not impact inpatient falls: A stepped-wedge, cluster-randomised trial. *Journal of Clinical Nursing, 29*, 4505-4513. https://doi.org/10.1111/jocn.15471							
To investigate the impact of removing a fall risk screening tool from an overall fall risk assessment program on the rate of falls, injurious falls, and completion of fall prevention activities by staff.	**Design:** A stepped-wedge, cluster-randomised controlled trial using a disinvestment approach **Methods:** The trial was carried out according to the Consolidated Standards of Reporting Trials (CONSORT). -Control condition contained a fall-risk screening tool element, full fall risk factor assessment, and intervention provision section -107,955 bed days for the trial period -15,210 episodes of care -1,023 falls -32 or 3% resulted in significant harm	**Setting:** -20 health service wards (9 units) across 4 hospitals sites within Peninsula Health over the 10-month study period **Sample:** 23 acute, mental & sub-acute units -patients participating had a generic "Patient admission Risk Screen."	**IV:** Intervention condition wherein the fall risk screening section of the Peninsula Health Fall Risk Assessment Tool was removed. **DV1:** # of Falls	Nursing surveys -cross-sectional survey/audits - incident reporting system -Medical records review -mock codes were assigned to each cluster.	-Incidence rate ratio -Poisson distribution family and log-link function for analysis of outcome -Gaussian distribution family for several occupied beds -a statistical comparison using mixed-effects, generalized linear model	- upper 95% Cl indicates 95% confidence that the risk tool is no more beneficial than a 5% reduction in the falls rate -177 staff responded to the survey -36 seconds reduction in time per patient to complete Peninsula Health Fall Risk Assessment Tool	**LOE: I-B** **WTP:** This is the first study to remove the fall risk screening tool that showed that by doing so, it is unlikely to impact the rate of falls or harm negatively and is likely to save staff time. With the current documentation requirement, the staff is overburdened with this task. The result of this project is helpful to the project as the possibility of using information already available in EHR to enhance the identification of the patient's risk for falls without adding more time for staff documentation is explored. **Strength:** -It is the first study to understand the effect of removing the patient's risk for falling. -sampling was adequate, and audits were done -random audits did not find any original Peninsula Health Fall risk tool in the intervention wards -allocated sufficient resources for this study -the limitation identified in the study regarding reporting falls through the incident report was mitigated by performing a medical record review.

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APA reference: Jellett, J., Williams, C., Clayton, D., Plummer, V. & Haines, T. (2020). Fall risk score removal does not impact inpatient falls: A stepped-wedge, cluster-randomised trial. *Journal of Clinical Nursing, 29*, 4505-4513. https://doi.org/10.1111/jocn.15471							
	or death Only the full fall risk assessment and intervention provision section were applied in the intervention condition, and the fall screening tool element was removed. -Fall rate extracted from hospital data -files were audited for tool completion. **Conceptual framework:** None						**Weaknesses:** -there were 2 days when the staff did not find the modified audit paper tool on one intervention ward. -may not be supported when it comes to resource allocation when replicated. -the possibility of unwitnessed and unreported falls, this happens in many hospitals (not mentioned in this study, but this is the case in DNP student organizations) **Feasibility:** While the result of this research is promising, Removing the risk screening tool applies to the DNP project. However, the decrease in the nurses' documentation time is promising. **Conclusion:** Removing the fall risk screening tool section did not negatively impact falls and reduced the time spent completing fall prevention paperwork. **Recommendation:** The result of the study is worth exploring, and DNP students must look at decreasing the time spent by providers on the computer, and more time must be spent interacting with patients. After all, this is well talked about in the clinical setting.

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APA reference: Jung, H. & Park, H. (2018). Testing the predictive validity of the Hendrich II Fall Risk Model. *Western Journal of Nursing Research, 40(12):*1785-1799. https://doi.org/10.1177/0193945918766554							
To examine the predictive validity of the HIIFRM using data at 3-time points during hospitalization in an acute-care setting to identify the HIIFFRM items influencing the occurrence of falls from EMR data.	**Design:** -Retrospective case-control **Methods:** -Data for HIIFRM was extracted from the initial nursing assessment sheet in the EMR. -'faller' was defined and reported in the adverse-event reporting system. **Conceptual framework:** None	**Setting:** --1,328 tertiary acute-care hospitals in Korea -255 beds **Sample:** -patients 18 years and older -admitted to Neurology, Neurosurgery, Hematology, and Oncology -310 falls during the study period -287 fallers from the narrative notes. -205 from AERS -182 fallers from both AERS and narrative notes	**IV:** HIIFRM **DV1:** Falls **DV2:** Fall risk	-incident reports -demographic data analyzed using descriptive statistics	HIIFRM extracted at three-time points: 1. fall risk score on admission 2. the maximum fall-risk score from admission to the fall (case group) 3. from admission to discharge (control group) 4. immediately before falling (case group) 5. Immediately before discharge (control group) -Predictive validity of the HIIFRM was examined by calculating sensitivity, specificity, accuracy, PPV, NPV, Youden Index, and AUROC. -logistic regression analysis -statistical analyses performed using R 3.3.2	-mean age of fallers: 65 y/o vs. 58 y/o for non-fallers -60% were male for fallers vs. 53.7 males for non-fallers -LOS – 23 days for fallers vs. 9 days for non-fallers -meantime to fall – 11 days -27.1% of fallers had surgery vs. 22.5% for non-fallers -highest fall risk scores between admission and event (case =5.3) (control =3.1) -fallers were classified as high risk before falling -predictive validity on admission was 0.674 for sensitivity, 0.651 for specificity, 0.652 for accuracy, 0.038 for PPV, 0.990 for NPV, and 0.325 for Youden index. -maximum fall risk scores between admission and falling or discharge were: 0.800 for sensitivity, 0.595 for specificity,	**LOE: II-A** **WTP:** The study's findings can be used in hospitals when designing or modifying their fall prevention strategies, particularly around staffing, education, and discharge instructions. **Strength:** The study proved that several variables of the HIIFRM contribute to a patient's risk of falling. It also showed the patient's risk from 3 data points, proving that patients could still fall even when clinically appropriate for discharge and after discharge. **Weaknesses:** The study was conducted in a single research site and observed only patients in 4 select groups: Neurology, Oncology, Hematology, and neurosurgery, and does not represent the other patient group. The investigators did not compare HIIFRM to other risk screening tools to examine the effectiveness of preventing falls. **Feasibility:** HIIFRM is the fall risk screening tool at the DNP student facility. While the tool proved helpful in the fall prevention program, the application

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						0.599 for accuracy, 0.039 for PPV, 0.993 for NPV, and 0.395 for Youden index -fall score immediately before falling or discharge was: 0.765 for sensitivity, 0.640 for specificity, 0.643 for accuracy, 0.042 for PPV, 0.993 for NPV, and 0.405 for the Youden index. -AUROC for 3 data sets was 0.701 for fall risk assessed on admission, 0.728 for maximum fall risk score assessed between admissions to falling or discharge, and 0.742 for fall risk score immediately before falling.	guiding the nurses' action to activate fall prevention measures must be evaluated further. **Conclusion:** -the risk of falling using HIIFRM was higher in the case group vs. the control group at the 3 points. -the risk of a patient falling did not decrease until the time of discharge -Get-up and go test revealed that the patient's risk worsens after a fall. -patients with symptomatic depression and the use of antiepileptic drugs did not increase the risk of falling. **Recommendation:** HIIFRM performed best to identify a patient's fall risk, particularly between admission to the time of fall and discharge. For hospitals not considering using cognitive computing fall risk scoring, there is a need to socialize on how best to use the HIIFRM and educate the nursing staff on using the tool properly.

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APA reference: Jung, H., Park, H. & Hwang, H. (2019). Improving fall risk prediction using electronic health record data with various types and sources at multiple times. *Computers in Nursing, 38(3):*157-164.https://doi.org/10.1097/CIN.0000000000000561							
To develop fall risk prediction models using electronic health record (EHR) data recorded multiple times with various data types and sources and to evaluate the overall predictive performance of these models by comparing the results to those from the HIIFRM.	**Design:** Case-control study **Methods:** - examined three types of predictive modeling methods • Logistic regression • Cox proportional hazard regression (Cox PH regression) • Decision tree **Conceptual framework:** CPGs from: • WHO • AHRQ • NICHE • Registered Nurses Association of Ontario • ACSQH • Ministry of Health Singapore • Hospital Nurses Association in Korea	**Setting:** -tertiary acute care hospital with 1328 beds in South Korea **Sample:** -15,480 patients were admitted from January 2015 to May 2016 to the following units: • Neurology • Neurosurgery • Hematology • Oncology *Case group = fallers *Control group = non-fallers	**IV:** A predictive model using Logistic regression, Cox PH regression, and decision tree. **DV1:** # of Falls	-data abstraction -fall incident-related narratives were documented using standardized nursing narratives built upon ICNP -data sources and types of features were identified with the assistance of 2 informatics nurses -incident reporting system	-*X*2 or Fisher exact test, independent *t*-test, or Mann-Whitney *U* test to develop a parsimonious model -the size of *d* and Gini impurity calculated -univariate analyses used for independent variables -performance of the final predictive model was measured using the testing set with sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and AUC - statistical analysis was performed using R version 3.4.4	-205 fall of the 15,480 patients -105 additional falls identified using nurses' notes -52 of 158 features were statistically significant, with $p< 0.05$ .using the forest algorithm, 8 features with Gini impurity values higher than the cutoff, which included lower limb weakness, fall prevention services, fall prevention services, post-operative day, acuity score, age, dysuria, type of admission route, and mental state.	**LOE: II-A** **WTP:** Using EHR to predict a patient's fall risk, especially at the event, helps prevent patient harm. Furthermore, the prediction model used in this study can guide the clinical decision support system. **Strength:** Results proved previous study findings that a reliable risk assessment tool to help decrease the incidence of falls. Various data helped identify the patient's risk status during the fall. **Weaknesses:** The study setting did not include other medical-surgical patients, cardiology, and orthopedics. **Feasibility:** Using a decision tree to help design the predictive model using the information in the EHR can be replicated. In doing so, this study stated that **Conclusion:** Data in various data points can be used for the fall prediction model. **Recommendation:** Evaluate the use of technology to improve nursing workflow, decrease time to document, and increase RN: patient interaction time.

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APA reference: Lindberg, D., Prosperi, M., Bjarnadottir, R., Thomas, J., Crane, M., Chen, Z., Shear, K., Solberg, L., Snigurska, U.A., Wu, Y., Xia, Y. & Lucero, R. (2020). Identification of important factors in an inpatient fall risk prediction model to improve the quality of care using EHR and electronic administrative data: A machine-learning approach. *International Journal of Medical Informatics, 143*. https://doi.org/10.1016/j.ijmedinf.2020.104272							
To use tree-based machine learning methods to determine the most critical predictors of inpatient falls and validate each via cross-validation.	**Design:** Case-control study **Methods:** -classification tree, bagging, random forest, and adaptive boosting applied to EHR. -sensitivity, specificity, and AUROC curve were computed via a ten-fold cross -validation and comparison via t-test -each case was matched with 2 randomly selected controls that overlapped at least one day of hospitalization	**Setting:** -14 medical surgical units -data collected between January 1, 2013, to October 31, 2013 **Sample:** -EHR data from the University of Florida's IDR and administrative records from the University of Florida Health Shands -patients who were 21 years old and older *cases = patients who experienced	**IV:** Machine learning prediction model for fall **DV1:** Risk for falls	-University of Florida Health's electronic incident reporting system validated patient fall -The Gini index was used for a single classification tree to identify the hierarchical structure of each feature -	-performance of machine learning was compared to a univariate logistic regression statistical model for the MFS score. -used a multivariate regression model of all features to both a random-effects model and a generalized estimating equation multivariate regression model. -ROC was produced for each tree-based	-The most important features for predicting inpatient fall risk are the history of falls, age, MFS total score, gait quality, unit type, mental status, and several high FRIDs. -AUROC results, bagging (0.89), random forest (0.90), and boosting (0.89) all outperformed the MFS (0.86), but no difference was measured at a *p*-value of 0.05.	**LOE: II-B** **WTP:** The large volume of clinical data captured in EHR suggests an opportunity to use these data to predict a patient's risk for falling. Improving the accuracy of the risk assessment model can enhance the clinician's ability to improve the quality of care and fall prevention practices. The result of this study can influence the current nurses' workflow and practices. **Strength:** A large sample to represent cases and controls was quickly accessible using the University of Florida Health's databases. The university's IRB approved and supported the study, and it was funded by the University of Florida's Quasi endowment fund and the National Institutes of Health National Institute on Aging. The study also identified variables for fall risk screening according to their importance and boasts of containing more accurate predictive models than existing fall risk assessment tools. **Weaknesses:**

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	-the MFS measured risk for falls Each machine-learning method included 38 patient, clinical, and administrative features. **Conceptual framework:** none	a fall during hospitalization *controls = patients who did not fall during hospitalization but were at risk of falling -272 patients fell (cases) & were matched with 542 patients (controls) who did not fall			model & MFS total score. -sensitivity, specificity, AUROC curve, and their Cis using ten-fold cross-validation. -Youden index was used to calculate statistics at cut-points of the ROC -pairwise t-test assesses the difference in sensitivity, specificity, and AUROC curve among the predictive models. -comparisons were made at a *p*-value of 0.05.		While the result of the study is considered one of the first to analyze the different variables by importance, there is a considerable population bias because the data used was only from the hospital system. Additionally, the generalizability of the application of this predictive model can be questionable since health systems use different fall risk assessment tools. **Feasibility:** Artificial intelligence to identify the patients at most risk outperformed the traditional fall risk screening tool. The result of this study can be a reference to the proposed DNP project. **Conclusion:** Clinical, individual, and organizational features can be used in fall prediction. The predictive model can support personalized care and improve the quality of care. **Recommendation:** Artificial intelligence in fall risk assessment must be explored and studied further.

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APA reference: Lucero, R. J., Lindberg, D. S., Fehlberg, E. A., Bjarnadottir, R. I., Li, Y., Cimiotti, J. P., Crane, M. & Prosperi, M. (2019). A data-driven and practice-based approach to identify risk factors associated with hospital-acquired falls: Applying manual and semi-and-fully-automated methods. *International Journal of Medical Informatics, 122*, 63-69. https://doi.org/10.1016/j.ijmedinf.2018.11.006							
Setting: -14 Medical/surgical units of a tertiary teaching hospital -Jan. 1, 2013, to Oct. 31, 2013 **Sample:** -patients 21 years and older admitted to the Medical/surgical unit	**Design:** Observational case-control study **Methods:** A manual and semi-and-fully automated method to identify fall risk factors - reviewed EHR from the University of Florida's Integrated Data Repository -Control group: two patients who did not fall but were at risk for falling for each patient who did fall (case) -control patients were eligible for selection if their hospital stays overlapped with at least one day during the week the case fell. Only one fall	**Setting:** -14 Medical/surgical units of a tertiary teaching hospital -Jan. 1, 2013, to Oct. 31, 2013 **Sample:** -patients 21 years and older admitted to the Medical/surgical unit	**IV:** Multivariable model-updating, expert, stepwise, and lasso prediction models **DV1:** Classification of patient's risk for falling	The automated incident reporting system -Chart abstraction and review	-Stepwise Regression approach (based on minimizing AIC) -AUROC curve using 10-fold cross-validation for all 4 models -Descriptive statistics of fallers, non-fallers	-272 patients fell (cases) -542 did not fall (control) -strongest patient predictors: p-value less than 0.01 were all of Morse Scale -a strongest predictor for staffing:p-values less than 0.01 was low nurse skill mix and low nurse certification -Individual risk of falling varies: Morse: 0.264 Model updating: 0.330 Expert: 0.297 Stepwise: 0.327 Lasso: 0.276	**LOE: II-A** **WTP:** The study provided new knowledge and multiple specific variables that can enhance the predictability of a patient's risk for falls. These variables are readily available in EHR. The decision tree is easy to follow and clearly distinguishes Morse risk scoring and the stepwise regression approach. Healthcare leaders must evaluate the use of embedded information in EHR to predict the risk of patient harm. **Strength:** -the study used theoretical, empirical, and expert knowledge. -it provides new knowledge that has been explored and more similar studies have been conducted after 2019. -this study is easily replicable and can be done in any institution that uses EHR. **Weaknesses:** -the use of step-wise for feature selection may not be optimal. This method is usually used for larger data sets -the study was done in one tertiary hospital; therefore, generalizing the result is challenging. -elaboration on the theoretical, empirical, and expert knowledge relevance of the study -re-estimation on a real-population

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	incident was included if a patient had repeat falls. -Described independent variables and dependent outcomes -conducted model-updating of the six Morse scale components -generated a multivariate logistic regression expert model -applied lasso regression procedures with cross-validated lambda. **Conceptual framework:** None						sample would be needed **Feasibility:** The study method was clearly described, and the information included is readily available in EHR. This DNP student can utilize the method and findings of this study as a blueprint for their project. **Conclusion:** The study showed that existing valid and new risk factors and others are changeable. The history of falls is reported less frequently in research with proper risk prediction tools. Drugs, hemoglobin (labs), physical therapy, comorbidity, and staffing skill mix are predictors. **Recommendation:** Electronic clinical data is a good source of information that can guide clinicians' decision-making at the bedside. Combining data with a practice-based approach can help improve patient care delivery. This study is beneficial and can help guide the DNP student’s project to understand if predictive analytics help decreases the number of falls with injury in the student’s organization.

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APA reference: Lytle, K., Westra, B., Whittenburg, L., Adams, M., Akre, M., Ali, S., Furukawa, M., Hartleben, S., Hook, M. Johnson, S., Settergren,T. & Thibodeaux, M. (2021). Information models offer value to standardized electronic health record flowsheet data: A fall prevention exemplar. *Journal of Nursing Scholarship, 53*(3), 306-314. https://doi.org/10.111/jnu.12646							
To describe a method of standardizing EHR flowsheet documentation data using IM to support exchange, quality improvement, and extensive data research.	**Design:** A consensus-based, qualitative, descriptive approach **Methods:** -Retrospective, observational study using an iterative, consensus-based approach to map, analyze, and evaluate nursing flowsheet metadata. - Metadata extracted for each flowsheet row included unique identifiers, descriptions, and names representing each organization's concepts. -two principles constrained assessment of fall documentation: (a) use in evidence-based patient care (b) documentation	**Setting:** -67 hospitals and multiple clinics in 4 states **Sample:** -Flowsheet data from 6.6 million pts. -27 million encounters -683 million observations	**IV:** an exemplar, EHR flowsheet metadata (input) from multiple organizations (reference IM) **DV1:** fall prevention minimum set of essential fall data concepts currently captured in the EHR flowsheet documentation (validated IM)	-Age-specific screening tools -Validated IM – used 7 classes -Reference IM used 4 classes	- FloMap Software using Boolean logic for data mapping - **Consensus-based concept analysis approach** **CRUD:** fall concepts including renaming, reclassifying, or combining concepts and associated value sets compared to a reference IM.	-Validated fall prevention IM focused on identifying and describing the minimum set of essential fall data concepts currently captured in the EHR flowsheet for evidence-based fall prevention documentation. -Reference IM had 4 classes, 57 concepts Validated IM expanded to seven classes, reduced concepts to 43, and added 157 value set items.	**LOE: III-A** **WTP:** The information model helped incorporate all nursing documentation entries in the EHR to enhance current validated tools for Fall risk screening. The validated information model provided helpful information with less documentation requirement for Fall risk screening. Information exchange to identify fall-risk patients will be accessible to enhance risk screening for patients **Strength:** -metadata available for review -multiple health systems in different parts of the United States participated in the project -EHR readily available and accessible to test the validated information model **Weaknesses:** -the 4 classes in the reference IM was not discussed extensively -In our hospital, post-fall huddle reports are not in a flowsheet row; therefore, data abstraction can be challenging -Documentation of falls in most hospitals and this study is not captured in EHR but Incident reporting system making it difficult to see the true # of falls. **Feasibility:** -Very promising, and data is available in EHR. However, data entry depends on

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	usefulness from a staff viewpoint Boolean logic to find data that match standardized concepts, allow similarities and differences to inform changes in fall prevention IM. **Conceptual framework:** None						nursing, and information may not be as complete as intended. **Conclusion:** Technology promises to be a tool to bridge the gap between the patient's clinical presentation and documentation. Standardizing reporting, documentation, and data sharing will help improve care delivery. **Recommendation:** Clinical Relevance: Opportunities exist to work with EHR vendors and the National Coordinator for Health Information Technology Office to implement standardized IMs within EHRs to expand the interoperability of nurse-sensitive data.

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APA reference: Moskowitz, G., Egorova, N., Hazan, A., Freeman, R., Reich, D. & Leipzig, R. (2020). Using electronic health records to enhance predictions of fall risk in inpatient settings. *The Joint Commission Journal on Quality and Patient Safety, 46*:199-206. https://doi.org/10.1016/j.jcjq.2020.01.009							
To develop an automated, comprehensive risk score to enhance the identification of patients at high risk for falls and examine its effectiveness.	**Design:** Cohort study **Methods:** - assessed associated factors for falls as identified with CMS data warehouse algorithm -data warehouse extracted nightly Data were collected from January 1, 2012, to December 31, 2014, and validated from January 1 to September 30, 2015. -Mixed logistic regression with random hospital service-specific intercept to identify fall risk factors. -EFA model risk-adjusted based on patient characteristics -EFA incorporates 4	**Setting:** -Academic medical center -January 1, 2012, through December 31, 2014 - **Sample:** -33,888 hospitalizations -2,161 falls	**IV:** EFA Model **DV1:** # of Falls	- data abstracted from EHR (EPIC) -incident report	-Pearson's chi-square test evaluates factors associated with falls categorical variables and *t*-test for continuous variables. -standardized difference to eliminate the cohort's large sample size on *p* values. -performance of the model was assessed using model discriminating *c*-statistics -compared the EFA and Morse fall risk tool between the AUC using the ROCCOCONT RAST statement -statistical analysis was performed using SAS 9.4	-Falls were observed in 1.6% of the cohort's 137,627 hospitalizations. -fall rate was 2.8 per 1,000 pt. days -88% had 1 event per hospitalization -9.8% had 2 events per hospitalization -2.2% had 3 or more events per hospitalization -median LOS was 12 days for patients with falls and 3 days for pts. without fall -the majority of falls occurred on 3rd day of hospitalization. - Those who fell were older (mean age 64 vs. 56, p <0.001) and more likely male (52.2% vs. 42.1%, p<0.001). -c-statistic (model discrimination) yielded a c-statistic of 0.805 vs. 0.687, p<0.001	**LOE: II-B** **WTP:** This study's results proved to be worth exploring. Hospitals that use Epic EHR should incorporate this AI/predictive analytics in the current fall prevention program to evaluate if it is helpful to decrease their fall rate. **Strength:** The study presented the result clearly, showing that EFA could accurately identify patients at risk for falling. **Weaknesses:** The decrease in the rate of falls cannot be solely attributed to the EFA since multiple nursing protocols have been started during the duration of the study. **Feasibility:** The widely adapted Epic system can perform cognitive computing. A similar study can be done in those facilities. **Conclusion:** The study result showed that HIIFRM gas has solid psychometric characteristics. This study identified a large number of inpatients that have multiple risk factors. **Recommendation:** The model for calculating variables in Epic is used for this student's DNP project. Since the model is readily available in Epic EHR, hospitals using this system should explore these predictive analytics.

Purpose of article or review	Design / Method / Conceptual framework	Sample/setting	Major variables studied with definitions	Measurement of major variables	Data analysis	Study findings	Level of evidence (critical appraisal score) / Worth to practice / Strengths and weaknesses / Feasibility / Conclusion(s) / Recommendation(s) /
APA reference: Moskowitz, G., Egorova, N., Hazan, A., Freeman, R., Reich, D. & Leipzig, R. (2020). Using electronic health records to enhance predictions of fall risk in inpatient settings. *The Joint Commission Journal on Quality and Patient Safety, 46*:199-206. https://doi.org/10.1016/j.jcjq.2020.01.009							
	groups of data: nursing assessment -Medications -Lab values collected -Hospital service **Conceptual framework:** none					-correlation between predicted and observed falls was 0.71. -medications that affect CNS increase the patient's risk of falling while immobile. A Braden score component was the only variable to decrease falls. -rehab patients were most likely to fall. -low risk increased from 52.8% to 66.5% -medium risk decreased from 19.2% to 17.4% -high risk decreased from 28.0% to 16.2%.	

Purpose of article or review	Design / Method / Conceptual framework	Sample/setting	Major variables studied with definitions	Measurement of major variables	Data analysis	Study findings	Level of evidence (critical appraisal score) / Worth to practice / Strengths and weaknesses / Feasibility / Conclusion(s) / Recommendation(s) /
APA reference: Tago, M., Katsuki, N. E., Oda, Y., Nakatani, E., Sugioka, T. & Yamashita, S. (2020). New predictive models for fall among inpatients using public ADL scale in Japan: A retrospective observational study of 7,858 patients in acute care setting. *PLoS ONE, 15*(7), e236130. https://doi.org/10.1371/journal.pone.0236130							
To develop and validate a new, easier-to-use predictive model for falls of adult inpatients using easily accessible information, including the public ADL scale in Japan.	**Design:** Retrospective cohort study **Methods:** -retrospective analyzed data in an acute care hospital from 2012 to 2015 -Two-thirds of the cases were randomly extracted to the test set and one-third to the validation set. -variables that showed a high correlation coefficient with others, one coefficient was selected, and others were removed (model 1) -a parsimonious model using predictive factors that showed a significant difference was made (model 2) **Conceptual**	**Setting:** -Yuak-kai Foundation and Oda hospital in Japan **Sample:** -all inpatients of age >20 years old from April 2012 to January 2015 -8,031 inpatients	**IV 1:** **Model 1 –** multivariate logistic regression with 13 factors **IV2:** **Model 2** multivariate logistic regression using 8 factors **DV:** Incidence of falls	-incident reports review -medical chart review -MHLW bedriddenness rank and cognitive function score	Falls Rate: multivariate logistic regression Model analysis with odds ratio, 95% CI, and *p*-value based on Wald test -cases were randomly divided into the test set and validation set at a ratio of 2:1 SAS version 9.4 and R version 3.6.0	-7,858 out of 8,031 were eligible for inclusion - test set = 5,257, 243 falls or 4.6% - validation set = 2,601, 122 falls or 4.7% -AUC of the predictive performance of Model 1 was 0.808 -AUC of the predictive performance of Model 2 was 0.806	**LOE: III-A/B** **WTP:** Being bedridden to screening patients on admission can help screen patients at risk for falling. Making the screening tool more straightforward will yield higher compliance. It is worth exploring whether the DNP student's organization can pull mobility status and determine if bedriddeness is part of the documentation option. **Strength:** -Reporting of falls is mandatory in this hospital **Weaknesses:** -degree of visual impairment was not clearly defined -ADLs are documented as expected based on the patient's features and behavior on admission. -underlying disorders or comorbid conditions were not included in the condition's relationship with falls. -the use of socks, bed sensors, rehab staff, and notification of the need to use the bathroom could have influenced the result of the study, particularly in the decrease in falls. This study did not verify the assessment of bedriddenness upon admission and discharge. **Feasibility:** Making screening tools more straightforward will improve compliance.

Purpose of article or review	Design / Method / Conceptual framework	Sample/setting	Major variables studied with definitions	Measurement of major variables	Data analysis	Study findings	Level of evidence (critical appraisal score) / Worth to practice / Strengths and weaknesses / Feasibility / Conclusion(s) / Recommendation(s) /
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	framework: None						**Conclusion:** .Assessing patients as soon as possible after admission can predict and prevent falls. -adding the MHLW bedriddenness rank to the screening tool has statistical significance. -HIIFRM is not widely used in Japan due to the multiple forms of exams such as the Mini-Mental exam, get-up-and-go, Koenig II depression rating scale, and Bender elimination. -Model 1 & Model 2 predictive models are convenient and help with complicated clinical situations. **Recommendation:** Simplifying fall risk assessment tools to improve compliance and accurately assess a patient's risk is a great goal. However, any simplified tool must ensure accuracy and capture the information to become meaningful. The addition of bedriddenness in the DNP student's project risk assessment is worth exploring.

Purpose of article or review	Design / Method / Conceptual framework	Sample/setting	Major variables studied with definitions	Measurement of major variables	Data analysis	Study findings	Level of evidence (critical appraisal score) / Worth to practice / Strengths and weaknesses / Feasibility / Conclusion(s) / Recommendation(s) /
APA reference: Teng, M., Singla, R., Yau, O., Lamoureux, D., Gupta, A., Hu, Z., Aissiou, A., Eaton, S., Hamm, C., Hu, S., Kelly, D., MacMillan, K., Malik, S., Mazzoli, V., Teng, Y., Laricheva, M., Jarus, T. & Field, T. (2022). Health care students' perspectives on artificial intelligence: Countrywide survey in Canada. *Journal of Medical Internet Research Medical Education, 8(1):*e33390. https://doi.org/10.2196/33390							
To explore and identify gaps in Canadian students' knowledge regarding AI, capture how healthcare students in different fields differ in their knowledge and perspectives on AI, and present student-identified ways that AI literacy may be incorporated into the healthcare curriculum.	**Design:** -non-experimental cohort study **Methods:** -the survey was developed from a narrative review of topics in attitudinal surveys on AI -final survey comprised 15 items, including multiple-choice questions, pick-group-rank questions, an 11-point Likert scale, slider questions, and narrative questions. -snowball and convenient sampling **Conceptual framework:** None	**Setting:** -country-wide Canada -18 Canadian universities -initiated in December 2020 -data collected between January 25 and May 31, 2021 **Sample:** -2167 students -10 different health questions -questions were in English and French	**IV:** Artificial intelligence **DV1:** Healthcare students' perception	-tables and analysis -questionnaire -an anonymous web-based survey	-Likert scale -Kruskal-Wallis analyses test for differences in attitudes by age, gender, year of training, previous degree, professional interest, and regional variations. -post hoc Conover test with Holm-adjusted P values to see which groups differed from each other -Phyton version 3.8 for all analyses	-78.77% predicted that AI would affect their careers within the coming decade -74.5% reported a positive outlook toward AI -students identified a need to incorporate a basic understanding of AI into their curricula -no statistically significant difference between the different age groups. -statistically significant from different groups based on their year of training. -medicine, dentistry, and physical therapy students had positive outlooks different from genetics, counseling, midwifery, nursing, OT, pharmacy, social work, and speech-language pathology.	**LOE: III-B** **WTP:** Basic AI information should be part of the curriculum. Nursing leaders and educators must use this information to improve the perception of healthcare students about AI. **Strength:** The study had a broad scope of participants and was performed in 18 universities across Canada. **Weaknesses:** Recruitment and participation bias because doctors heavily did the recruitment. Hence, MD students were overly represented. **Feasibility:** This study can be repeated in healthcare institutions. **Conclusion:** An AI-friendly curriculum is essential as future healthcare providers will be responsible for algorithmically interpreting patients' healthcare information. **Recommendation:** Incorporating primary AI information benefits healthcare students. Therefore, universities and allied health schools should include AI in their curricula.

Purpose of article or review	Design / Method / Conceptual framework	Sample/setting	Major variables studied with definitions	Measurement of major variables	Data analysis	Study findings	Level of evidence (critical appraisal score) / Worth to practice / Strengths and weaknesses / Feasibility / Conclusion(s) / Recommendation(s) /
APA reference: Tricco, A. C., Thomas, S. M., Veroniki, A. A., Hamid, J. S., Cogo, E., Strifler, L., Khan, P. A., Robson, R., Sibley, K. M., MacDonald, H., Riva, J. J., Thavorn, K., Wilson, C., Holroyd-Leduc, J., Kerr, G. D., Feldman, F., Majumdar, S. R., Jaglal, S. B., Hui, W. & Straus, S. E. (2017). Comparison of interventions for preventing falls in older adults: A systematic review and meta-analysis. *JAMA, 318* (17), 1687-1699. https://doi.org/10.1001/jama.2017.15006							
To assess the potential effectiveness of interventions for preventing falls	**Design:** Systematic review and meta-analysis **Methods:** -pairs of reviewers, resolved by 3rd reviewer -independently screened studies -abstracted data -risk-of-bias appraised -pilot-testing eligibility criteria for citations and full-text screenings **Conceptual framework:** None	**Setting:** -community -acute care -data sources MEDLINE EMBASE Cochrane Central Register of Controlled Trials Ageline **Sample:** -238 RCTs -54 network meta-analysis	**IV:** **Interventions for falls:** -exercise -combined exercise & vision assessment and treatment -combined exercise, vision assessment and treatment, and environmental assessment and modification -combined clinic-level quality improvement strategies, multifactorial assessment, and treatment **DV:** Incidence of falls	-rank-heat plot -systematic reviews	-EPOC used to appraise studies -variance-stabilizing Freeman-Turkey double arcsine approach -R software version 3.3.3 -pairs of reviewers, resolved by 3rd reviewer -independently screened studies -abstracted data -risk-of-bias appraised -pilot-testing eligibility criteria for citations and full-text screenings	-overall, each intervention (listed under IV) was associated with fewer injurious fall	**LOE: III-B** **WTP:** Combining multiple fall prevention must be adopted in hospitals and is consistent with best practices. **Strength:** -registered in PROSPERO (CRD42013004151). -no significant inconsistencies across network meta-analysis and no publication bias **Weaknesses:** -study reported a high proportion of the unclear risk of bias for allocation concealment, contamination, and selective outcome reporting **Feasibility:** The study provides evidence to include assessing intrinsic information to predict fall risk. **Conclusion:** The main elements of an effective fall-prevention program remain uncertain, which continuously challenges implementing effective fall-preventive interventions. **Recommendation:** Various combinations of interventions are effective ways to prevent falls. This learning must be translated into practice in all acute care settings.

Purpose of article or review	Design / Method / Conceptual framework	Sample/setting	Major variables studied with definitions	Measurement of major variables	Data analysis	Study findings	Level of evidence (critical appraisal score) / Worth to practice / Strengths and weaknesses / Feasibility / Conclusion(s) / Recommendation(s) /
APA reference: Yokota, S., Endo, M. & Ohe, K. (2017). Establishing a classification system for high fall-risk among inpatients using support vector machines. *Computers, Informatics, Nursing, 35(8)*:408-416. https://doi.org/10.1097/CIN.0000000000000332							
To construct a system that can assist nurses in evaluating the fall risk of patients caring for on a particular day.	**Design:** Quasi-experimental: data sets divided into two groups • Training data • Testing data **Methods:** - collected the following data: • Intensity-of-nursing-care-needs data • Data from the admitting hospital ward • Fall report data -Data preprocessed using LIBSVM **Conceptual framework:** none	**Setting:** -University of Tokyo Hospital, Japan **Sample:** -1,223,687 patient days -1950 cases of falls -1,221,737 non-falls -23,309 were males -21,948 were females	**IV:** FiNDS model **DV1:** # of Falls	-Standardized Structured Medical Information eXchange (SS-MIX2) to get information on the intensity of nursing care, falls, and the timing of the fall. -Incident reporting system	-R 3.3.0 and e1071 version 1.6.7 -accuracy formula was used to evaluate true positives and true negatives -a discriminant model for testing data for each parameter	-sensitivity of 64.9% and specificity of 69.6% -	**LOE: II-B** **WTP:** This study focuses on understanding the ability of the FiNDS model to identify the patient's risk of falling the following day using information from the EHR. With hospitalized patients changing conditions at any time during hospitalization, would it be better to have the ability to see the patient's risk more often than looking one day ahead? The WTP of this study is to use the results as a comparison to other published articles and identify opportunities to include in practice changes to improve patient outcomes. **Strength:** The investigators claim this is the first model that removes the possibility of causal inversion and shows apparent sensitivity and specificity toward unknown data. This study is unique because it focuses on finding out if a patient will fall on the following day by their status on the current day. **Weaknesses:** The intensity of nursing care is a system for measuring the work volume of nurses and is influenced by patient classification. While the validity of this instrument has been studied, its confidence coefficients, such as Cronbach's α, have not been clarified. **Feasibility:**

Purpose of article or review	Design / Method / Conceptual framework	Sample/setting	Major variables studied with definitions	Measurement of major variables	Data analysis	Study findings	Level of evidence (critical appraisal score) / Worth to practice / Strengths and weaknesses / Feasibility / Conclusion(s) / Recommendation(s) /
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							The external validity of FiNDS is unknown since the study was conducted in Japan, where the intensity of nursing care differs from other countries. For this reason, generalizing the findings of this study can only be applied across Japan. **Conclusion:** The FiNDS model helps determine if a patient will fall on a given day based on the information from the previous day. In Japan, this is a model that can be generalized. One of the findings supporting the DNP project is that this model can provide objective information that the nurses can use to assist in their care plan without putting extra burdens on nurses or patients. **Recommendation:** Organizations must continue to explore the benefits of using EHR to decrease nurses' time for documentation.

Appendix C

Institutional Review Board Approval

El Camino Hospital
THE HOSPITAL OF SILICON VALLEY

Institutional Review Board
2500 Grant Road (ECH-1C35)
Mountain View, CA 94040

June 29, 2022

Anna Aquino, RN
Principal Investigator

RE:	**ECH 22-08:** Implementing Cognitive Computing Using Artificial Intelligence to Predict a Patient’s risk for falling with Analytics
Items Reviewed:	Request for Approval Application (via eProtocol), Flyer for Fall Predictive Staff, Qualitrics pre and post survey, CITI Training Certificate and CV

Dear Investigator:

Thank you for your submission of reports for the above-referenced activity conducted at this site. At its meeting of June 17, 2022, the ECH Institutional Review Board reviewed, approved, acknowledged and accepted the following documents as submitted:

The purpose of the QI project seeks to understand if Epic's capability to cognitively compute fall risk factors using information embedded in EHR improve the predictability of patient's risk for falling, increase the nursing staff's confidence in using EHR to help clinicians with their care plans, and decrease the rate of falls with and without injuries. This is a Quality Improvement Study. Current information in Epic EHR will be de-identified. Using data collection tool, patient charts will be assigned numbers and MR# will not be included in data collection. PI and research coordinator will conduct audits of fall risk predictive scores and compare to reported # of falls incidents at designated intervals within this pilot study's 3-month period. There are no patient-facing procedures or visits involved, and retrospective chart and report reviews will use the hospital's electronic health record system (i.e. Epic's Fall Predictive model) in compliance with privacy and security competencies per El Camino Health users.

The primary use of the data and QI outcomes will be to disseminate information about evidence-based improvement at ECH and standardize the use of assessment measures for making treatment decisions. Per the Quality Checklist, all questions were answered yes, which confirms your project, as submitted, is a Quality Improvement project and not research involving human subjects. *This project was undertaken as a Quality Improvement Initiative at El Camino Hospital, and as such was not deemed research, nor formally supervised by the Institutional Review Board per their policies.* Any posters, abstracts, publications or outcomes reporting resulting from the project as submitted is deemed Quality Improvement reporting of a QI project.

The secondary purpose will be to use the data and outcomes for education purposes at USF. Per a presentation by the PI, the IRB confirms the project meets the following requirements for a primary purpose of Quality Improvement, and a secondary purpose of contributing to an Educational Degree, noting: 1. The QIP study aligns with the operational plans of the hospital to improve patient care. 2. This Quality Improvement Project will be implemented at El Camino Health across all impacted patients to support evidence-based practice for new processes. 3. All source data will ONLY be accessed to perform the primary aim of Quality Improvement. The Quality Improvement data set will be the sole source of data for the secondary purpose of an Educational Degree. To clarify, source data WILL NOT be re-accessed to accomplish the secondary purpose of contributing to an Educational Degree. 4.Any data and/or reports/conclusions provided to the Educational Program/Professors will be aggregated data and not include patient identifiers.

The IRB concurs that the primary and secondary uses of data collected for this QIP are for Quality Improvement purposes and subsequent educational purposes and not for research purposes; therefore, no IRB approval or oversight is required. Please provide any revisions to the QIP directly to the Nursing Research Committee for additional consideration.

Sincerely,

DocuSigned by:
Christine Terbijhe
A5B3E0685B894B3...

Christine Terbijhe and Michael S. Greenfield, MD
ECH Institutional Review Board

Appendix D

Gap Analysis

Current State

Fall-risk assessment is manually performed by nurses using Hendrich II Fall Risk Model (HIIFRM)

Fall risk assessment is performed on admission, every 12-hours, and whenever a change in the patients' condition occur. This is specified in the hospital policy.

Gaps

The HIIFRM does not take into consideration intrinsic factors such as laboratory results, vital signs, multiple medications administered to the patient, and the patient's length of stay.

Nurses are not triggered to perform fall risk assessment screening when the patient condition changes.

Failure to accurately assess the patient's risk of falling can cause the rate of falls and injuries for hospitalized patients.

Future State

The implementation of Epic's Fall Predictive Analytics

Automated, timely, and more accurate identification of patients at risk of falling.

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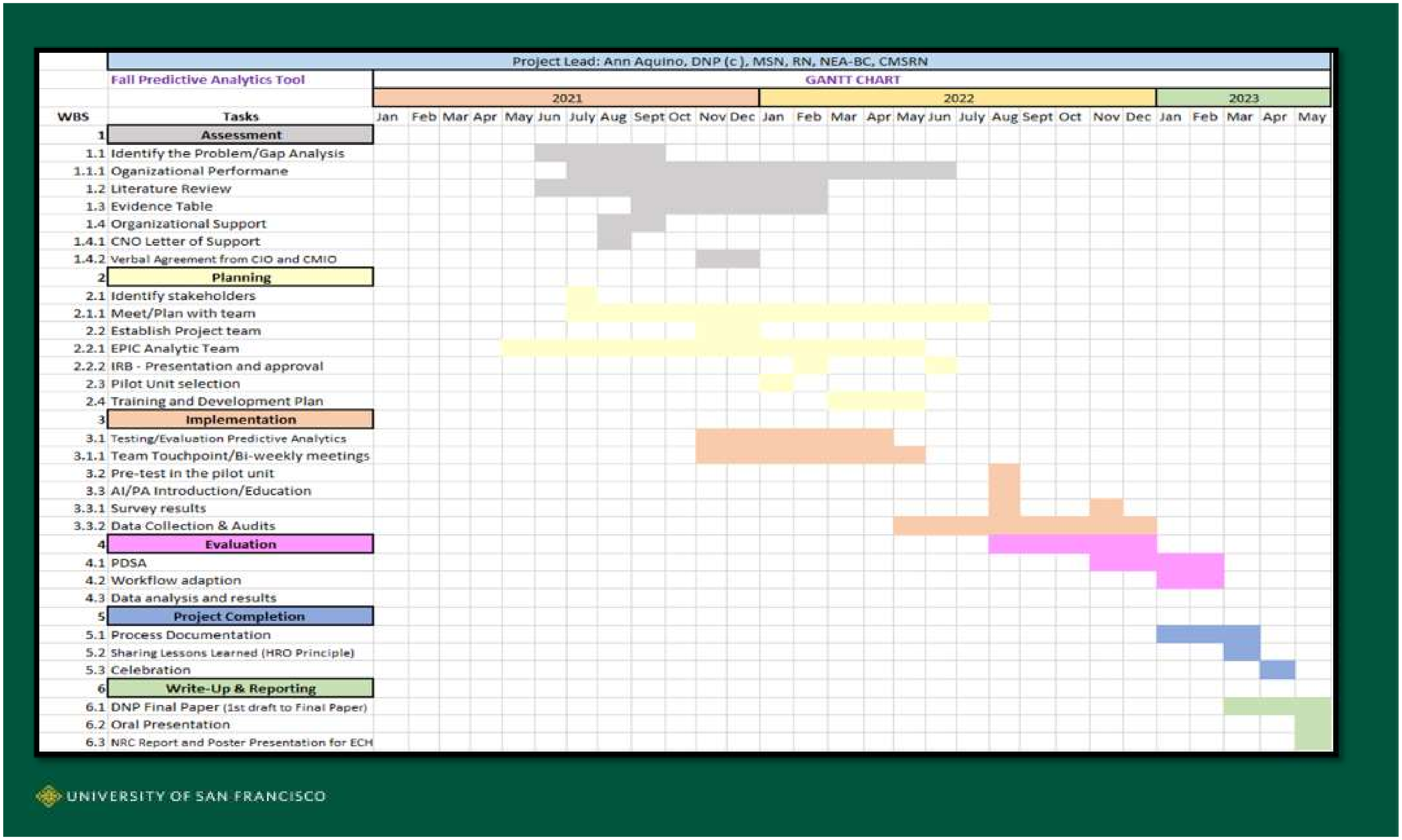
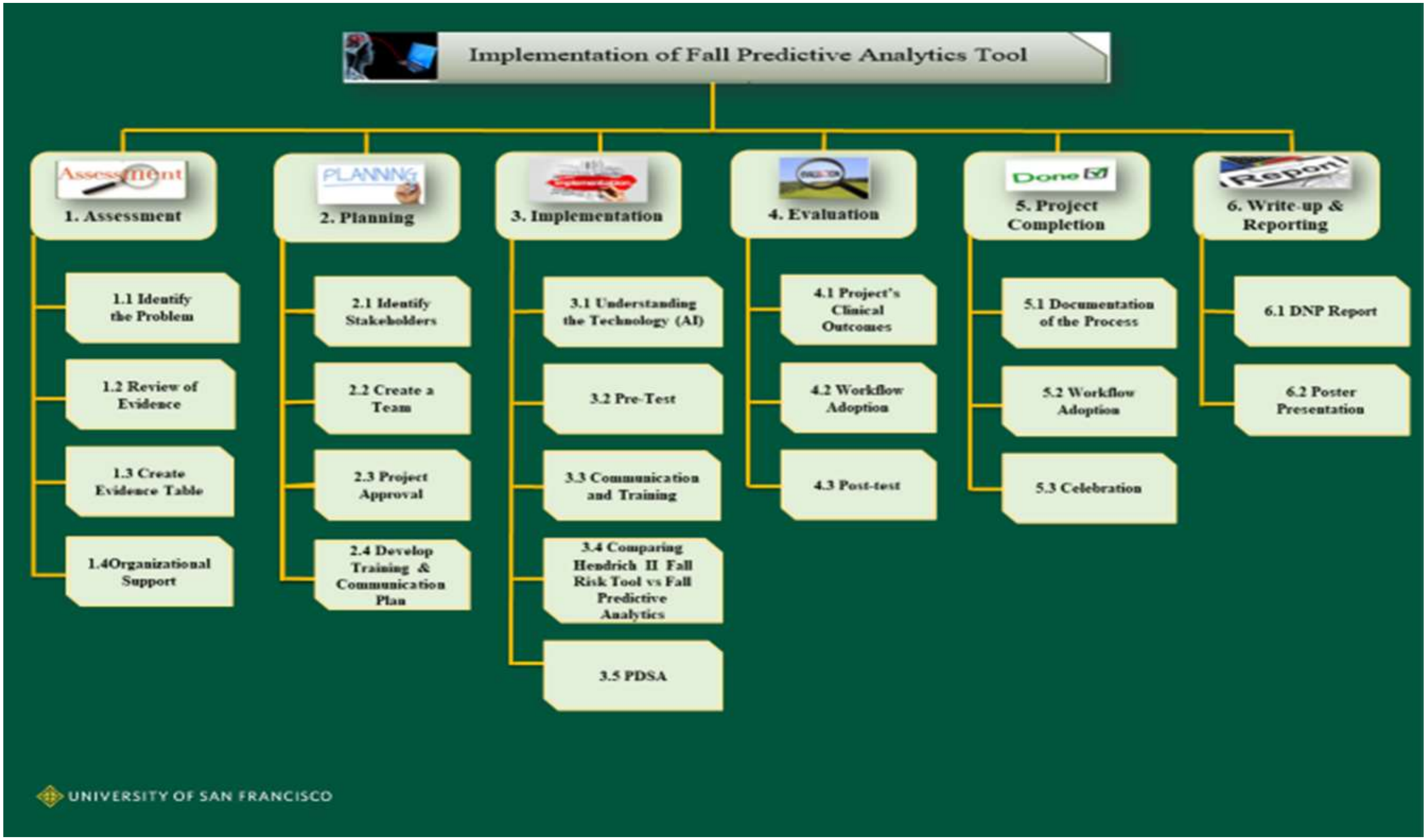
Appendix E

Gantt Chart



Appendix F

Work Breakdown Structure



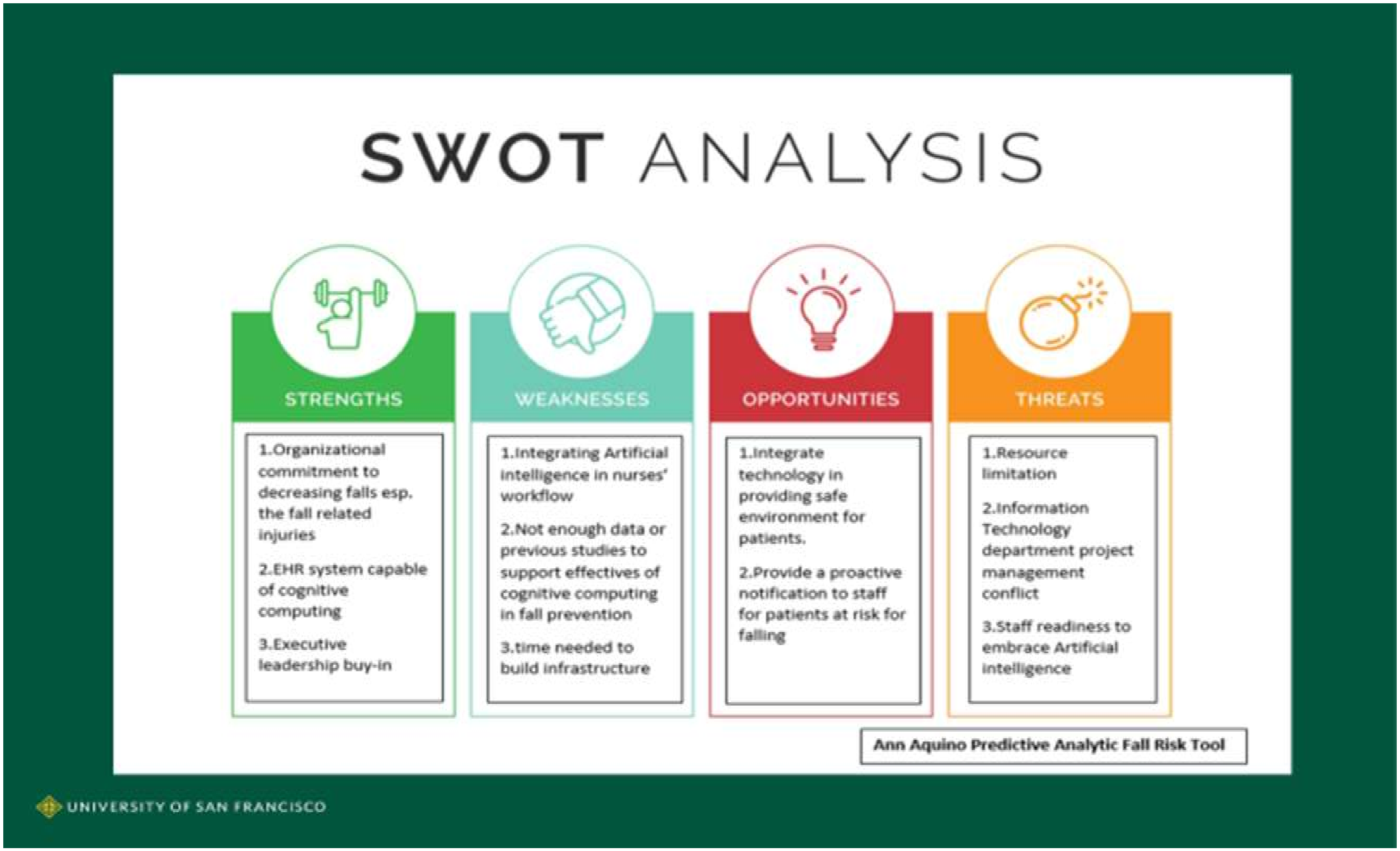
Appendix G

Responsibility & Communication Matrix

Stakeholder	Objective	Meeting Cadence	Format	Person-in-Charge
Executive Sponsor: Chief Nursing Officer	Communicate project status and any barriers to the success of the project implementation. Provide information on executive-level assistance.	Monthly	In-person 1:1	DNP Student
Chief Information Officer	Obtain approval on Fall Predictive Analytics project implementation—request a commitment to IT resources and support.	Before project implementation and as needed	In-person	DNP Student
Chief Quality Officer	Gain support during project implementation and presentation to the different quality committees and teams.	Quarterly	In-person 1:1	DNP Student
Patient Care Clinical Leaders	Provide project design, goals, status, and needed support, particularly staff time and participation in meetings and project implementation.	Project Implementation and after each PDSA cycle review.	In-person during leadership meetings	DNP Student
Fall Prevention Committee	Inform project design, goals, implementation, and status. Continuous updates are provided monthly and after each PDSA cycle.	Monthly	In-person meetings during Committee meetings	DNP Student
Project Team	Communicate and inform about project progress and issues. Tasks are monitored and reported regularly to stay on track.	Every 2 weeks and as needed	Zoom meetings and emails	DNP Student
Direct Care Informatics Team	Inform project design, goals, implementation, and status. Continuous updates are provided monthly and after each PDSA cycle.	At the beginning of the project implementation and as needed	Zoom meetings and emails	DNP Student
Nursing Informatics Team	Inform project design, goals, implementation, and status. Continuous updates are provided monthly and after each PDSA cycle.	Monthly	Zoom meetings during Committee meetings	DNP Student
Patient Care Clinical Leaders	Announce Project Pilot completion and sharing of lessons learned	After the Pilot project	In-person during leadership meetings	DNP Student
Nursing Research Council	Share project success and plan on dissemination, i.e., poster presentations.	After the Pilot project	In-person at the committee meetings	DNP Student and NRC team
Shared Governance/Magnet Council	Share project success and plan on dissemination, i.e., poster presentations.	After the Pilot project	In-person at the committee meetings	DNP Student and Shared governance team

Appendix H

SWOT



Appendix I

Comprehensive Financial Analysis
Budget/ROI

Assessment, Planning & Implementation		**3-year Annual Cost Saving/Avoidance**			
Expenditure	**Start-up Cost**	**Year 1 with 4% Inflation**	**Year 2 with 4% Inflation**	**Year 3 with 4% Inflation**	**Total Cost**
Executive Sponsors	$1,500	-$	-$	-$	$1,500
Pilot Unit Champions	$14,268.24	$1,524	$1,584.9	$1,648.2	$4,757.1
Pilot Unit – Medsurg/Oncology RNs & LVNs *After the pilot phase, all RNs & LVN in 15 inpatient units will receive the Healthstream Module of FPAT	$5,122.2	$127,725.312 $294.12	-$	-$	
Clinical Applications Manager	$1,625.76	-$	-$	-$	
Information Technology Analyst	$1,259.52	$327.44	$340.52	$354.12	$1,022.08
Fall Prevention Committee Chair & Co-Chair	$1,266.6	-$	-$	-$	
Quality Analyst	$261.76	$273.6	$284.54	$295.92	$854.06
Informational Campaign	$400	-$	-$	-$	
Contingency (10%)		$12,772	$13,282.88	$13,814	$39,868.88
TOTAL	$25,704.08	$142,916.472	$15,492.84	$16,112.24	$200,225.63
Cost Savings/Avoidance	**Base Year (FY22)**	**Year 1 with 4% Inflation (FY23)**	**Year 1 with 4% Inflation (FY24)**	**Year 1 with 4% Inflation (FY25)**	**Total Estimated Cost Savings**
Estimated cost avoided from the reduction of fall rate	-$1,110,148.2	$504,781.8	$284,074.01	$159,972.873	$948,828.68
Reduction in the nursing documentation time	No reduction -$32,560.27	$36,978.13	$39,994.42	$43,255.06	$120,227.61
Total Savings/Cost Avoidance	- $1,142,708.47	$541,759.93	$324,068.43	$203,227.933	$1,069,056.29
ROI		**3.79**	**20.92**	**12.61**	**5.34**

Comprehensive Financial Analysis
Start-up Budget

Employee Hours	Number of Employees	Estimated Average Hourly Rate	Total Hours	Total Cost
Executive Sponsors Chief Nursing Officer & Chief Medical Information Officer	2	$250	6 *4 hrs. with CNO *2 hrs. with CMIO	$1,500
ClinicalNurse III Pilot Unit Champions	6 1 - Step 10 Clin III 1 - Step 9 Clin III 4 - Step 7 Clin III	$ 102.86 $ 100.85 $ 97.70	72 *2 hours per RN per week x 12 weeks	$14,268.24
Pilot Unit– Medical/Surgical/OncologyNurses	54 - Clin II RNs 2 - LVNs	$ 93.04 (Ave) $ 49.02	56	$5,122.2
Clinical Applications Manager	1	$ 101.61	16 *Bi-weekly meeting	$1,625.76
Information Technology Analysts	1	$78.72	16 *Bi-weekly meeting	$1,259.52
Fall Prevention Committee Chair & Co-Chair	2	105.55	12 *1 hr. per month committee meeting x 4 months plus 30minute agenda meetings	$1,266.6
Quality Analyst	1	$ 65.77	4	$ 261.76
Informational Campaign	N/A	N/A	N/A	$400 *Flyers, candies/snacks
			Total:	$25,704.08

Note: The Fall Predictive Analytics Module is part of Epic EHR's program.

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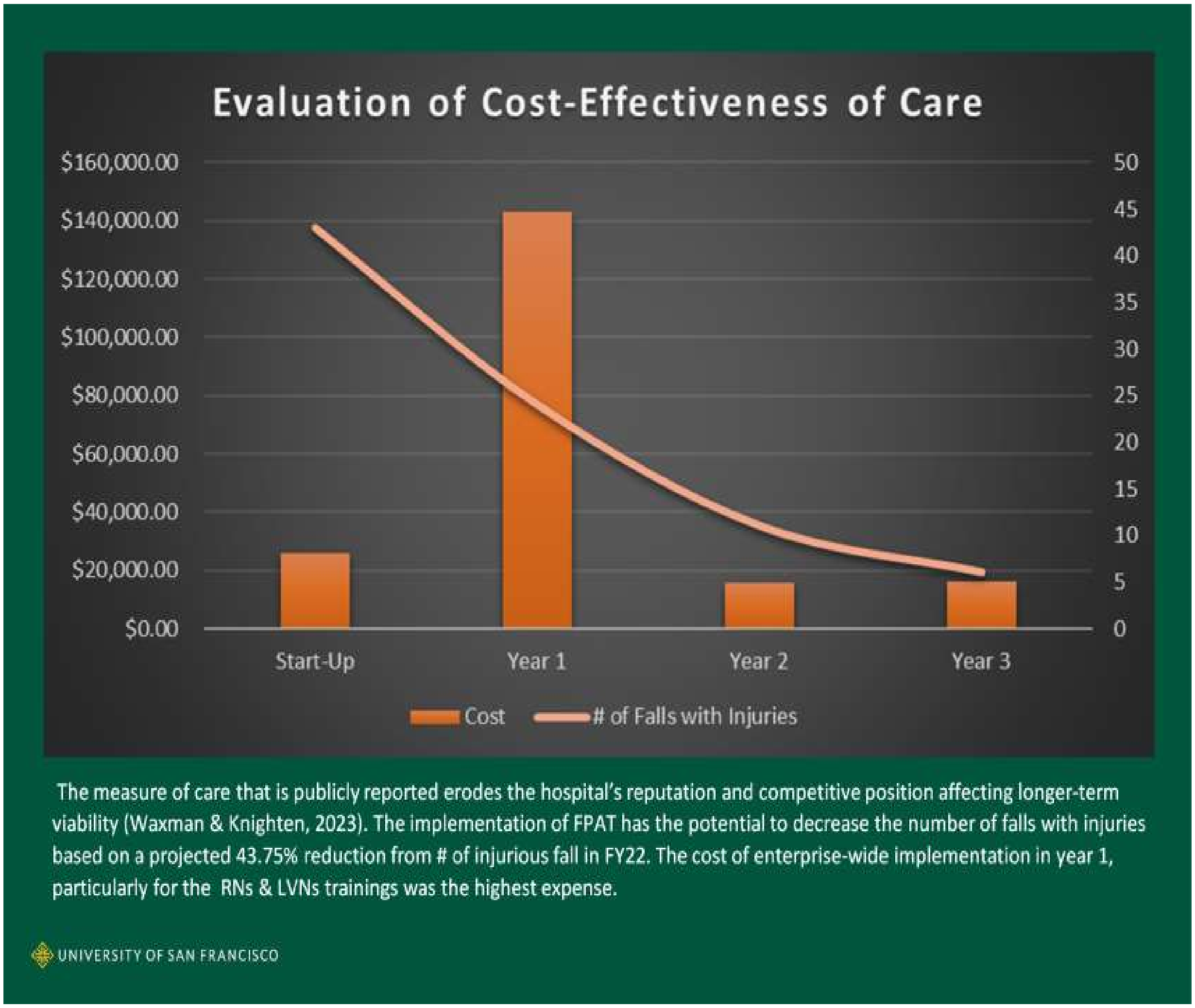
Comprehensive Financial Analysis
Evaluation of Cost-Effectiveness of Care



Appendix J

Qualtrics Survey

Survey: Nurses Partnering with Technology: Using Artificial Intelligence in Predicting a Patient's Risk for Falling

***By voluntarily completing the survey, you are giving your consent to participate. All responses are deidentified and remain anonymous.**

Do you believe there is a potential in the use of Artificial Intelligence (AI) in predicting a patient's risk for falling?

- ○ No
- ○ Maybe
- ○ Yes

In a nutshell, machine learning and predictive analytics fall under the umbrella or AI. This application produces a predictive score which informs actions that the nurses should take.
Do you think AI provide a better way to predict the patient's risk for falling compared to Hendrich II Fall Risk Tool?

- ○ No
- ○ Maybe
- ○ Yes

Will the use of AI assist the nurses in the actions they will take to prevent their patients from falling?

- ○ No
- ○ Maybe
- ○ Yes

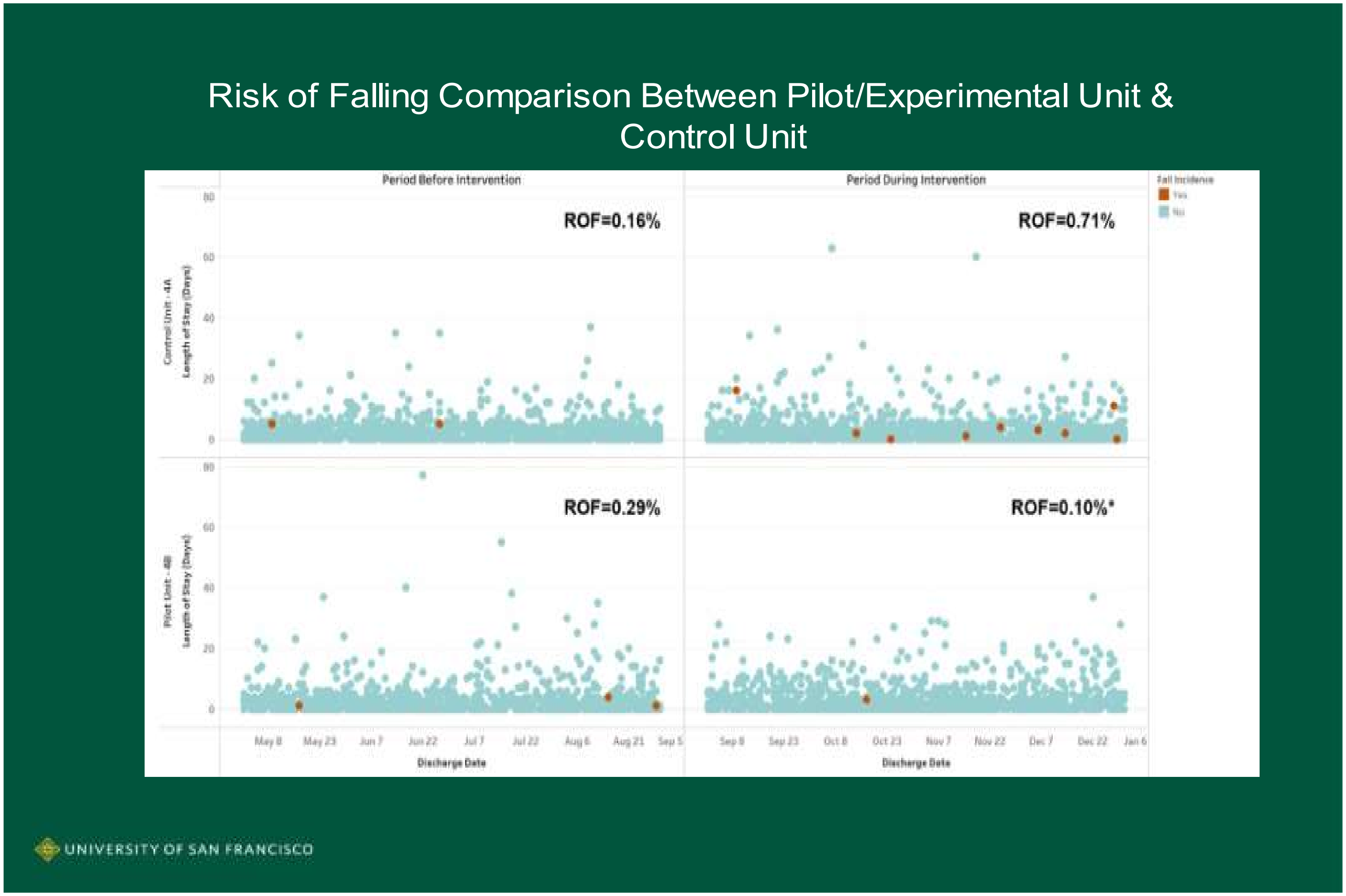
Can AI improve the nurses' workflow?

- ○ No
- ○ Maybe
- ○ Yes

Please provide feedback on how AI help protect our patients from harm. This survey is anonymous and the text field is strictly voluntary.

Appendix K

Rate of Fall (ROF)



Rate of Fall (ROF)

Risk of Falling Comparison Between Pilot/Experimental Unit & Control Unit

Pre-FPAT implementation	**Control (4a)**	**Experiment (4b)**
Fall	2	3
No fall	1270	1055
Fall rate	0.16%	0.29%

Pearson Chi-square: p-value = 0.510
Fisher's Exact Test: p-value = 0.413

These results suggest that the pre-implementation rate was not different between the 2 units.

Pilot cycle	**Control (4a)**	**Experiment (4b)**
Fall	9	1
No Fall	1259	1015
Fall rate	0.71%	0.10%

Pearson Chi-square: p-value = 0.028
Fisher's Exact Test: p-value = 0.050

During the pilot period the rates are statistically different between unit 4A and unit 4B. This would suggest the AI tool significantly reduced the ROF

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