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Nurses Partnering with Technology to Predict the Patients' Risk of Falling Using Artificial Intelligence

Ann Aquino
University of San Francisco, adaquino@dons.usfca.edu

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Ann Aquino, MSN, RN, NEA-BC, CMSRN

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Dr. Nicholas Webb, DNP, RN, ESQ

University of San Francisco

School of Nursing and Health Professions

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Abstract

Artificial intelligence's influence on human lives has captured the attention of healthcare professionals around the globe. There is high optimism for healthcare transformation for better and more efficient care delivery using technology in a highly complex work environment. Because of machine-learning models, predicting the likelihood of harm, such as a fall, is possible. Artificial intelligence (AI) calculations create predictive analytics that can be an objective mediator between the patients' clinical presentation and the nurse's judgment. Further, standardization of documentation is made possible because of the technology behind AI. Information models create a clinical support system that guides nurses in preventing falls. The potential of improving documentation efficiencies and preventing documentation burden with AI can impact the partnership between technology and nursing.

While technology has a great potential to improve the nurses' workflow, there are challenges with the nurses' acceptance of the use of AI. Locsin's "Technological Competency as Caring in Nursing" theory demonstrated the simultaneity paradigm that shows the relationship between nursing care and technology working side by side to deliver the best possible patient outcomes. Nursing professionals who understand AI's benefits, challenges, and potentials are instrumental in leading the workforce in collaborating, designing, integrating, and implementing technology into practice.

Keywords: *Artificial intelligence, predictive analytics, Technological Competency as Caring in Nursing theory, clinical support system, information models,*

Introduction

Technology has influenced all aspects of human lives, from shopping, entertainment, and healthcare. Bohr and Memarzadeh (2020) authored an article titled "*The rise of artificial intelligence in healthcare."* They discussed how artificial intelligence (AI), a technology concept, impacts the modern world. Netflix, Amazon, and Google know which shows, products and topics are people interested in (Bohr and Memarzadeh, 2020). It is fascinating how Bohr and Memarzadeh (2020) connected the applicability of personal profiling to predicting healthcare trends. For instance, precision medicine aims to tailor healthcare treatments to utilize the patient's biological information and profile, such as age, gender, familial history, immune and metabolic profile, and environmental vulnerability. Precision medicine ingenuities using a complex algorithm from electronic health records and demographic information could provide a prediction of prognosis and optimum treatment approach. Further, digital health applications that measure a patient's food intake, emotional state or activity, and health monitoring using wearables and sensors help identify trends to assist in personalized treatment recommendations and better predict vulnerabilities for diseases. The same authors are optimistic that AI can provide substantial improvement in all aspects of healthcare, from diagnosis to treatments. Additionally, subject matter experts believe AI supports healthcare staff with documentation, clinical decision support, and patient monitoring.

The nursing care process (NCP), first conceptualized by Ida Jean Orlando in 1958, is a tool used by nurses to recognize and address the problems of individual patients. She described it as a systematic approach to patient care using the fundamental principles of critical thinking, client-centered treatment, goal-oriented tasks, evidence-based practice (EBP), and nursing recommendations (Toney-Butler and Thayer, 2021). Comprised of five steps: *assessment,*

diagnosis, planning, implementation, and *evaluation*, each step is carried out to keep nurses focused on identifying the patient's problem, selecting and implementing interventions to the problem, and evaluating the patient's response interventions. Artificial intelligence (AI) could serve as the eyes and ears of nurses, enhancing the ability of nurses to assess better, strategize appropriately, and evaluate the effectiveness of the care plan. A systematic review looked at the nursing decision support system (DSS) and which steps apply to the NCP (Akbar et al., 2021). The result showed that most DSS focused on two NCP steps: the assessment and intervention. Using AI to provide a more comprehensive assessment of a patient's risk of falling, nurses can cater to the patients' individual needs instead of the more traditional way of using a traditional risk assessment tool. Moreover, Akbar et al. (2021) encourages future research to augment automation, particularly at the information acquisition stage, to help improve nurses' decision-making, delivery of care, and patient outcomes. '

For decades, falls and related injuries have been safety and quality care concerns (Moskowitz et al., 2020). In the United States, about thirty-six million adults 65 years and older report falling each year; 37% of those who fall need medical attention because of injuries (Centers for Disease Control and Prevention, 2021). Approximately fifty billion dollars are spent on healthcare expenditures in the United States each year (Centers for Disease Control and Prevention, 2021). Appropriate risk screening and fall preventive measures are critically necessary for avoiding falls and maintaining the patients' quality of life. Additionally, preventing falls could avert the high cost of healthcare expenses (Yokota, 2017).

In a special issue of the New England Journal of Medicine (NEJM) Catalyst, a free webinar showcasing AI and machine learning for health care delivery was made available to healthcare professionals. In this Webinar, Li (personal communication, March 24, 2022)

presented AI as a tool for continuous clinical monitoring, an objective mediator between the clinician and the patient. Technology, such as device integration, robotic-assisted procedures, and computerized diagnostic imaging, to name a few, offer great potential for better outcomes (Li, 2022). One would wonder, "is it possible for nursing and technology to partner and co-exist in a profession primarily driven by the caring principle?"

The Theory of Technological Competency as Caring in Nursing

Locsin, a contemporary theorist, demonstrated the simultaneity paradigm that shows the relationship between nursing care and technology working side by side to deliver the best possible patient outcomes. Nursing communication, a dynamic nurse-patient relationship, requires observation and interaction. Today, nurse-patient communication involves integrating complex and constantly changing patients' needs using technology. The theory of *Technological Competency as Caring in Nursing* (TCCN) expands the concept of caring to demonstrate knowing the person in a multidimensional process that utilizes technology in caring for the individual (Locsin, 2016). Further, the theory describes that technology allows the nurse to know the patient better by using information previously collected and documented in the EHR to better care for patients.

Computerization of nursing documentation, medication bar code scanning, and diagnostics results integration help create clinical decision support (CDS) systems that guide nurses in providing the best care pathways for patients. Several studies look at the use of AI in predicting patients' risk of falling and how the risk scores influence the CDS deployed by nurses. Compared to manually inputted fall risk screening tools, the predictive analytics using AI outperformed the manually inputted tool in the accuracy and timing of fall risk assessment based

on the studies of Lytle et al. (2021), Cho et al. (2019), Moskowitz et al. (2020), Yokota et al. (2017) and Jung et al. (2019).

Fall Predictive Analytics Using Cognitive Computing, Machine Learning, and AI

Electronic health records (EHR) produce metadata used for research and advanced clinical practice. A study by Lytle et al. (2021) used twenty-seven million patient encounters to develop the content format and standard documentation workflow for the fall prevention information model. Using FloMap software, EHR data were mapped and grouped into concepts that form the information model (IM). The fall prevention IM includes nursing assessment, interventions, and outcomes. The concept of IM allowed data comparison across other organizations and provided a better understanding of how nursing documentation can best be utilized. An earlier study conducted by Cho et al. (2019) utilized nursing records to create a predictive model to assess a patient's falling risk, showing an error rate of 11.7% and c-statistics of 0.96, which showed superior performance compared to manually inputted fall risks screening tools.

Cho et al. performed a follow-up study in 2021 to review the impact of an electronic analytic tool for predicting falls and the nurses' response to the patients' risk. The authors used a control group and an intervention group to compare the effects of a project called Intelligent Nursing @ Safety Improvement Guide of Health Technology Systems (IN@SIGHTS). There was a decrease in the mean fall rate in the intervention group from 1.92 to 1.72, which revealed that the analytic tool could lower the number of falls and lead to positive changes in the nursing intervention (Cho et al., 2021).

Pharmacology side effects proved to be a fall risk contributor coined as Fall-Risk Inducing Drugs or FRIDs (Choi et al., 2018). A dynamic EHR-based fall risk prediction model

for hospitalized patients given FRIDs using machine learning and AI showed an unbiased c-statistics of 0.62 compared to the Morse Fall Score of 0.69. Each FRIDs administered increases the patients' odds of falling by 8% (Choi et al., 2018). Current fall risk screening tools commonly used in healthcare facilities do not consider most drugs in the FRIDs category. The Fall Predictive Analytics Tool, a program in the Epic EHR, can cognitively compute the number of FRIDs doses and medications administered at a given point in time and assign a patient's fall risk status along with other variables the nurses would typically not have the time to review at the time of them performing their patients' fall risk assessment.

The timing of risk evaluation and re-evaluation is crucial as patients' conditions change (Yokota et al., 2017). A discriminant model called Find Fall Risk of inpatients from Nursing Data (FiND) was created to evaluate the patient's risk of falling using the previous day's nursing documents. The model showed a sensitivity of 64.9% and a specificity of 69.6%, which means the model provided an objective evaluation of a patient's risk for falling. Another risk prediction model uses representative values collected at various times and compares the patients' risk for falling using a validated fall risk tool entered manually by nurses. Lower limb weakness and dysuria were the two most significant factors affecting falls with a $P<.05$. The study showed the possibility of identifying the patient's fall risk status at the time of the fall using AI (Jung et al., 2019).

Nursing Perception, Attitudes, and Understanding of AI

The advancement of healthcare informatics and the emergence of AI have the potential to transform clinical care. A non-experimental study explored the health care employees' perceptions and attitudes towards implementing AI in Saudi Arabia. It showed moderate acceptance of AI, and respondents were concerned that AI would eliminate their jobs (Abdullah

& Fakieh, 2020). Students from eighteen universities received a survey to identify and explore AI knowledge gaps in Canada. The results show that 78.77% of Canadian students believe that AI will affect their careers shortly, and 74.5% reported a favorable outlook toward AI (Teng et al., 2022).

Akbar et al. (2021) conducted a systematic review of twenty-eight articles to review the different decision support systems (DSS) concerned with two nursing care plan (NCP) steps: the *assessment* and *intervention.* Nurses use critical thinking skills to develop a care plan and implement interventions. DSS had an overall positive effect on nurses' decision-making in 18 out of 22 outcome measures. Additionally, there is an increase in DSS used in the clinical setting, but the awareness of the benefits of automation is understudied (Akbar et al., 2021).

Artificial Intelligence Improving Documentation Efficiency and Prevention Documentation Burden

A controversial element of a fall prevention strategy is risk screening (Jellett et al. (2020). According to a previous study in 2018, an estimated 8% of the total hospital fall prevention resources are allocated to performing screening; risk assessment consumes 12 % of the resources for fall prevention allocation (Jellett et al., 2020). Interestingly, removing the risk screening did not negatively impact the number of falls per month but positively impacted the fall risk screening documentation time. Moreover, it showed a 36-second reduction of time per patient to complete the fall risk screening tool.

The American Recovery and Reinvestment Act of 2009 incentivized healthcare organizations to implement Electronic Health Records (EHRs) and focus on their adoption and meaningful use (Lytle et al., 2021). A 2015 O'Brien et al. study showed that the rapid implementation of EHR produced unstructured metadata, inefficient and duplicative data entry,

causing a documentation burden (Lytle et al., 2020). The use of information models (IMs) can standardize data across organizations and can support the creation of clinical decision support, such as the fall prevention IM.

In an attempt to quantify the number of documentation "clicks" saved when the manually entered fall risk tool is replaced by the predictive model using artificial intelligence; the following information was reviewed:

(a) The total number of adult inpatients admitted to the medical/surgical/oncology unit in three months from December 1, 2021, to February 28, 2022

(b) The total number of fall risk screening documents entered within the three months

The setting for the project is the medical/surgical/oncology unit of a 454 licensed bed, not-for-profit, two-campus community hospital in Mountain View, California. All patients admitted to the medical/surgical/oncology unit 18 years and older were included in this project. There were 47,252 total patients admitted between December 1, 2021, to February 28, 2022. The total number of documentation "clicks" was 756,032 based on the eight rows needed to complete the fall risk screening tool and the number of times they have to document. Nurses performed the fall risk screening every twelve hours per hospital policy. That number can be converted to 210 hours, assuming that one click is equivalent to one second. The result of this project is auspicious and shows clinical relevance in decreasing the time nurses spend on documentation (see Appendix A).

Using Artificial Intelligence to Predict the Patients' Risk for Falling

The use of technology in predicting the patients' risk for falling is promising. Embedded information from clinical documentation could help create clinician decision support that could assist in an individualized approach for a fall prevention strategy to prevent falls and improve

outcomes. Implementing the Epic Cognitive Computing Fall Risk Model can capture variables embedded in the EHR to enhance the predictability of a patient's risk for falls and potentially decrease nurses' 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-sensitive data possible and a priority because healthcare organizations are incentivized for meaningful use of HER (Lytle et al., 2020). Standardization of flowsheets with AI improves data exchange and supports research. Further, such standardization assisted in creating several fall risk screening and assessment models, allowing the use of intrinsic factors and variables in real-time.

For decades, nurses have been practicing using their clinical skills guided by the nursing process of assessment, planning, intervention, implementation, and evaluation. Nurses have masterfully executed these nursing skills and behaviors. The caring nature of nurses drives the patient-nurse relationship; this relationship is dynamic and interactive. In today's modern world, the technological encounter facilitates communication throughout the continuum, pre-hospitalization, during hospitalization, and post-discharge. Locsin's Theory of Technological Competency as Caring in Nursing provides a framework for a nurse-patient interactive relationship using the technological domains.

It is crucial to assess the nurses' understanding, perception, and acceptance of AI. Abdullah and Fakieh (2020), Akbar et al. (2021), and Teng et al. (2022) evaluated nurses' perception of AI and showed the need to start incorporating clinicians in designing and implementing workflows for better acceptance. A pre-implementation survey helps obtain

baseline information on how nurses view AI in predicting a patient's risk for falling and compared to the post-implementation survey.

Conclusion

Integrating AI technology can assist nurses in making the best clinical decision to provide quality care by protecting the patients from falling. Nurses rely heavily on manually documenting the patients' risk for falling. While many healthcare organizations have explored a predictive model for falls, more data must be shared to understand the challenges and benefits of using AI.

Understanding the nurses' perception of AI is essential to the success of the adaption of the predictive analytics tool. The impact of the nurses' readiness to embrace technology could open the possibility of more predictive model creation and implementation to enhance current workflows and processes.

References

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

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

Bohr, A. & Memarzadeh, K. (2020). The rise of artificial intelligence in healthcare applications. *Artificial Intelligence in Healthcare*, 25-60. https://doi.org/10.1016/B978-0-12-818438-7.00002-2

Centers for Disease Control and Prevention. Older adult fall prevention. (2021, July 14). https://www.cdc.gov/falls/index.html

Cho, I., Boo, 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

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.or/10.2196/26456

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

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

Jung, H., Park, H. & Hwang, H. (2019). Improving prediction of fall risk 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

Li, R. (2022). *AI and machine learning for health care delivery [Webinar].* NEJM Catalyst. https://events.catalyst.nejm.org/events/ai-and-machine-learning-for-health-care-deliver

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/10.1111/jnu.12646

Moskowitz, G., Egorova, N., Hazan, A., Freeman, R., Reich, D. & Leipzig, R. (2020). Using electronic health records to enhance the predictions of fall risk in inpatient setting. *The Joint Commission Journal on Quality and Patient Safety, 46*:199-206. https://www.doi.org/10.1016/j.jcjq.2020.01.009

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

Toney-Butler, T. J. & Thayer, J. M. (2021). *Nursing process.* StatPearls. https://pubmed.ncbi.nlm.nih.gov/29763112

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

Appendix A
Potential Nursing Documentation Time Saved with Artificial Intelligence

Time Frame	Total # of Patients	Total number of clicks using the screening tool	Total Number of Hours Saved on clicks
December 1, 2021, to February 28, 2022	47, 252	756, 032	210 hrs

Fall Risk Screening is done every 12 hours per hospital policy. There are eight clicks to complete the Fall Risk screening tool. The first risk screening tool will be completed, and the succeeding assessment will be done using artificial intelligence.