HEALTHCARE ANALYTICS AT A PERIOPERATIVE SURGICAL HOME IMPLEMENTED COMMUNITY HOSPITAL

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree

of

Doctor of Philosophy

in

Engineering

MONTANA STATE UNIVERSITY
Bozeman, Montana

December 2022

DEDICATION

I would love to dedicate this dissertation to my parents Sridhar Srinivasan and Radha Sridhar. Words cannot describe how grateful I am for your unconditional love, support, and care. Thank you Amma, thank you Appa!

ACKNOWLEDGEMENTS

I first would like to thank God for giving me the strength, courage, wisdom, and health both mentally and physically to accomplish this huge achievement. I would like to express my gratitude to my committee chairman, Dr. Bernadette McCrory, for her patience and faith in me. Her mentorship in pushing me past my own perceived limits in all stages of my journey as a Ph.D. student was instrumental in achieving this Doctorate. I would like to thank my current and past committee members: Dr. Bradley Whitaker, Dr. Andrew Hoegh, Dr. Nicole Carnegie, Dr. Nicholas Ward and Dr. Sage Kittleman for their insightful comments and suggestions.

I am very thankful to all M&IE Faculties and staff particularly Dr. Durward Sobek, Kathy Campbell, and Dagny Mest for their support and assistance. I am deeply indebted to the staff of the Office of International Programs especially Deborah Chiolero and Holly Jeide for all their help over the years. I would like to thank Dr. Amy Mouat-Hunter, Dr. Jessica Hoge, and the entire perioperative team at the Bozeman Deaconess for their assistance and collaboration. My deep gratitude to all my friends, colleagues, and family for alleviating and cheering me up during the toughest times of my research. Last but not least, I would like to thank my fiancé Gaayathri Sankar for being supportive and wonderful.

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ABSTRACT

The Perioperative Surgical Home (PSH) is a novel patient-centric surgical system developed by American Society of Anesthesiologists (ASA) to improve surgical outcomes and patient satisfaction. Compared to a traditional surgical system, the PSH is a coordinated interdisciplinary team encompassing all surgical care provided to patients from the perioperative phase to recovery phase. However, limited research has been performed in augmenting the PSH surgical care using healthcare analytics. In addition, the spread of the PSH is limited in rural hospitals. Compared to urban hospitals, rural hospitals have higher surgical care inequality due to limited availability of clinicians, resources, resulting in poor access to surgical care. With an increase in the rate of Total Joint Replacement (TJR) procedures in the United States (US), rural hospitals are often under-resourced with coordinating perioperative services resulting in inadequate communication, poor care continuity, and preventable complications.

This study focused on developing a novel analytical framework to predict, evaluate, and improve TJR outcomes at a PSH implemented rural community hospital. The study was segmented into three parts where the first part explored the effectiveness of the digital engagement platform to longitudinally engage with TJR patients located in rural areas. The second part evaluated the impact of PSH system in the rural setting by analyzing and comparing the TJR surgical outcomes. Finally, the third part explained the importance of machine learning in the rural PSH system to identify critical patient factors, enhance decision-making, and plan for preventive interventions for better surgical outcomes. Results from this research demonstrated the importance of healthcare analytics in PSH system and how it can help to enhance TJR surgical outcomes and experience for both clinicians and patients.

CHAPTER ONE

INTRODUCTION TO PERIOPERATIVE SURGICAL HOME (PSH)

In 2010, the Center for Medicare and Medicaid Services (CMS) introduced bundled payment to increase the quality of care while attempting to control healthcare cost (Glickman et al., 2018). The bundle payment replaced the traditional fee-for-service model where clinicians were reimbursed solely based on the volume of the procedures performed (Chimento & Thomas, 2017). Instead, the bundle payment focused on "pay for value" driving caregivers to adopt a care model that leads to higher quality and coordinated care at a lower cost for Medicare (Desebbe et al., 2016; Miller et al., 2011). The bundle payment model was first introduced in 1984 and was adopted by CMS in 2009 and has been wildly spreading in many healthcare departments including surgeries (Froimson et al., 2013). This incentivized hospitals and clinical organizations to streamline and optimize surgical process and reduce duplicative or unnecessary services including redundant laboratory analysis, tests, check-ups, and other clinical visits, that contributed to higher operating cost (Miller et al., 2011). In addition, hospitals were encouraged to curtail certain measures of surgical outcomes such as Length of Stay (LOS), discharge rates to skilled nurse facilities, and readmissions post-surgery to better manage cost and patient experience, while maintaining revenue (Desebbe et al., 2016; Kim et al., 2021; Miller et al., 2011).

According to the CMS, the hospitals that were consistently expensive across surgical services had higher chances of financial risk with the bundle payment model; compared to hospitals with low to moderate cost for surgeries that maintained the same or improved care quality (Miller et al., 2011; Zaccagnino et al., 2017). In this context, the American Society of

Anesthesiologist (ASA) introduced a new surgical model, the Perioperative Surgical Home (PSH), in 2013, which is compatible to the new bundle payment and also attempts to optimize perioperative process and surgical outcomes (Chimento & Thomas, 2017; Desebbe et al., 2016; Kain et al., 2014; B. A. Kash et al., 2014; Zaccagnino et al., 2017).

Perioperative Surgical Home (PSH)

The Perioperative Surgical Home (PSH) model of care was created by the leaders within American Society of Anesthesiologists (ASA) (B. Kash et al., 2014; Vetter et al., 2013). Compared to a traditional surgical system, the PSH is a coordinated interdisciplinary team encompassing all surgical care provided to patients from the preoperative phase (30 days before surgery) to the recovery phase (90 days after surgery) (Al-Shammari et al., 2017; Alvis et al., 2017; Cline et al., 2020; Desebbe et al., 2016; Kain et al., 2014; Vetter et al., 2013). According to the ASA, the PSH is defined as "a patient-centered and physician-led multidisciplinary and team-based system of coordinated care that guides patients throughout the entire surgical experience" (Garson et al., 2014; B. Kash et al., 2014). The PSH was developed as a solution to achieve the healthcare 'triple aim' in perioperative setting, which is improving patient experience, improving the health of the patient population, and remaining compatible with the new payment system to reduce costs (Alvis et al., 2017; Duncan, 2019).

Before PSH, Enhanced Recovery after Surgery (ERAS) protocols were widely used in the US, Canada, and different countries in Europe to reduce postoperative complications and shorten inpatient LOS without use of new or expensive technology (Cannesson & Kain, 2014; Varadhan et al., 2010). The ERAS was first introduced in Denmark in the 1990s which consisted of more than 20 specific clinical practices including preoperative fasting, carbohydrate loading, avoidance of premedication, and other evidence based protocols (Cannesson & Kain, 2014; Gramlich et al., 2017; Kain et al., 2014; Melnyk et al., 2011). These protocols were primarily designed for colorectal surgery and were expanded to other surgical procedures as well to facilitate outcomes improvement (Cerantola et al., 2013; Melnyk et al., 2011). Elements of ERAS exist in the PSH system; however, the PSH system encapsulates a larger scope of the perioperative process (B. Kash et al., 2014). In other words, the PSH incorporates ERAS elements in its system but also uses engineering management methods to coordinate performance management techniques such as, Lean methods and six sigma to optimize overall perioperative care (Alvis et al., 2017; Cannesson & Kain, 2014; Desebbe et al., 2016; Nicolescu, 2016).

Perioperative Surgical Home Model

Unlike the traditional surgical system, the PSH surgical pathway is centered on the patient rather than on the clinicians, ensuring that the patient receives coordinated care from the entire surgical team in all phases of the surgical process (Desebbe et al., 2016). Treating the entire perioperative episode of care as one continuum rather than discrete elements is vital in the PSH system to reduce variability, that increases likelihood for errors and complications (Vetter et al., 2013; Vetter & Jones, 2015). Standardizing the perioperative process and emphasizing continuous transitions between different surgical phases has proven to reduce cost and redundant perioperative testing, consultation visits, and same-day cancellations (Desebbe et al., 2016; Dexter & Wachtel, 2014; Kaye et al., 2017). Another key component in the PSH model is broadening the role of the Anesthesiologist in the perioperative process (Dexter & Wachtel, 2014; Duncan, 2019). In PSH, the role of the anesthesiologist extends beyond the Operating Rooms (OR) to other leadership work including staffing and case scheduling, leading the surgical home along with a hospitalist, leveraging resource allocation for each patient's requirements, and accounting of patient care (Desebbe et al., 2016; Dexter & Wachtel, 2014; B. Kash et al., 2014). Before entering the PSH system, whether the patient should have a surgery or not is decided by the surgeon and in most cases, by both the primary care physician and the surgeon. The PSH pathway includes different phases of surgery: preoperative, intraoperative, postoperative, and recovery (Figure 1.1) (Kain et al., 2014; B. Kash et al., 2014).

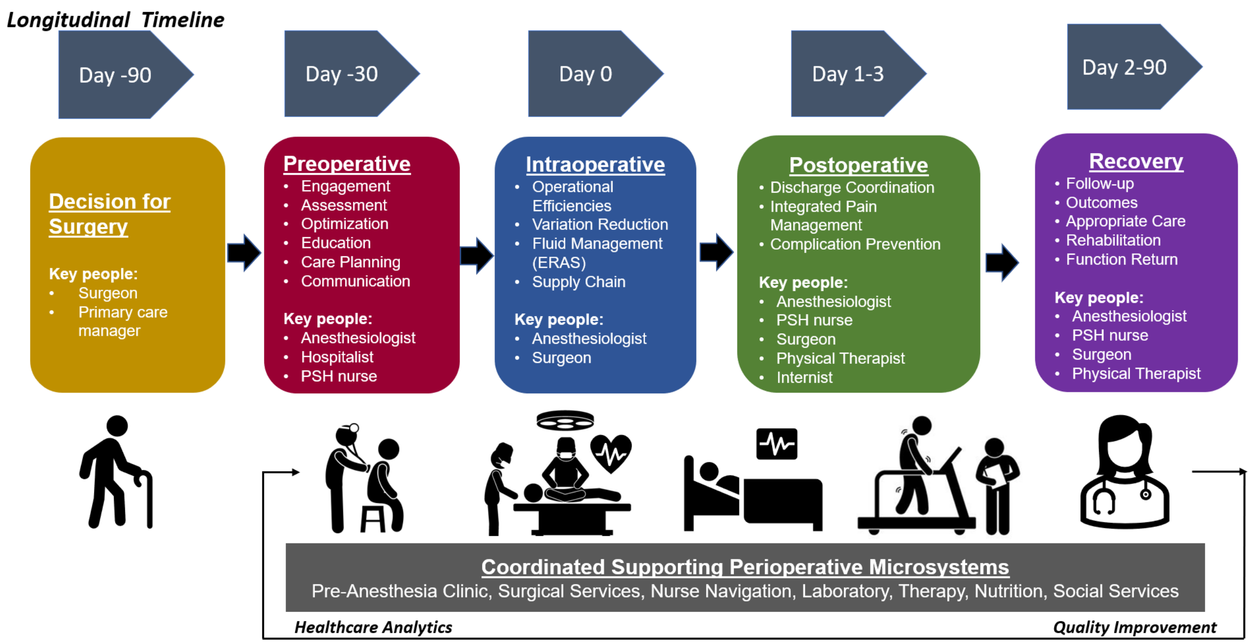

Figure 1.1 Perioperative Surgical Home (PSH) system

Preoperative The preoperative phase in PSH focuses on optimizing rather than clearing the patients for surgery (Duncan, 2019; Kain et al., 2014). The key elements in the PSH preoperative phase include early patient engagement (approximately 30 days before surgery), assessment, patient education, surgical care planning, and optimization (B. Kash et al., 2014;

Kaye et al., 2017). Patient optimization is an active process where clinicians assist patients in preparing for surgery (Lee, 2014). The preoperative assessments are ideally done between 15 to 30 days before surgery. The goal of the assessment is to identify, communicate, and whenever possible to minimize risk factors of surgery and anesthesia (Vetter et al., 2013). Clinicians perform necessary interventions on identified risk factors such as hypertension, diabetes, and smoking that could cause adverse events such as longer LOS, readmission, and postoperative complications after surgery (Garson et al., 2014; Kaye et al., 2017). Patient education is delivered regarding pain, postoperative assistance, and other management options that assist patients to anticipate post-surgical background and get prepared accordingly (Kaye et al., 2017; Yoon et al., 2010).

Intraoperative The intraoperative phase in the PSH involves optimizing OR efficiency by eliminating surgical delays, surgery cancellation, improving patient flow, and coordinating supply chain management to facilitate surgical tools and supplies (Dexter & Wachtel, 2014; B. Kash et al., 2014). Clinicians also follow elements of ERAS protocols to standardize perioperative nutrition, intraoperative fluid management, avoidance of post-operative nausea and vomiting, temperature management, and use of multimodal analgesia (Alvis et al., 2017; Duncan, 2019; Qiu et al., 2016).

Postoperative The postoperative phase in PSH focuses on improved integrated pain management, patient care transition after discharge, postoperative patient engagement, and faster recovery through therapy (Chimento & Thomas, 2017; Garson et al., 2014; B. Kash et al., 2014). After surgery, the PSH clinicians coordinate with the discharge team to plan for early ambulation, nutrition management, educate recovery plans, and guide patients on their discharge settings (Duncan, 2019; Kain et al., 2014). Most inpatients stay in the hospital between one to three days post-surgery depending on clinical severity, risk, and recovery.

Recovery Finally, in the recovery phase, patients are discharged to home or other settings including skilled nursing facilities, the PSH nurse (also known as nurse navigators) performs early follow-ups with the patient remotely using telephone calls or virtual telemedicine (Chimento & Thomas, 2017; Garson et al., 2014; Vetter et al., 2013). Home health visits are often scheduled for patients who are discharged to home and requiring additional care. Pain management and physical/occupational therapy rehabilitation are implemented periodically to enhance recovery with most patients expected to return to complete daily functional activities between 30 to 90 days after surgery (Duncan, 2019; B. Kash et al., 2014; B. A. Kash et al., 2014; Kaye et al., 2017).

Design of Perioperative Surgical Home (PSH) at a Rural Hospital

Patients in rural and socioeconomic deprived communities typically require more perioperative optimization for all surgery types (Lese & Sraj, 2019; McCrory et al., 2019). With increasing demand for orthopedic surgeries such as Total Joint Replacements (TJR), hospitals located in rural areas often struggle to deliver surgical care to TJR patients (Dowsey et al., 2014; Jeschke et al., 2017; Singh et al., 2019). Often rural and frontier health systems have siloed perioperative care that is spread across many disciplines and geographical locations (McCrory et al., 2019). Often, rural TJR patients experience less-than-optimal surgical outcomes and satisfaction primarily due to poor patient engagement, non-standardized care, poor coordination among clinicians, and inadequate patient awareness in rural healthcare systems (Lese & Sraj, 2019; Tsai et al., 2015). A local community hospital in rural Montana implemented a PSH system to address these factors.

A team-based PSH clinic was implemented at a rural community hospital in Montana in November 2018. The hospital was an 83-bed, licensed level-III trauma center primarily serving three counties, but frequently provided care to patients from more than 10 surrounding counties which spans 9,000 square miles and approximately 136,000 residents. With limited resources and supporting microsystems, this PSH clinic was successfully initiated with the help of a strong team-based coordination among clinicians. The PSH multi-disciplinary team consisted of a surgeon, anesthesiologist, hospitalist, physician assistant, registered nurse, and primary care physician. This collaboration focused on improving surgical care and enhancing patient engagement perioperatively. The PSH clinicians communicated using clinical notes and frequent in person meetings. This effective communication between clinicians helped for communal decision-making. Among practitioners, this is known as, “physician co-management” which is defined as arrangement between the hospitals and group of physicians that establish shared responsibility for particular healthcare services (Norful et al., 2018).

In the preoperative phase, PSH procedures utilized assessment and patient education approximately 30 days before surgery. Preoperative assessments were performed by the nurse navigator and physician assistant within 30 days before surgery. The assessments helped PSH clinicians to identify patients with high-risk factors such as diabetes, high or low blood pressure, sleep apnea, obesity, and heart or respiratory complications. Based on these identified risks, the patients received treatment care to improve existing conditions, undiagnosed conditions, and surgical outcomes (i.e., presurgical conditions).

On average (n = 20 patients), the PSH clinicians – nurse navigator and physician assistant – took 71 minutes (SD = ± 14 minutes) to evaluate a patient (Figure 1.2). Patients were also asked to attend the total joint education class hosted by the PSH clinicians. The total joint class informed patients on how to prepare for surgery, manage pain, plan for postoperative discharge, and contact clinicians for postoperative assistance.

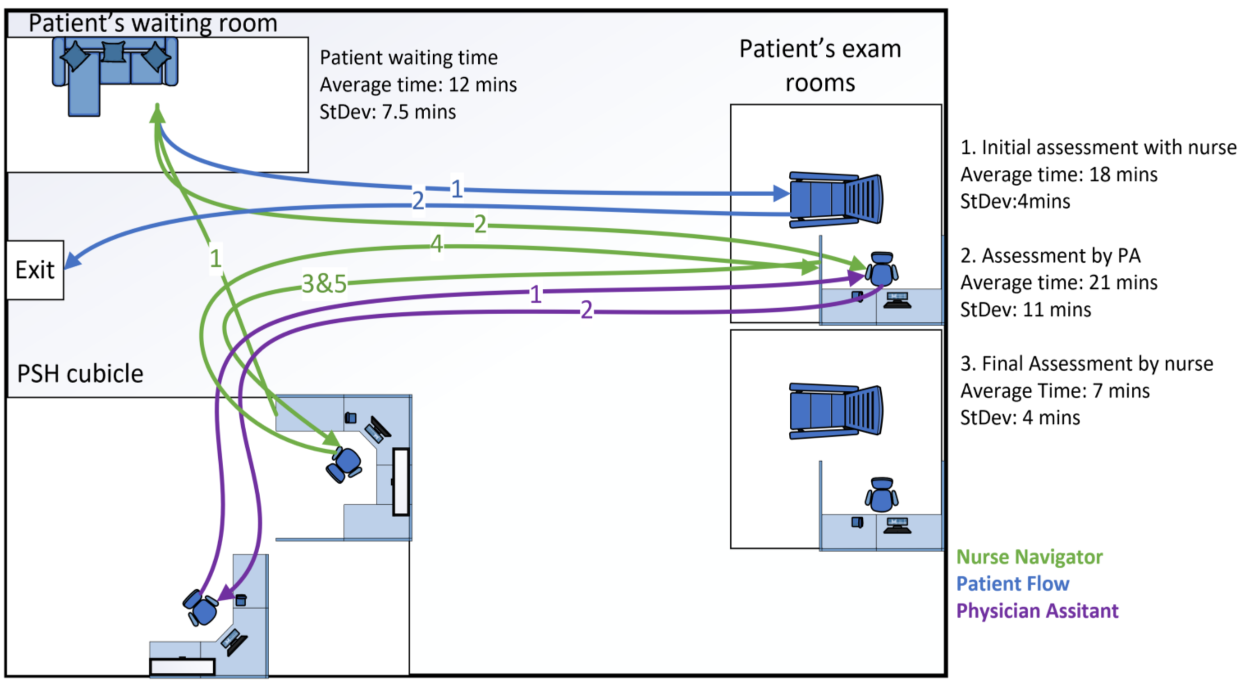

Figure 1.2 Rural PSH preoperative assessment (pilot study of clinic operational flow, n = 20)

In the intraoperative phase, the clinicians followed ERAS protocols to minimize postoperative complications and augment faster recovery. In the postoperative phase, PSH clinicians practiced an improved discharge protocol where the PSH nurse coordinated with discharge services in assisting in the discharge process for efficient patient care transitions. In addition, hospitalist co-management was implemented with high-risk patients that required additional care in the postoperative phase before discharge. Finally, a digital platform was initiated in the recovery phase to improve patient-clinician coordination and communication after surgery. The digital platform allowed the clinicians to monitor patient recovery progress by recording longitudinal patient-reported outcomes.

CHAPTER TWO

THESIS FRAMEWORK AND GOAL

It is self-evident that healthcare data, primarily patient data, is indispensable for clinicians and healthcare organizations, including while providing surgical care to patients. Proper utilization of healthcare data has helped researchers and clinicians in increasing efficiency, quality, reducing cost, and standardizing patient care (Hersh & Hoyt, 2018). Collecting, managing, and extracting knowledge from data is crucial for the healthcare teams to address problems more comprehensively. The process of adopting patient data for caregiving emerged a new discipline called Health Informatics (Hovenga, 2010).

Health Informatics (HI) is a field of information science focused on management of healthcare data and information using computers and technologies (Hersh & Hoyt, 2018). The HI gained its popularity in the last 40 years due to technological progress in modern computers which enabled researchers and clinicians to collect, store, and process vast volumes of data seamlessly (Cesnik, 1996). Although its recently gaining popularity, the origins of HI were spotted in the 1950s (Cesnik, 1996; Gibson et al., 2015). Clinicians during the late 1950s collected, stored, and used patient data in paper format, in an effort to monitor patient care and practice a version of evidence-based medicine (Gibson et al., 2015; Masic et al., 2008). Between 1960s and the 1990s, the medical practitioners actively used patient data to enhance patient care, which later progressed to a more formal version of HI (Hersh & Hoyt, 2018; Sur & Dahm, 2011).

The emergence of advanced communication and information technologies such as internet, Electronic Health Record (EHR), and cloud storage advanced the HI, allowing healthcare practitioners to replace paper format and store all patient data digitally (Hovenga, 2010). The digitization of data not only helped the clinicians to store and share large volumes of data effortlessly, but also resolved the difficulty of searching and even incorrect retention of patient data (Hersh & Hoyt, 2018). However, increase in adoption of modern technologies has risks for patient's privacy, especially when the chances of data leakage are higher in digital format compared to paper format (Koczkodaj et al., 2019). To address that concern and reinforce the security and privacy of patient data, several policies and reforms were introduced including: Health Insurance Portability and Accountability (HIPAA) in 1996, the American Recovery and Reinvestment Act (ARRA) in 2009, and Health Information Technology for Economic and Clinical Health Act (HITECH) in 2009 (Hersh & Hoyt, 2018; Hovenga, 2010). Based on the evidence related to HI influence in healthcare, the researchers argue that HI will continue to benefit the healthcare community including clinicians, patients, and insurance payers constructively in the future (Hersh & Hoyt, 2018).

Healthcare Analytics

With advancements in computers and software, the healthcare industry is capable of producing vast amounts of data, close to 19 Terabytes of clinical data each year (Khanra et al., 2020). These patient data are comprehensive and if not analyzed or knowledge is not extracted, it provides little to no benefit to clinicians (Hersh & Hoyt, 2018; Islam et al., 2018). In that notion, the role of analytics emerged as a key component within HI, specifically to understand and leverage the data stored in EHRs for decision-making (Gibson et al., 2015; Hersh & Hoyt, 2018; Predmore et al., 2019; Simpao et al., 2014).

Analytics is a process of generating insights through efficient use of data for planning, management, measurement, and learning purposes (Islam et al., 2018; Simpao et al., 2014). There are different types of analytics in healthcare: descriptive, diagnostic, predictive, and prescriptive analytics (Banerjee et al., 2013). Descriptive analytics is comprised of exploratory analysis mainly focusing on ‘What happened?’ Visualization tools “dashboard” and descriptive statistics are often used to interpret and understand the story behind the data. Diagnostic analysis is similar to causal analysis; evaluates ‘Why did it happen?’ Inferential statistical analysis, visualization, and brain storming methods, like root cause analyses, were implemented to recognize the cause and effect (Ma & Sun, 2020). Predictive analytics focuses on predicting future events and outcomes. Elements of Artificial Intelligence (AI) such as Machine Learning (ML), Deep Learning (DL), and statistical models were frequently used to make predictions for risk and outcome assessment (Ma & Sun, 2020). Finally, the prescriptive process utilizes analytics to determine or make decisions for an optimal course of action. Prescriptive analytics are mostly derived from predictive analytics, where tools like simulation and interpretive predictive models (that aid to make decision after predictions), were often used for decision support (Ma & Sun, 2020).

Healthcare analytics has advanced substantially compared to how it begun. In the early 20th century, scientists and researchers performed descriptive analysis and applied basic statistics like correlation and regression, to only a few hundred cases. The technological advancements in computing power introduced analytical and statistical software, which enabled researchers to apply various analytical tools to large volumes of data. The concepts of advanced statistical methods and ML were introduced and present even during the 1940s (Dinsmore, 2016).

However, researchers at that time lacked the necesary computing power and the actual application of analytics were not widely used until the 1980s (Dinsmore, 2016; Hall et al., 2016). To summarize the evolution of analytics chronologically, it started with descriptive, and progressed to diagnostic, predictive, and prescriptive (Figure 2.1) (Dinsmore, 2016; Hall et al., 2016; Hung, 2019; Selamat, 2018).

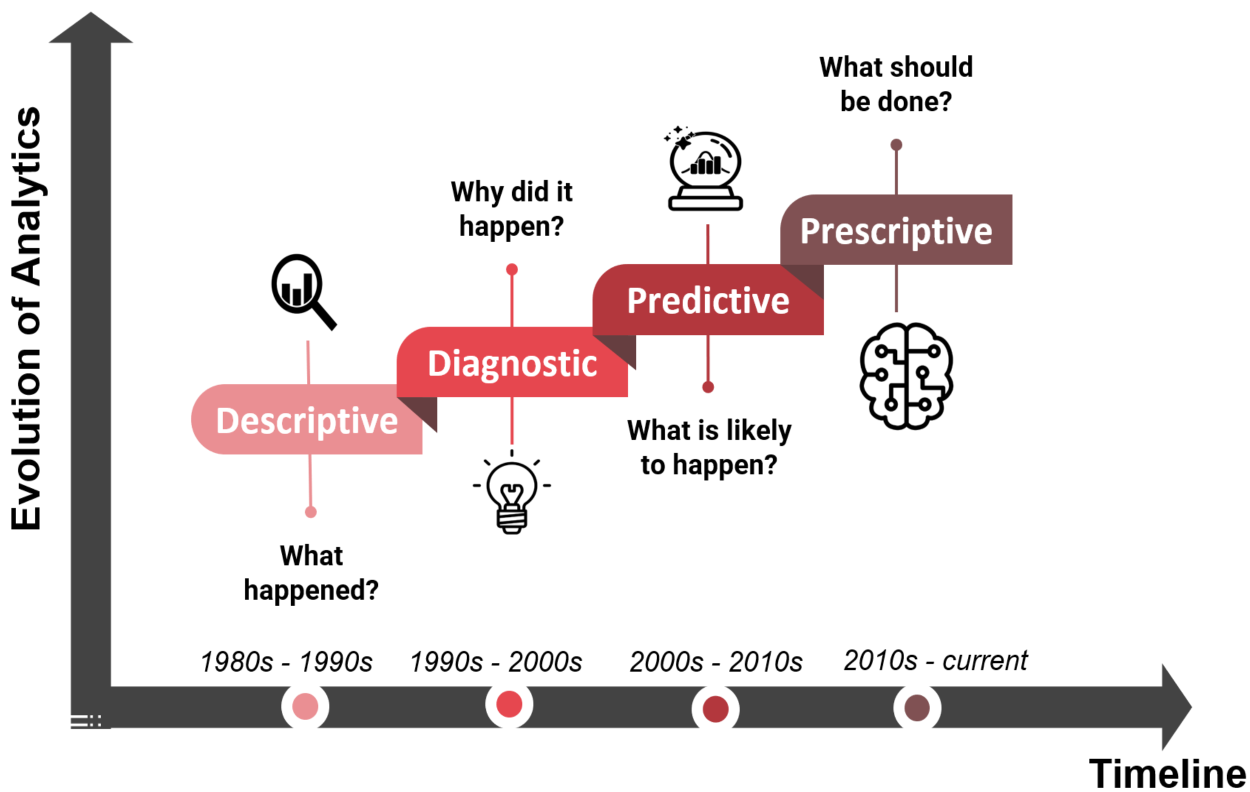

Figure 2.1 Evolution of analytics in healthcare from 1980s

In the past decade, the role of healthcare analytics proliferated in response to developments in big data and analytics, including statistical and machine learning tools (Galetsi & Katsaliaki, 2020; Islam et al., 2018; Khanra et al., 2020; Shafqat et al., 2020). The emergence of the EHR facilitated access to patient data including demographic, comorbidities, vital signs, and laboratory data (Hersh & Hoyt, 2018). This motivated many researchers to use standard and emerging analytical tools to improve healthcare (Galetsi & Katsaliaki, 2020; Petit et al., 2018; Shafqat et al., 2020).

Healthcare Analytics in Surgical Care

The modern healthcare system is a large domain and the presence of analytics has disseminated to different health services, including surgical care (Elfanagely et al., 2021; Loftus et al., 2020; Maier-Hein et al., 2017a). Despite surgical care being an indispensable part of healthcare, incorporation of analytics in surgical care is still in its nascent phase (Maier-Hein et al., 2022; Vedula & Hager, 2017). However, due to the deluge of data, advancement in analytical techniques, and the necessity to enhance quality and value of surgical care, hospitals and surgical centers are implored to utilize data analytics to improve and transform care delivery (Vedula & Hager, 2017). Researchers named this concept as Surgical Data Science (SDS), which aims to enhance the quality of surgical care and value through capture, organization, analysis, and modeling of data (Maier-Hein et al., 2017a; Maier-Hein et al., 2017b; Vedula & Hager, 2017).

According to Maier-Hein et al. (2017b), SDS is critical for fundamental understanding of surgical procedures, variability in the system, hidden structures, success and failure of methodologies, and the basic principle driving surgical education, training, and practice. Past studies have highlighted the pertinent scope for SDS in conceptual categories including: 1) data acquisition and curation, 2) analytics to transform and improve existing methodology, 3) analytics to inform surgical process, 4) analytics to enable smart collaboration between clinicians and technology, and 5) analytics to enhance learning and performance of care provider (Maier-

Hein et al., 2022; Vedula & Hager, 2017). These conceptual categories lay the framework for the SDS where it is actively researched and applied progressively mostly in urban health systems or academic health centers.

Healthcare Analytics in Orthopedic Surgeries

Orthopedic procedures, including TJRs are one of the most commonly performed surgeries in the US (Singh et al., 2019). It is not atypical to see the role of analytics perforate rapidly in orthopedics as well (Kunze et al., 2022; Kurmis & Ianunzio, 2022). To provide evidence-based care, clinicians and researchers still use and widely apply the components of traditional statistics and biostatistics in orthopedics (Hoppe & Bhandari, 2008; Kocher & Zurakowski, 2004; Petrie, 2006). One such area commonly used is to evaluate and assess the success or failure of clinical or surgical interventions (Kocher & Zurakowski, 2004; Petrie, 2006; Zhang, 2020). Healthcare interventions are activities that maintain or improve patient health by preventing disease, curing or reducing the severity, or restoring the function lost from disease or injury (A Ross et al., 2015). Surgeons institute interventions to improve outcomes and patient experience perioperatively. Biostatistical study design, hypothesis testing, and statistical modeling are some of the frequently used analytical methods to evaluate clinical interventions and the effect on surgical care (Kocher & Zurakowski, 2004; Petrie, 2006; Zhang, 2020).

For example, Bebko et al. (2015) performed a Surgical Site Infection (SSI) prevention program and examined SSIs on elective orthopedic patients using a prospective cohort study. These authors used a regression model and determined that patients who followed chlorhexidine washcloth and intranasal providone-iodine as part of the intervention program, experienced reduction of SSI by 50% compared to the control cohort. Similarly, Lovecchio et al. (2019)

intervened lumbar patients with provider education and prescribed guidelines to determine its effects on the patient's postoperative opioid consumption. The authors compared pre- and postintervention groups using statistical analysis and found that postintervention group had 40% lower opioid consumption than preintervention group. Relatedly, Schneider (2018) determined that listening to music had a positive effect on patient pain scores and satisfaction using a quasi-experimental design in the postoperative orthopedic patient. The above examples are some of many studies in orthopedics which employed statistical analytical methods to determine the effectiveness of intervention on patient's surgical experience and outcome. As demonstrated by these studies, evaluating interventions quantitively enabled clinical researchers to determine if they should incorporate intervention in the surgical process to enhance the patient experience and care delivery (Clarke et al., 2019; Jangland et al., 2012).

To maximize the effectiveness of analytics, researchers collected and incorporated patient data (e.g., patient reported outcomes) beyond what is available in standard EHRs (Kambhampati et al., 2021; Zarowin et al., 2020). Integration of new technologies to include sensors, smartphones, and wearables enabled researchers to collect real-time patient data at different surgical phases (Bahadori et al., 2018; Zarowin et al., 2020). Analysis of these data combined with EHR helped clinicians and researchers to monitor, measure outcomes, initiate interventions as necessary, and holistically assess the patient's surgical experience (Bahadori et al., 2018; Krumholz et al., 2016).

For example, Crizer et al. (2017) tracked daily step count in preoperative and postoperative for TJR patients using a smart phone to determine activity and recovery after surgery. The authors compared the step count against the patient self-reported functional recovery and identified that tracking step count is significantly reliable to monitor patient's functional status postoperatively and return to normal daily activities of living. In addition, examining the step count data, the authors discovered Total Hip Arthroplasty (THA) patients regained functional return faster than Total Knee Arthroplasty (TKA) patients postoperatively. Ramkumar, Haeberle, et al. (2019) performed a remote patient monitoring on TKA patients using a wearable knee sleeve evaluated patient's recovery across a spectrum of subjective, objective, mobility-based, and pain-related parameters. Höll et al. (2018) used a smart watch to track steps to measure the activity levels of patients before and after THA procedure. After investigating, the authors determined the recovery patterns, which were completely independent of the patient variables extracted from the EHR – age, body mass index, and American Society of Anesthesiologist score. Likewise, to improve surgical care experience for both patients and clinicians, many studies were performed recently using sensors and smart devices to collect and analyze patient data in real time related to functional work, posture, opioid consumption, blood pressure, heart rate, oxygen saturation level, and pain scores (Bahadori et al., 2018; Stienen et al., 2020; Yang et al., 2018; Zarowin et al., 2020).

With the recent AI boom in the last decade, predictive analytics are becoming increasingly important and gaining massive interest particularly in orthopedic surgery (Kunze et al., 2022; Lopez, Gazgalis, et al., 2021). AI has many definitions but is commonly known as an application of algorithms that allows machines to learn, solve problems, plan, and interpret, similar to humans thinking and cognitive function (Hashimoto et al., 2018; Kunze et al., 2022; Myers et al., 2020). There are many subfields of AI, mainly comprised of Machine Learning (ML), Natural Language Processing (NLP), Artificial Neural Networks (ANN), and Computer

Vision (Bini, 2018; Hashimoto et al., 2018). Each of the subfields are broader concepts on their own and therefore, the scope of this dissertation mainly focuses on the role and application of ML in orthopedics.

ML is a subset of AI that enables machines to learn and generate predictions by recognizing patterns (Hashimoto et al., 2018). ML utilizes different algorithms that are capable to learn from experiments and input data through adjusting internal parameters to strengthen relevant association for accurate prediction (Kunze et al., 2022; Maffulli et al., 2020; Myers et al., 2020). There is more than one type of learning in ML: supervised learning, unsupervised learning, and reinforced learning. Supervised learning is when data are labelled, and the machine is able to recognize the pattern based on the labelling (Lalehzarian et al., 2021; Myers et al., 2020). Conversely, in unsupervised learning, the data are not labelled, and the machine looks for the pattern and generates clusters or groupings within the data (Lalehzarian et al., 2021; Myers et al., 2020). In other words, supervised learning is used to predict an outcome of an interest and unsupervised learning is used to search for linear or non-linear patterns and generate clusters within the data (Hashimoto et al., 2018). Lastly, the reinforced learning is typical to a reward and punishment system where the machine learns to achieve a task while learning from its own successes and mistakes (Hashimoto et al., 2018; Lalehzarian et al., 2021; Sutton & Barto, 2018).

Over the last decade, in response to subpar predictions by traditional statistical methods such as multivariate and logistic regressions, ML models were extensively used in predicting risks and outcomes in orthopedic surgeries (Lalehzarian et al., 2021; Lopez, Gazgalis, et al., 2021; Maffulli et al., 2020; Ramkumar, Navarro, et al., 2019). ML models were incorporated in predicting various orthopedic outcomes including: adverse events, transfusion, LOS, SSI, return to operating room, patient reported outcomes, inpatient readmission, discharge disposition, and cost (Lalehzarian et al., 2021; Lopez, Gazgalis, et al., 2021; Ogink et al., 2021). However, it was observed that readmission, patient LOS, and discharge disposition were more consistently predicted amongst other outcomes (Lopez, Constant, et al., 2021; Ogink et al., 2021). Majority of the past studies predicted LOS, readmissions, and discharge disposition because these outcomes attribute to increased surgical cost and negatively affect the quality of care (Ogink et al., 2021; Tsai et al., 2015). Regarding ML algorithms, random forest was a frequently used algorithm in predicting most orthopedic surgical outcomes (Ogink et al., 2021). These research evidences indicate that the application of ML is growing in orthopedics and is expected to further grow in the future (Kurmis & Ianunzio, 2022).

Analytics in PSH Integrated hospitals

Researchers and perioperative care experts have unanimously agreed that the scope of the PSH system will expand beyond the surgical clinicians in the future (Mahajan et al., 2021; Pal & Kertai, 2020). The PSH surgical system which is, so far, mainly comprises of clinicians, is expected to add multi-disciplinary fields to include data science and basic science experts (Nirvik & Kertai, 2022). The multi-disciplinary team will not only focus on optimizing and improving surgical process, but also delivering personalized patient care (Nathan, 2022; Nirvik & Kertai, 2022). However, the PSH system is in its infancy phase and has not adopted robust analytics into the system to a greater extent (Nirvik & Kertai, 2022).

The most common use of analytics was used to evaluate the PSH implementation on different surgical outcomes (Cline et al., 2020). The majority of the past studies have used descriptive or inferential statistics in conjunction with biostatistical methods to evaluate and quantify the effect of PSH on various surgical outcomes like: LOS, readmissions, operating time, postoperative recovery, discharge destination, surgical costs, operational efficiency, etc. (Cline et al., 2020; B. A. Kash et al., 2014). Yet, no studies have been performed in utilizing advance analytics, including predictive analytics, at a PSH implemented institution (Nirvik & Kertai, 2022). One such reason for that is limited data collection by the PSH hospitals. Aforementioned, to enhance the strength of analytics, the PSH organization should resort to wider forms of data collection beyond what is collected in the EHR during the patient's clinical visits and assessments (Kunze et al., 2022). This is because the patient's life is intertwined with various components in modern society where factors related to medical conditions (mostly documented in EHR) account for only 10% of influence to determining their health (Hu et al., 2016; Johnson et al., 2021). Whereas the factors related to physiological, behavioral, psychological, and socioeconomics account for the majority of influence to determining patient's health (~60%), followed by patient genetics data accounting for 30% influence in determining patient's health (Johnson et al., 2021). Researchers have identified that, currently, the most efficient way to collect influential patient data (patient-reported outcomes, vitals, etc.) by utilizing modern technologies such as biosensors and digital engagement platforms (Kassanos et al., 2020; Kavolus et al., 2021; Nirvik & Kertai, 2022; Simpao et al., 2015). Therefore, a theoretical framework was developed to emphasize the inclusiveness of analytics for PSH implemented hospitals, stretching from data collection to decision-making, to delivering improved surgical care for patients.

Theoretical Framework

This theoretical framework demonstrates how to leverage data analytics within the PSH surgical system to achieve personalized and enhanced surgical care. The main components that are included in this framework are the Data Source, Data Center, Organization, and Process (Figure 2.2).

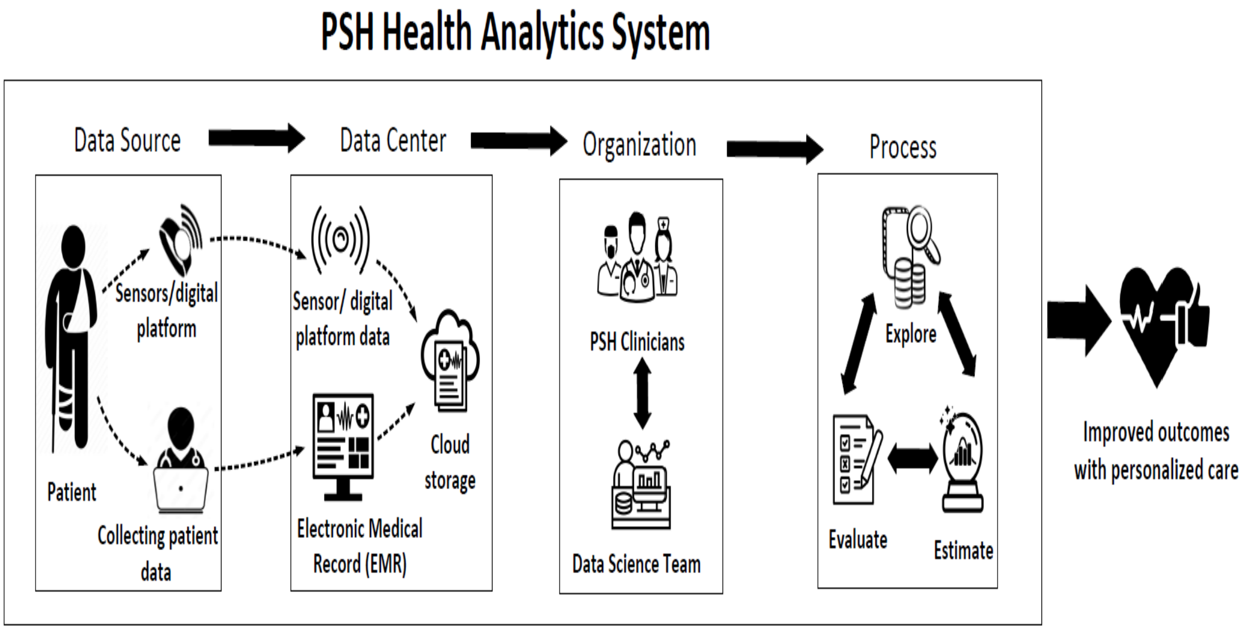

Figure 2.2 Theoretical framework

Data Source

The data source here primarily refers to patients. In the PSH system, the patients data are mostly collected by the clinicians during the clinical visits, labs, consultations, and assessments (B. Kash et al., 2014). Even so, to measure patient's health and their recovery effectively, technologies such as sensors, wearables, and digital platforms should be used to collect influential data (Boer et al., 2018; Simpao et al., 2015). Using smart technologies is critical in

PSH systems because the perioperative period is longitudinal (120 days) and it's arduous for clinicians and patients to do frequent office consultations and clinical visits (Campbell et al., 2020).

Data Center

With an increase in healthcare data, the EHR has been a convenient way to store patient data (Gellert et al., 2015). Advancements in software and usability has transformed the EHR capability of storing heterogenous and complex data including structured (in tabular form) and unstructured data (clinician notes, images). The EHR data are mostly populated by the clinicians and the hospital administration. Storage for the data that are collected using external devices or digital platforms is dependent on the device or platform manufacturer. To summarize, all patient data collected during the perioperative period are stored in an encrypted digital format (cloud-based system) where PSH clinicians and the hospital data team can access as needed.

Organization

The difference between the current PSH system and this framework is the inclusion of a data science team. The data science team here can coordinate and help PSH clinicians understand the patient data and assist in data-driven decision-making. The size of the data science team will depend on the size of the hospital and volume of the data generated. In most organizations, the data science team is mostly comprised of data scientists, but also includes other roles like data engineers, data analysts, and machine learning engineers (Saltz & Grady, 2017).

Process

There are three elements in process: explore, evaluate, and estimate. The explore process in this framework is an important step for data analysis. This includes preliminary research, defining scope for data collection, data cleaning/preprocessing, and exploratory data analysis using visualization and descriptive statistics. Oftentimes, exploratory processes are more time and resource consuming in data science (Kuhn & Johnson, 2019).

The evaluation process in this context emphasizes assessing the effectiveness of an activity on a particular outcome. The activity can be an intervention or a drug, initiated with patients to monitor its effect on the outcome of interest. The evaluation process can be both retrospective and prospective studies. The study designs (case-control, observational, clinician trials) and statistical methods (odds ratio, hypothesis testing, measure of association) are frequently used to quantify the activity's success or failure on a particular outcome. For example, Yajnik et al. (2019) performed a retrospective study at a PSH hospital, evaluated how patient education aids to reduce patient's opioid consumption in the postoperative period for knee patients. In this case, the activity was patient education, and the outcome of interest was patient postoperative opioid consumption.

The estimate process in this framework expands the scope of predictive analytics by including prediction interpretations for enhanced decision support. For predicting an outcome, ML methods, like Decision Trees (with ensemble models), Support Vector Machines, Linear Models, and Neural Networks are frequently used (Bhardwaj et al., 2017; Callahan & Shah, 2017). The global and local agnostic methods are used for ML interpretation to help clinicians to understand predictive relationships between the dependent and independent variables (Molnar, 2020; Ribeiro et al., 2016). Chronologically, the process explore, evaluation, and estimation can be performed in any order, individually or overlapped, depending on the PSH organizational goals and objectives (Kuhn & Johnson, 2019).

Thesis Goal and Objectives

The main goal of this dissertation is to improve Total Joint Replacement (TJR) surgical outcomes and experiences for patients and clinicians at a Perioperative Surgical Home (PSH) implemented in a rural community hospital using data analytics. This goal has three main objectives:

Objective 1: Longitudinally analyze patient engagement and Patient Reported Outcome Measures (PROMs) at a PSH integrated rural community hospital using a digital platform

The purpose of this objective was to collect longitudinal patient data (such as PROMs) in the perioperative period to measure patient's health and their recovery while improving patient satisfaction.

Hypothesis 1: Patient engagement with the digital platform will be successful for longitudinally recording PROMs and monitoring patient's progress towards recovery after surgery.

Expected Outcome 1: The digital platform will be successful for longitudinal patient engagement to track PROMs.

Objective 2: Evaluate a newly implemented PSH system at a local community hospital by analyzing and comparing TJR surgical outcomes.

The purpose of this objective is to study the impact of PSH system on TJR patient's surgical outcomes (LOS, rate of readmissions, and discharge disposition).

Hypothesis 2: Implementation of PSH in a community hospital affects the TJR outcomes positively – shorter LOS, low readmissions, and increases rate in home discharge.

Expected Outcome 2: Shorter LOS, low readmission rate, and increase in home discharge will be observed on TJR surgeries after implementation of PSH.

Objective 3: Develop a machine learning model to predict TJR patients' outcome (LOS) and determine its feasibility by comparing it against the NSQIP surgical risk calculator.

The purpose of this objective is to explicate the importance of machine learning and its ability to deliver more accurate predictions and interpretation than the NSQIP risk calculator at a PSH facility.

Hypothesis 3: The developed machine learning model will be a better tool for predicting TJR outcome (LOS) compared to the NSQIP risk calculator at a PSH implemented community hospital.

Expected Outcome 3: The developed machine learning model will be more accurate and reliable for clinical decision-making.

Comparing the theoretical framework, the objectives 1, 2, and 3 overlap with the process explore, evaluate, and estimate, respectively (Figure 2.3).

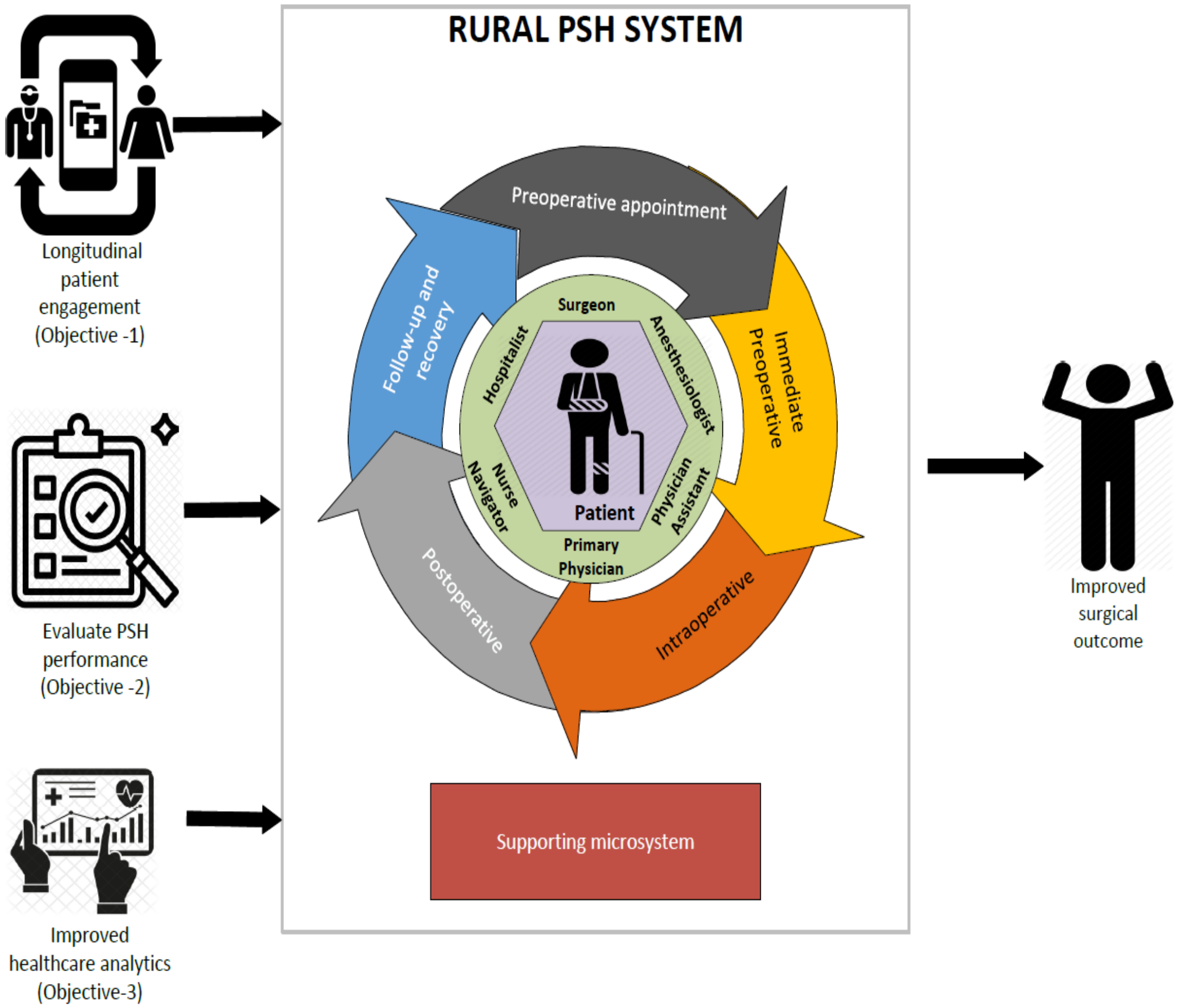

Figure 2.3 Conceptual model of thesis goal

CHAPTER THREE

DIGITAL PATIENT ENGAGEMENT AT A PERIOPERATIVE SURGICAL HOME IMPLEMENTED COMMUNITY HOSPITAL

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Manuscript Information

Srinivasan Sridhar, Amy Mouat-Hunter, Bernadette McCrory

Patient Experience Journal

Status of Manuscript:

_________ Prepared for submission to a peer-reviewed journal

___☑___ Officially submitted to a peer-reviewed journal

_________ Accepted by a peer-reviewed journal

_________ Published in a peer-reviewed journal

October 1st, 2022

Abstract

Background: Patients in rural areas typically require more perioperative 'optimization' for surgery. The rural healthcare systems often overwhelmed with coordinating perioperative services and deliver less than optimal surgical outcomes. This is due to limited supporting microsystems and ability to effectively engage and track patients over the 120-day perioperative period to limit post-surgical complications.

Objective: The study assessed longitudinal patient engagement within a newly established Perioperative Surgical Home (PSH) at a rural community hospital serving 10+ surrounding counties to identify barriers and best practices for engagement.

Methods: A digital patient engagement platform was implemented and used to assess longitudinal patient outcomes and engagement from 30 days preoperative to 90 days postoperative. The research team (health systems engineers teamed with clinicians) analyzed 2-years of collected patient data (n= 301) primarily consisting of Total Joint Replacement (TJR) procedures.

Results: The digital patient engagement system's email and text messages allowed patients and PSH staff to track outcomes, experience, and collaborate on post-surgical events. The average patient engagement was low (less than 40%). However, the average survey completion was 90%, i.e., if a patient responded to a survey on a particular day, on average patients finished 90% of the survey.

Conclusion: Patient engagement was critically important to improving surgical care in rural areas. Digital longitudinal patient engagement implemented by PSH clinic was successful at rural community hospitals serving patients from 10+ surrounding counties.

Introduction

With increased demand of total joint surgery (TJR) in the United States (US) (Singh et al., 2019), patient engagement has become a critical part in reducing surgical cost while ensuring patient safety, quality of service, and patient satisfaction (Alokozai et al., 2021; Andrawis et al., 2015; Milliren et al., 2022). Patient engagement is an active clinical process to coordinate closely with patients for preventive surgical care and to improve overall patient outcomes (James, 2013). Engagement events like patient education and postoperative follow-ups play a vital role in the shared decision-making process that allows clinicians to counsel patients, establish pain management plans, and prepare for surgery (Berger et al., 2014; Cook et al., 2013). These events help clinicians monitor patient's recovery and overall quality of life, to intervene as necessary during the postoperative period to ensure patient satisfaction (Dawson et al., 2010). Past studies have demonstrated that tracking patient reported outcome measures (PROMs) via engagement events improved patient satisfaction and overall surgical outcomes including better pain management, faster recovery, lower rate of readmission, and reduced emergency department visits (Alokozai et al., 2021; Andrawis et al., 2015; Lavallee et al., 2016). PROMs are health status reports that are received directly from the patients (Cella et al., 2015). PROMs such as the Harris Hip Score, Knee Society Score, and Oxford Shoulder Score were typically collected for TJR procedures that were performed on hip, knee, and shoulder, respectively (Daw et al., 2019; Siljander et al., 2018). These PROMs commonly focus on patient's feedback related to their current pain level, joint range of motion, functional or independent status, and ability to perform activities of daily living (Dawson et al., 1996; Insall et al., 1989; Söderman & Malchau, 2001).

Engagement platforms are emerging as one of the efficient ways to collect PROMs for TJR procedures (Kavolus et al., 2021). These platforms like patient portals, mobile health, and chatbots utilize digital applications that are designed to automate activities including patient engagement throughout the 120-day perioperative period – 30-days preoperative to 90-days postoperative (Campbell et al., 2020). The spread of technologies such as smartphones, internet, and mobile services are conducive to the surge in utilizing engagement platforms for TJR procedures in the US (Kavolus et al., 2021). Moreover, orthopedic clinicians are often overburdened with the increasing demand of TJR procedures. This makes it difficult for them to perform effective engagement events with patients through office consultations and postoperative clinic visits as frequently as needed (Campbell et al., 2020). The outbreak of COVID-19 exacerbated the issue of in-person patient engagement, forcing both patients and clinicians to interact virtually (Lesher et al., 2021). Engaging virtually using a digital platform has proven effective because it aids both clinicians and patients by minimizing the number of non-emergent clinical visits help to reduce clinical workload and surgical cost (Kavolus et al., 2021; Simpao et al., 2015).

Another reason for utilizing the engagement platform is due to the burgeoning of a new coordinated surgical system in orthopedics – the Perioperative Surgical Home (PSH) (Cline et al., 2020). Compared to the traditional surgical system, the PSH is a coordinated interdisciplinary team encompassing all surgical care provided to patients from preoperative phase (30-days before surgery) through recovery (Cline et al., 2020; B. Kash et al., 2014; Vetter et al., 2013). In other words, in PSH, patient engagement is performed longitudinally throughout the perioperative period through physician co-management and nurse navigation. Longitudinal patient engagement in PSH includes the combination of both remote and in-person appointments (B. Kash et al., 2014). The combination of in-person (such as preoperative assessment/education) and remote (virtual engagement platforms or phone) are convenient for longitudinal patient engagement, which in turn helps to promote shared decision-making and patient value through continued clinical interaction and management postoperatively (B. Kash et al., 2014; Lyman et al., 2020; Simpao et al., 2015).

Recent studies illustrated that tracking PROMs using an engagement platform was effective and helped to increase patient satisfaction, surgery experience, and optimize surgical outcomes (Campbell et al., 2020; Kavolus et al., 2021). For example, Lyman et al. (2020) used a mobile health engagement platform for total hip arthroplasty (THA) and total knee arthroplasty (TKA) to longitudinally track step count postoperatively. Step count (PROM) was tracked once every two-weeks to six-months after surgery. Lyman et al. (2020) found that 96% of the cohort engaged at least once in the engagement platform. This enabled Lyman et al. (2020) to understand the pattern and association of how an increase in step count led to earlier patient recovery during the postoperative period ($p < 0.01$). Likewise, Holte et al. (2021) used a web-based engagement platform with hip and knee patients to track PROMs longitudinally for 12-months after surgery. PROMs like Patient-Reported Outcomes Measure Information System Global Physical Health (PROMIS-GPH), Hip Disability and Osteoarthritis Outcome Score (HOOS JR), Knee Disability and Osteoarthritis Outcome Score (KOOS JR), and patient satisfaction were successfully collected using the platform. Holte et al. (2021) observed that on average, more than 60% responded to all engagement opportunities through the engagement platform. Through the study, Holte et al. (2021) found that the use of the engagement platform was positively associated with rapid improvement and higher joint-specific function at the 12 months postoperative period ($p = 0.013$).

Despite these successes to engage with patients using the engagement platforms, limited research has evaluated orthopedic surgical outcomes and patient engagement for rural healthcare systems (McCrory et al., 2019). Surgical care inequality is higher among rural community hospitals due to limited resources, socioeconomic differences, and poor access to healthcare (Kaufman et al., 2016; Nakayama & Hughes, 2014; Weichel, 2012). Compared to urban settings, rural hospitals' surgical outcomes have higher odds of in-hospital mortality and higher costs of hospitalization (Chaudhary et al., 2017), because many rural patients are uninsured, older, and have one or more medical complications (Gruca et al., 2016; Snyder et al., 2017). In addition, the exceeding demand for TJRs can often overwhelm rural hospitals coordinating perioperative services. This results in inadequate communication, poor care continuity, limited patient engagement, and preventable complications (Lese & Sraj, 2019). Moreover, large geographical distances and remote communities often limit the ability to co-manage care across physicians.

Thus, this study longitudinally assessed patient outcomes of a rural community hospital that integrated Perioperative Surgical Home (PSH) utilizing digital PROMs. The objective of this paper was to explore the patient's response rate when longitudinally engaged over 120-days using a digital platform at a community hospital. The study expected that patient engagement would be challenging due to primitive geographically-limited digital infrastructure and duration of the extended perioperative follow-up of 120-days. Specifically, Montana ranks 50th for internet access in the US where only 72.4% of the people living in Montana have access to broadband internet connection (BroadbandNow, 2021).

Method

A rural community hospital formed a Perioperative Surgical Home (PSH) in October 2018. The PSH outpatient clinic was affiliated with the hospital and began assessing patients preoperatively for TJR including hip, knee, and shoulder replacements. The community hospital is an 83-bed, level III trauma center primarily serving three counties, but also provides care to 10+ surrounding counties in the region. After consent, all orthopedic and spine patients were enrolled in the digital tracking engagement platform (On-Q*Trac, Avanos Medical Inc., Alpharetta, Georgia) to assess longitudinal PROMs. The baseline patient characteristics included age, gender, surgery type, surgeon, and service modality (inpatient or outpatient). The research study was approved by the Institute Review Board (IRB).

PROM Collection

PROMs were collected a total of nine times (within 30-days prior to surgery, day of the surgery, post-operative days 1, 2, 3, 7, 30, 60, and 90) to monitor and track recovery. Based on the patient's preference, a survey hyperlink was sent to them either by text message or email or by both to complete the digital self-assessment. Each survey event took an average of three minutes to complete. The self-assessment included questions related to pain, hospital readmission, emergency room visits, side effects, sleep, patient satisfaction, and recovery.

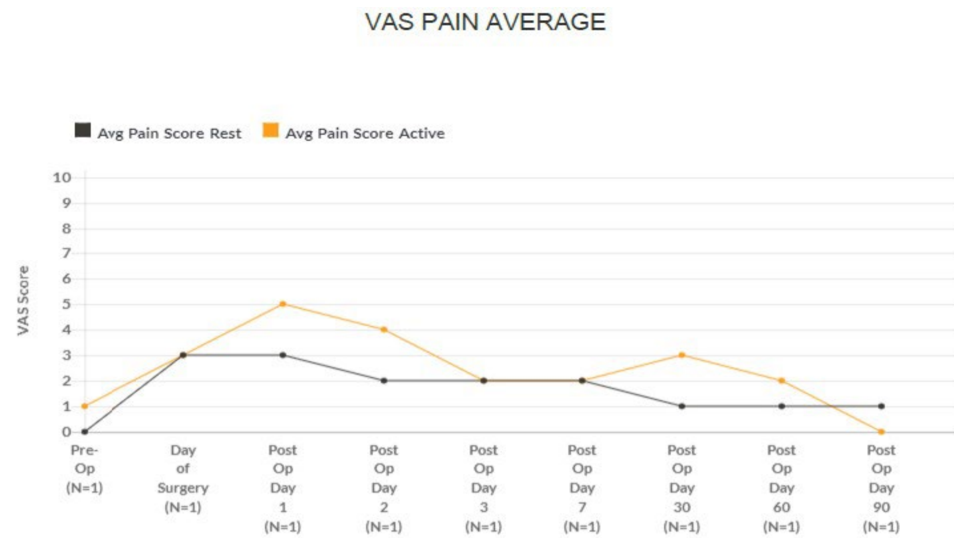
Questions on pain levels (active and resting) and pain compared to their expectations were tracked before and after surgery. Active and resting pain were recorded on a 10-point scale where 0 was no pain and 10 was severe pain. Patients responded to the pain experience, compared to their expectation, by selecting one of the Likert-scale options: much less, slightly less, as expected, slightly more, and much more. Questions about recovery were asked to monitor patient's progress, while performing activities of daily living (e.g., standing, walking). Patients were asked to select one of the options: cannot perform any activity, need human assistance, need assistance from an aid, can perform the activity on my own. Patients were asked to provide satisfaction regarding their pain management and overall surgery experience, by selecting one of the options: very satisfied, somewhat satisfied, neutral, somewhat unsatisfied, and very unsatisfied. Patients were also asked to select the following side effects if they had: none (no side effects), nausea, vomiting, drowsiness, dizziness, constipation, hallucination, and itching. Patients reported sleep interruptions due to pain after surgery (sleep interrupted - never, rarely, sometimes, often, and always.) Lastly, the patients were asked if had been readmitted or visited the emergency department (ED) during recovery.

There were fifty-seven (57) PROM questions; five questions for the pre-operative period, day of the surgery, and postoperative day 1, four questions for postoperative day 2, eight questions on postoperative days 3, 7, 30, and seven questions for postoperative days 60 and 90 (Appendix Table A.1). Questions about pain and recovery (daily activities) were asked in all engagement surveys. PROMs including side effects and sleep interruption were asked on the first-week post-surgery; a sleep question was also asked on postoperative day 30. Questions on readmission/ED visits and patient satisfaction related to pain and surgery management were asked at the end of the engagement period i.e., on days 30, 60, and 90. Patient engagement was determined if a patient responded to at least one question (out of 57) in the engagement platform. A patient's survey completion was determined by how many questions were answered. The research team (health systems engineers and clinicians) collected and analyzed the data from patients enrolled in the engagement platform between November 2018 to March 2021.

Engagement Platform – Dashboard And Alerts

The outcomes reported by the patients were securely stored in an encrypted server and were accessed only by the authors and the clinicians requiring access. The On-Q*Trac engagement platform generated an outcome dashboard that helped clinicians monitor the PROMs. For example, Figures 1-3 exhibit a dashboard for pain, daily activities, and side effects of a specific patient (N=1). The clinicians also had the option to add multiple patients to the dashboard and examine the PROMs in an aggregate report. For example, the VAS Pain Average in Figure 1 exhibits the active and resting pain levels for one patient. If a clinician preferred to add more patients to the dashboard, then it will display the average active and resting pain levels of all patients (N) included in it. Correspondingly, the percentage of respondents in pain compared to expectations graph displays (Figure 3.1) the categories selected by the patients for different time points. In this case, there was only one patient included in the dashboard. Therefore, it shows 100% for the selected category in all time points. However, if there were two patients (N = 2) and both of them selected different categories for a particular day, there will be 50% for each category for that particular day. In other words, the percentage was calculated by the number of patients who responded to a particular category by the total number of patients who responded on the particular day. Figures 3.2 and 3.3 were interpreted similarly to Figure 3.1.

The engagement platform provided digital alerts through text messages or emails to PSH staff when a patient reported high pain (more than 7), visited an ER or was readmitted, or requested to speak with a clinician for a non-emergent issue. The nurse navigator in the PSH, who acted as a mediator, received these alerts and reached out to the patients by phone after consulting with the PSH team – anesthesiologist, surgeon, and hospitalist.



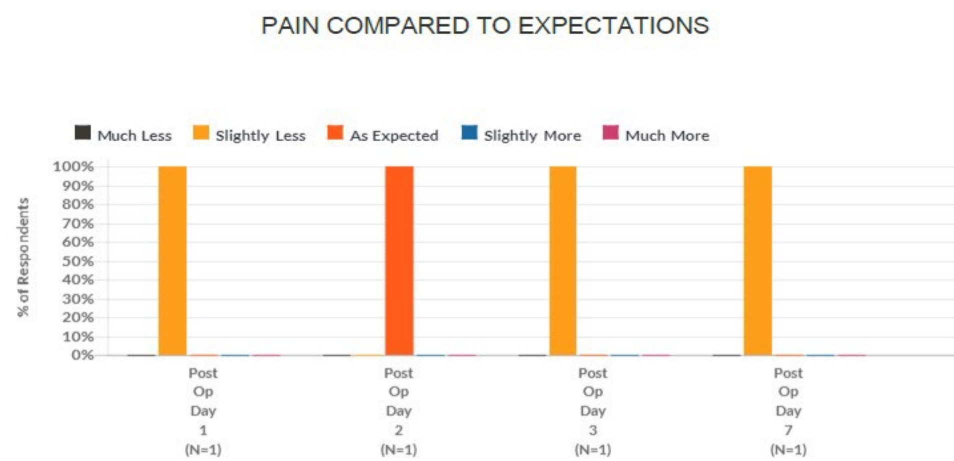


Figure 3.1 The outcome dashboard for pain – VAS average pain and pain compared to expected
*N is the number of patients included in the dashboard and in this case, it is 1

Figure 3.2 The outcome dashboard for recovery – daily activities, stand, and walk
*N is the number of patients included in the dashboard and in this case, it is 1

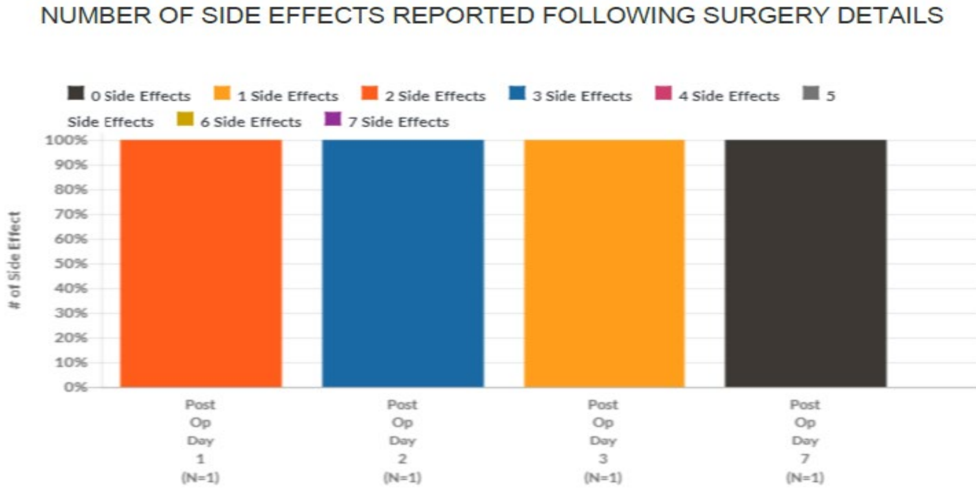


Figure 3.3 The outcome dashboard for side effects
*N is the number of patients included in the dashboard and in this case, it is 1

Either the Fischer's exact test or Chi-square test for association were used to compare the categorical variables. The continuous variables were analyzed using the Mann-Whitney test or Student's t-test, as appropriate. Binomial logistic regression was used to fit the adjusted model of patient engagement with the baseline variables. All data handling, visualizations, and statistical analysis (alpha (α) = 0.05) were performed using R (V 4.0.3, Vienna, Austria).

Results

A total of 376 patients were enrolled in the digital platform. Seventy-five (n = 75) patients were excluded from this study because either they had spine procedures (n = 64) or not TJR procedures (n = 11) (Figure 3.4). Out of 301 TJR patients reviewed, the most common procedure was knee arthroplasty (n = 147, 49%) and included both total (n = 111) and unicompartmental (n = 28) procedures. A total of 134 (45%) hip arthroplasties were performed and included both total (n = 125) and partial procedures (n = 9). Lastly, 20 (6%) shoulder arthroplasties and revisions (n = 5) were included. Two hundred and eighteen (n = 218) patients (71%) responded to at least one question (out of 57 questions) in the engagement platform. The remaining 83 (29%) patients provided no feedback in the longitudinal engagement platform. Only 36 (12%) out of 218 participants responded to at least one question in all nine surveys, and out of those 36 patients, only 13 (4.3%) completed all 57 questions. Of the 301 TJR patients, there were on average 68.4 years old (standard deviation 8.4) and predominantly female (n = 182, 60%). Out of four surgeons, a single surgeon performed 82% of the included procedures. The service modality was predominantly inpatient (n = 82%) and was not associated with respect to surgeons (P-value > 0.05) (Appendix Table A.2).

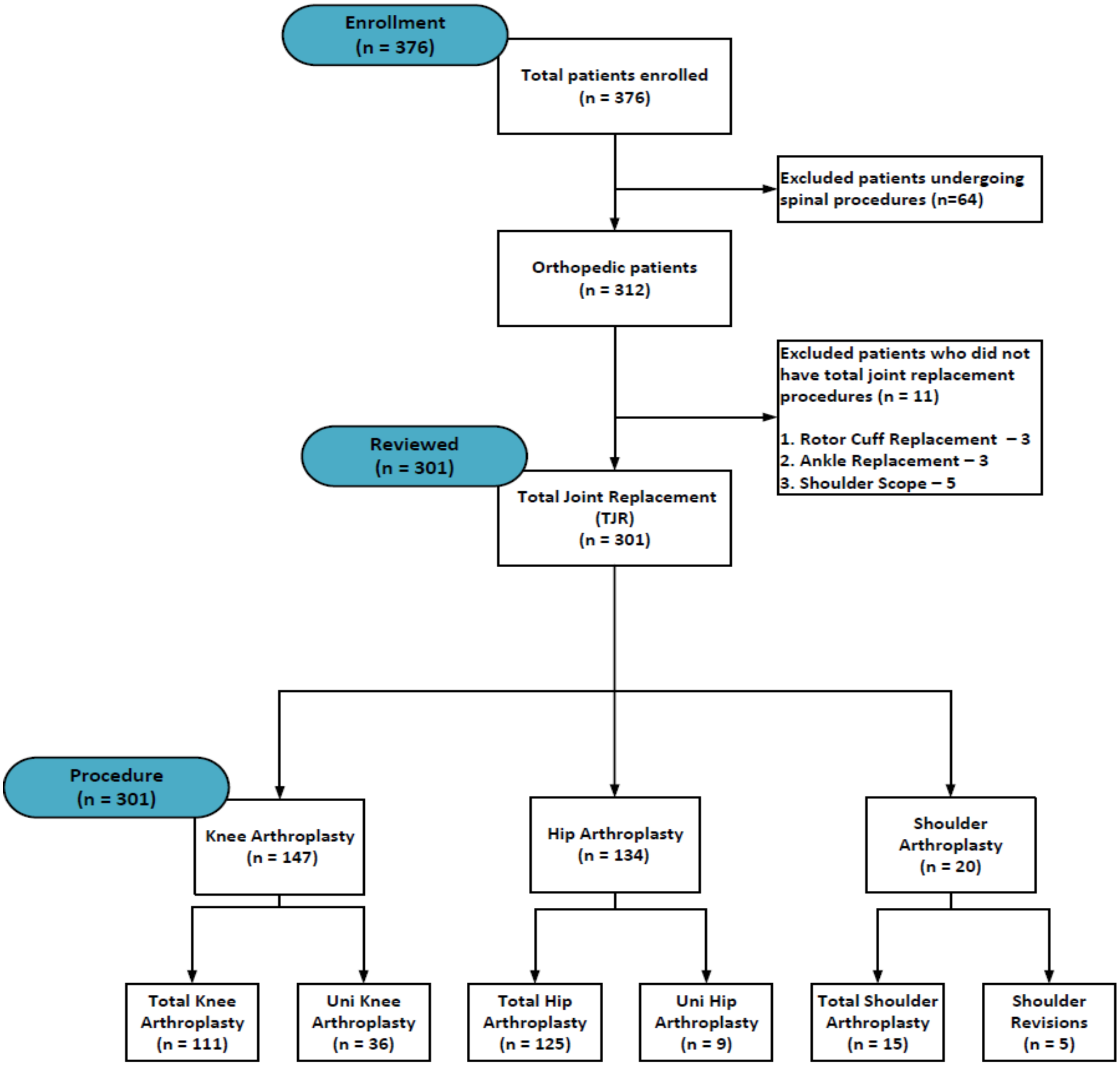


Figure 3.4 Patient allocation in the cohort study

Comparing the engagement (n = 218) and non-engagement cohort (n = 83), there was no significant difference observed in the baseline variables age, gender, procedure type, and service modality (P-value> 0.05) (Table 1). However, a moderate difference was observed between cohorts for the surgeon variable (P-value = 0.04). Surgeon C included more patients from the non-engagement cohort compared to the engagement cohort; vice-versa for surgeon B (Table 3.1).

Table 3.1 Comparison of baseline characteristics between Engagement and Non-Engagement cohort

Variables		Engagement Cohort[4] (n = 218) Mean (SD) [Min, Max] or n(%)	Non-Engagement Cohort[5] (n = 83) Mean (SD) [Min, Max] or n(%)	P-Value
Age		68.3 (8) [39, 84]	68.3 (9.35) [35, 84]	0.74[1]
Gender				
	Male	79 (36%)	40 (48%)	0.08[2]
Procedure Type				0.6[3]
	Hip	100 (46%)	34 (41%)	
	Knee	105 (48%)	42 (51%)	
	Shoulder	13 (6%)	7 (8%)	
Service Modality				0.91[2]
	Inpatient	179 (82%)	67 (81%)	
	Outpatient	39 (18%)	16 (19%)	
Surgeon				0.04[3]
	A	183 (84%)	65 (74%)	
	B	12 (6%)	2 (2%)	
	C	12 (6%)	13 (16%)	
	D	11 (5%)	3 (4%)	

[1]Mann-Whitney Test. [2]Chi-Square Test. [3]Fischer's Exact Test. [4] Patients who used the engagement platform. [5]Patients who did not use the engagement platform

Based on the logistic regression, the baseline variables age, procedure type, and service modality had no effect on the patient engagement on the digital platform (P-value > 0.05) (Table 3.2). There was a negligible effect observed in gender (P-value = 0.051), where the odds of male patients responding on the digital platform was 41% lower than female patients (OR = 0.59). Similarly, there was a difference observed in the adjusted analysis for the surgeon variable (P-value < 0.05). The odds of surgeon C patients responding on the engagement platform was 63% (OR = 37) lower than surgeon A patients (Table 3.2).

Table 3.2: Adjusted analysis of Engagement and Non-Engagement cohort

Variables	Odds Ratio (OR)	95% CI	P-value
Age	1.01	0.98 - 1.04	0.62
Gender			0.051
Male	0.59	0.34 - 1	
Procedure Type			
Knee	0.88	0.49 - 1.58	0.88
Shoulder	0.25	0.04 - 1.51	0.13
Service Modality			
Outpatient	1.07	0.49 - 2.3	0.87
Surgeon			
B	1.96	0.42 - 9.07	0.39
C	0.37	0.15 - 0.88	0.03
D	5.4	0.6 - 49	0.14

Of 301 patients, the most patient engagement was observed during the preoperative period, with 140 (46%) patients responding in the engagement platform, followed by on postoperative day 30, with 147 (49%) patients responding in the engagement platform (Figure 3.5). The lowest response rate was observed on postoperative day 90, with only 76 (25%) patients responding in the engagement platform (Figure 3.5). Regarding the survey completion, of 218 patients who responded in the engagement platform, the highest and lowest survey completion percentage per day was observed on postoperative days 60 and 30 with 93% and 86%, respectively (Figure 3.6). In other words, for day 60, a total of 89 patients responded in the engagement platform, where on average they completed more than six questions (6.55 questions, 93%) out of seven. In the same way, for day 30, there were 140 patients who responded in the engagement platform, and on average, they completed around seven questions (6.88 questions, 86%) out of eight. The average overall survey completion percentage was 90% (i.e., if a patient responded to a survey on a particular day, on average, they finished 90% of the survey) (Figure 3.6).

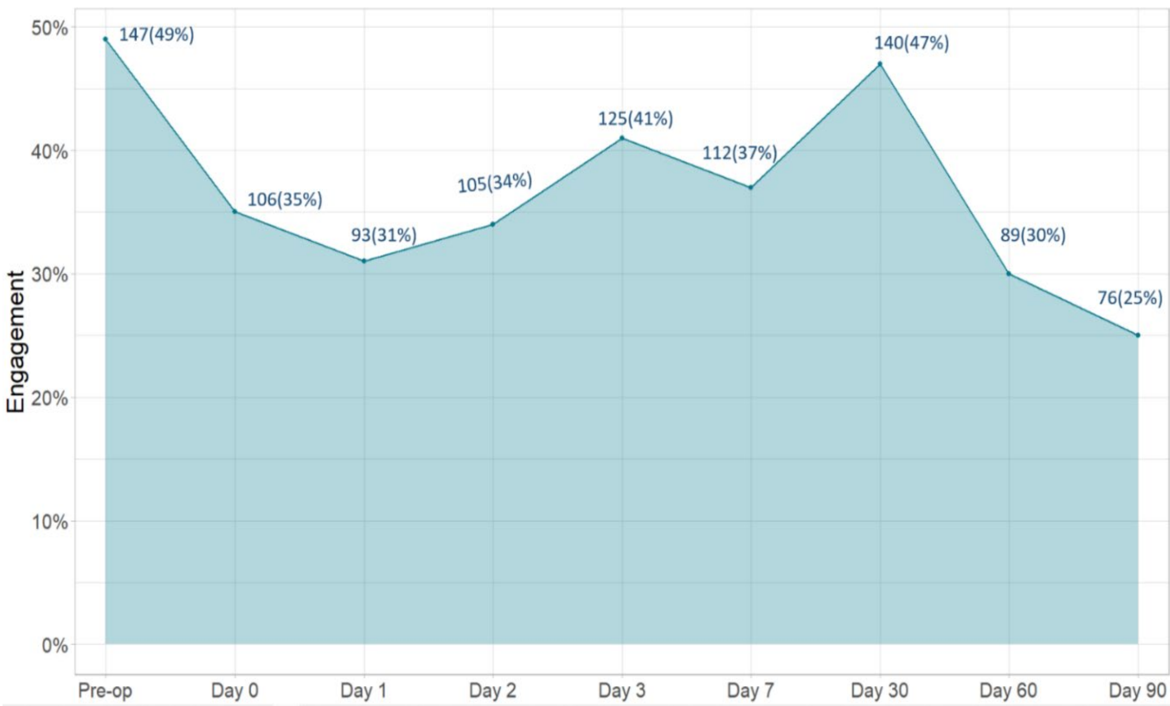


Figure 3.5 Patient engagement at different time points (out of 301 patients)

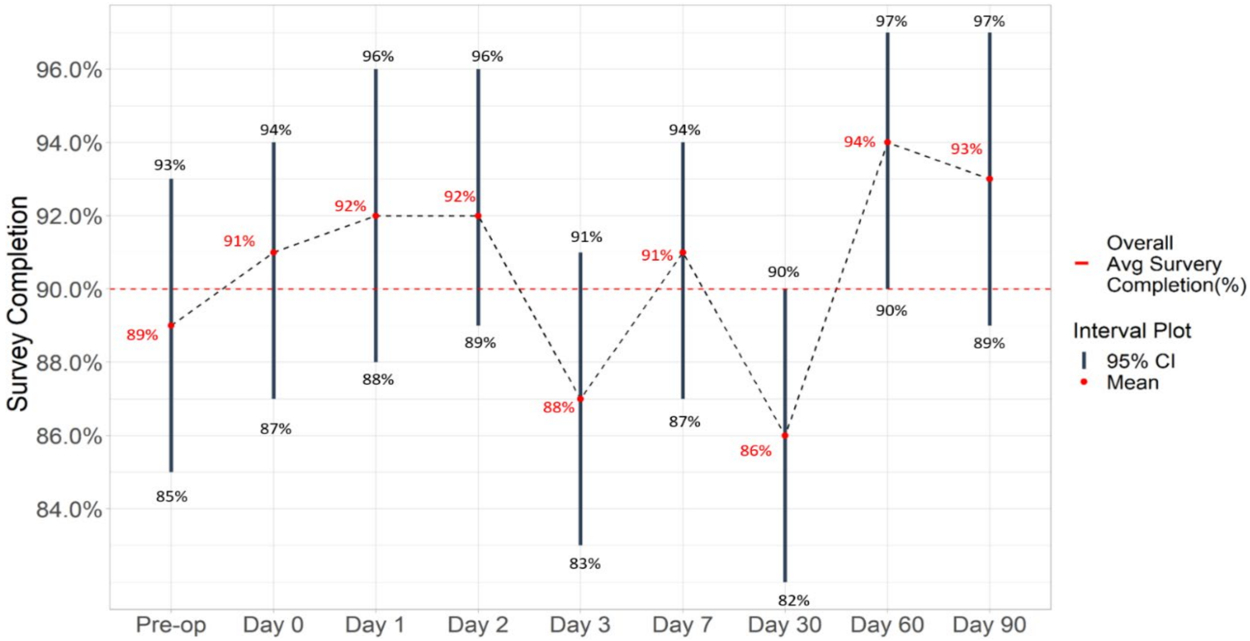


Figure 3.6 Survey completion percentage at different time points (out of 218 patients)

For a particular day, on average, the questions including resting pain, active pain, pain compared to expected, side effects, surgery satisfaction, and pain satisfaction had a higher completion percentage by the patients (greater than 95%) in the engagement platform (Appendix Table A.3). The daily activities functional recovery question had the lowest average completion with 76% (Appendix Table A.3).

More than 90% reported they were very satisfied or somewhat satisfied with the overall surgical experience and pain management; less than 5% reported they were unsatisfied. There was a total of 61 alerts received by PSH staff from patients: 12 ER alerts, 39 pain alerts, and 10 alerts for non-emergent issues. The alerts effectively helped PSH clinicians to facilitate patient care transitions, as needed.

Discussion

Patients in rural areas often face barriers and lack access to high-quality surgical care (Stanislav, 2020). Generally, rural areas are more socioeconomically deprived and have less healthcare awareness, often resulting in less patient engagement and poorer outcomes (Fleming et al., 2017; Gong et al., 2019; Levy et al., 2017). This reflects negatively on patient satisfaction, i.e., rural patients compared to urban patients, are often less satisfied with their surgical experience (Esguerra et al., 2014; Tsai et al., 2015). In this study, a digital engagement platform was implemented by a rural community hospital that adopted the PSH system to improve TJR outcomes, value, and satisfaction. Similar to other studies, the engagement platform was found beneficial to monitor patients' progress longitudinally considering clinician's workload and the COVID-19 outbreak, that restricted frequent in-person clinical visits (Campbell et al., 2020; Lesher et al., 2021).

In this setting, a longitudinal patient engagement was successfully performed on rural patients over the critical 120-day time-period (30 days preoperative to 90 days postoperative). Physician co-management as part of the PSH system incorporated a hospitalist, anesthesiologist, surgeon, and primary care physician, which was effective in educating and engaging rural patients, thus minimizing some barriers for surgical care. The patient engagement was highest during the preoperative period (0 to 30 before surgery) and then gradually decreased through postoperative period. Knapp et al. (2021) and Molloy et al. (2020) demonstrated similar results, where most patient engagement was observed before surgery when engaged with TKA and THA patients. It was observed, that patient education performed by the clinicians in the preoperative period led to more engagement and alleviated patient's anxiety. Education events not only helped patients build confidence and practice self-care, but also motivated them to engage with clinicians and receive more personalized care (Kennedy et al., 2017). However, in the postoperative period, especially 30-days after the surgery, most patients were confident as they were almost or completely recovered, which made them less responsive on the engagement platform (Knapp et al., 2021).

Though a decrease in patient engagement was expected over time, a steady increase was observed on days 3 and 30 (Figure 3.5). The study accounts that patients' service modality and postoperative follow-ups by clinicians were contributing reasons. For instance, in this study, the majority of the patients were inpatients (82%) and on average, stayed two days after surgery. During the time in the hospital (Days 0, 1, and 2), patients preferred communicating with clinicians directly rather than providing feedback on the engagement platform. Whereas on day 3, most patients were discharged from the hospital and considered using the engagement platform to communicate with clinicians. Another main contributing reason for higher engagement on day 3, was due to follow-up of the nurse navigator in the PSH clinic. The PSH nurse performed regular follow-up with most patients via phone on day 3, and reminded them to utilize the engagement platform (B. Kash et al., 2014). Similarly, around 30-days post-surgery, the surgeon or a PSH clinician followed up with patients by clinical visit or by phone and encouraged them to use the engagement platform. These factors explain why there were low patient engagement on days 0, 1, and 2, and high engagement on days 3 and 30.

The average patient engagement was low (less than 40%) (Figure 3.5). The main reason was that many patients were inconsistent in responding to the survey at all time points (i.e., patients responded survey at a few time points but not all). Also, a total of 83 (29%) patients did not use the engagement platform at any time in the longitudinal period. Reasons that are associated with low and inconsistent engagement across the 120-day time period, include limited availability of internet, engagement platform connectivity/maintenance issues, and limited mobile service access (Philip & Williams, 2019). Other reasons include patients' loss of interest, experiencing mental health issues or depression, or other personal obligations, including work (Fleming et al., 2017; Nelson et al., 2016). The adjusted logistic regression demonstrated that there was no association in baseline variables gender, service modality, and procedure type between patients who used the engagement platform and the patient who did not (Molloy et al., 2020). The surgeon variable had a moderate effect on patient engagement in the digital platform (P-value = 003). However, the study suspects this might be due to limited sample sizes (less than 10%) within the surgeon variable, as one surgeon performed the majority of the procedures.

Despite the low patient engagement, the average survey completion per day was comparatively high (90%) (Figure 6). In other words, many patients failed to respond to most engagement surveys (nine points), but if they responded to a survey on a particular day, on average patients finished most of the survey (~90%) (Figure 6). The PROM questions related to pain (active pain, resting pain, and pain compared to expected) had the highest average completion (more than 95%) in the engagement platform (Appendix Table 3). In the postoperative period, pain is an important PROM, and most patients prioritize communicating their pain with the clinicians for faster recovery and improved surgical experience (Knapp et al., 2021; Noiseux et al., 2014; Rakel et al., 2012; Yang et al., 2019). The functional recovery question - daily activities, had the lowest completion (76%). This was because the daily activity question was broader compared to other functional recovery questions: walking and standing (i.e., patients may not be sure what daily activities were referred to). Therefore, many patients skipped the daily activity question and instead, completed walking and standing functional recovery questions (Appendix Table A.3).

Among the patients who responded on days 30, 60, and 90, more than 95 % reported they were satisfied with the surgery and the pain management. The engagement platform and PSH system enhanced patient care and value by educating and longitudinally engaging with patients, and reducing preventable surgical complications (Milliren et al., 2022). Patients experienced shorter length of stay, increased discharge to home, and reduced readmission rates and surgical site infection (McCrory et al., 2019). These factors contributed to improving patient satisfaction that was lacking in rural hospitals (Lese & Sraj, 2019; Niemi-Murola et al., 2007; Tsai et al., 2015).

Limitations of this study, include an analysis of patient engagement and PROMs with limited covariates. Covariates such as insurance, employment status, marital status, economic background, American Society Anesthesiologists Score (ASA), and Body Mass Index have been associated with arthroplasty patients' responses on the engagement platform (Harris et al., 2022; Holte et al., 2021; Papas et al., 2018; Patel et al., 2015; Plate et al., 2019). Inclusion of these factors would have provided better clarity of patient engagement in rural surgical systems. Second, there was a digital platform server connectivity/maintenance outage period, which impacted an unknown number of responses during a 30-day window of this study. Third, the study is retrospective, which may contain data collection biases that could alter the results and key findings (Hess, 2004). Finally, this study was performed at a community hospital located in a micro-statistical area (with a population of less than 50,000). The results from this study may not be generalizable to more rural places (e.g. with a population of less than 10,000).

Conclusion

Patient engagement was critically important to optimize care in a rural area served by community hospitals. Digital (email/text message) longitudinal engagement was successful across the 10+ rural county areas, as deployed by the PSH clinic. To the authors' knowledge, this study is the first of its kind to assess patient engagement at a rural community hospital with a coordinated PSH surgical system. Future research should assess engagement with rural patients and primary care managers in the region, to determine actual and perceived perioperative barriers. Additional future studies, should focus on evaluating PROM outcomes such as pain, sleep, side effects, and recovery. Finally, advanced analytics such as predictive modeling and machine learning should also be incorporated into future research to predict PROMs and improve rural surgical outcomes (Kurmis & Ianunzio, 2022).

CHAPTER FOUR

RURAL IMPLEMENTATION OF THE PERIOPERATIVE SURGICAL HOME: A CASE-CONTROL STUDY

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Strobe Statement: The guidelines of the strobe statement have been adopted

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Manuscript Information

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World Journal of Orthopedics

Status of Manuscript:

_________Prepared for submission to a peer-reviewed journal

___☑___Officially submitted to a peer-reviewed journal

_________Accepted by a peer-reviewed journal

_________Published in a peer-reviewed journal

August 28th, 2022

Abstract

Background: Perioperative Surgical Home (PSH) is a novel patient-centric surgical system developed by American Society of Anesthesiologist (ASA) to improve outcomes and patient satisfaction. PSH has proven success in large urban health centers by reducing surgery cancellation, operating room time, length of stay (LOS), and readmission rates. Yet, only limited studies have assessed the impact of PSH on surgical outcomes in rural areas.

Aim: Evaluate the newly implemented PSH system at a community hospital by comparing the surgical outcomes using a longitudinal case-control study.

Method: The research study was conducted at an 83-bed, licensed level-III trauma rural community hospital. A total of 3,096 TJR procedures were collected retrospectively between January 2016 and December 2021 and were categorized as PSH and non-PSH cohorts (n = 2305). To evaluate the importance of PSH in the rural surgical system, a case-control study was performed to compare TJR surgical outcomes (Length of Stay (LOS), discharge disposition, and 90-day readmission) of the PSH cohort against two control cohorts (C1-PSH (n= 1413) and C2-PSH (n= 892)). Statistical tests including Chi-square test or Fischer's exact test were performed for categorical variables and Mann-Whitney test or Student's t-test were performed for continuous variables. The general linear models (Poisson regression and binomial logistic regression) were performed to fit adjusted models.

Results: The LOS was significantly shorter in PSH cohort compared to two control cohorts (median PSH = 34 hours, C1-PSH = 53 hours, C2-PSH = 35 hours) (P-value <0.05). Similarly, the PSH cohort had lower percentages of discharges to other facilities (PSH = 3.5%, C1-PSH = 15.5%, C2-PSH = 6.7%) (P-value <0.05). There was no statistical difference observed

in 90-day readmission between control and PSH cohorts. However, the PSH implementation reduced the 90-day readmission percentage (PSH = 4.7%, C1-PSH =6.1%, C2-PSH = 3.6%) lower than the national average 30-day readmission percentage which is 5.5%. The PSH system was effectively established at the rural community hospital with the help of team-based coordinated multi-disciplinary clinicians or physician co-management. The elements of PSH including preoperative assessment, patient education and optimization, and longitudinal digital engagement were vital for improving the TJR surgical outcomes at the community hospital.

Conclusion: Implementation of the PSH system in a rural community hospital reduced LOS, increased direct-to-home discharge, and reduced 90-day readmission percentages.

Introduction

The demand for orthopedic surgeries including Total Joint Replacement (TJR), which are primarily performed on hips, knees, and shoulders, are drastically increasing each year (Singh et al., 2019). Yet, delivering quality surgical care to large volumes of TJR patients is a challenge to many hospitals, specifically those hospitals located in rural areas (Dowsey et al., 2014; Jeschke et al., 2017). Rural and frontier health systems have siloed perioperative care that is spread across many disciplines and institutions, which contributes to inadequate communication, high cost, poor care continuity, and preventable complications (McCrory et al., 2019). On average, TJR patients are 65 years or older, and have one or more health conditions (e.g., comorbidities). Due to generally higher risk of surgery in these populations, there is a 1% to 50% chance of adverse events in TJR surgeries including major cardiac incidents, healthcare-acquired conditions, extended Length of Stay (LOS), readmission to inpatient facilities, improper pain management, and side effects (Lese & Sraj, 2019; McCrory et al., 2019).

To improve surgical outcomes and patient experience, the Perioperative Surgical Home (PSH) model of care was created by the leaders within American Society of Anesthesiologists (ASA) (B. Kash et al., 2014; Vetter et al., 2013). Compared to a traditional surgical system, the PSH is a coordinated interdisciplinary team providing all surgical care to patients from the *preoperative phase* (30 days before surgery) to *recovery phase* (90 days after surgery) (Figure 4.1) (Al-Shammari et al., 2017; Cline et al., 2020; Desebbe et al., 2016; Kain et al., 2014; Vetter et al., 2013).

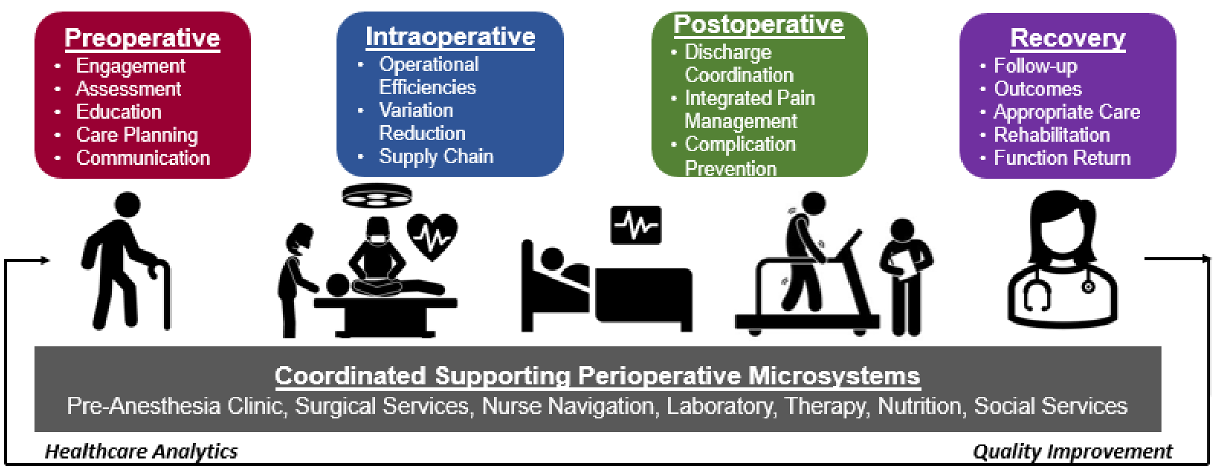

Figure 4.1 Perioperative Surgical Home model (Adapted from (McCrory et al., 2019))

The components of PSH also included patient-centered coordination programs and enhanced recovery after surgery (ERAS) (Cannesson & Kain, 2014; Nicolescu, 2016). The implementation of PSH in larger healthcare systems and academic medical institutions has shown promising results in surgical outcomes, especially in orthopedic procedures (Cline et al., 2020). For example, Qiu et al. (2016) and Alvis et al. (2017) observed that the PSH cohort had a day shorter LOS than the control cohort when examining hip and knee procedures. Kim et al. (2019) analyzed 1194 TJR procedures and found that the PSH cohort had higher discharges to home by 8.1% compared to the non-PSH cohort. The authors also noticed the surgical cost in the non-PSH cohort was 14.9% greater cost than the PSH cohort. Yajnik et al. (2019) retrospectively analyzed 40 knee procedures and demonstrated that the PSH cohort experienced optimized post-surgical pain management with less consumption of opioids than the non-PSH cohort. Likewise, past researchers found that PSH contributed to improved surgical outcomes including, lower readmission rates, faster postoperative recovery, improved operational efficiency, and higher patient satisfaction (Alvis et al., 2017; Chimento & Thomas, 2017; Kim et al., 2017; Qiu et al., 2017; Raman et al., 2017).

Despite these successes, some researchers found no change in surgical outcomes with PSH in similar size urban health centers. For example, Vetter et al. (2017) and Powell et al. (2017) found no significant difference in LOS after implementing PSH for orthopedic surgeries. Qiu et al. (2016) and Vetter et al. (2017) found no difference in readmission rates using the PSH system. In terms of surgery cost, Leahy et al. (2019) found there was no significant reduction for pediatric patients. These examples exhibit that there is no standard PSH program to achieve a standardized surgical outcome (Cline et al., 2020). These PSH studies were performed in urban healthcare systems and academic-affiliated medical centers. To authors' knowledge only our pilot study (McCrory et al., 2019) has explored PSH systems in rural or frontier healthcare service area. This current study addresses this gap by assessing TJR outcomes at a rural hospital with a newly implemented PSH system using a case-control study design.

Surgical care inequality is greater within rural community hospitals due to limited resources, socioeconomic differences, and poor access to healthcare (Kaufman et al., 2016; Nakayama & Hughes, 2014; Weichel, 2012). Compared to urban hospitals, rural surgical outcomes have higher odds of in-hospital mortality and higher hospitalization cost (Chaudhary et al., 2017). One of the reasons for this is many rural patients are uninsured, older, and have one or more medical complications (Gruca et al., 2016; Snyder et al., 2017). Rural hospitals in the United States can often be overwhelmed by the growing demand for TJR surgeries and factors such as poor coordination among clinicians, lack of patient education, poor patient care transitions, limited patient engagement (pre-operative and post-operative), and inconsistent/non-standardized care delivery affect rural orthopedic surgical care negatively (Lese & Sraj, 2019; Singh et al., 2019).

A newly implemented PSH at a community hospital in rural Montana was created to address the factors mentioned above, which have plagued the rural orthopedic surgery system. With limited resources and supporting microsystems, the PSH was successfully initiated with the help of strong team-based coordination amongst clinicians. The PSH multi-disciplinary team consisted of the patient's selected surgeon, anesthesiologist, hospitalist, physician assistant, registered nurse, and the patient's primary care manager. This collaboration focused on improving surgical care and enhancing patient engagement perioperatively. Effective communication between clinicians was established for communal decision-making for patient-centric – "physician co-management" (Norful et al., 2018).

This research study's primary objective was to evaluate the newly implemented PSH system at a local rural, community hospital by comparing TJR surgical outcomes using a longitudinal case-control study design. Based on our preliminary study (Sridhar et al., (in press)), it was hypothesized that the implementation of the PSH in the rural community hospital would positively impact patients' TJR outcomes (i.e., shorter LOS, reduced readmissions, and increased rate of home discharge) across three distinct cohorts for the case-control design.

Methods

The PSH clinic affiliated with the local community hospital began seeing TJR patients in November 2018. The hospital was an 83-bed, licensed level-III trauma center primarily serving three counties. However, based on initial analyses, the hospital was serving patients from more than 10 surrounding counties covering 9,000 square miles and approximately 136,000 residents. The research team (health systems engineers and clinicians) retrospectively collected and analyzed all TJR data from January 2016 to December 2021. The observational timeframes were reviewed, and three distinct cohorts were determined for the case-control study design. This retrospective analysis was approved by the Montana State University Institutional Review Board (Approval# BM050819-EX).

Data Collection and Pre-Processing

Data were extracted from the Electronic Medical Record (EMR) for a total of 6,685 orthopedic procedures that were performed on knees, hips, and shoulders between January 2016 and December 2021 (Figure 4.2). Six hundred and forty-eight (n = 648) procedures were included that had CPT codes – 27447 (total knee), 27130 (total hip), and 23472 (total shoulder). The remaining 6,037 did not have CPT codes and were filtered for TJR procedures by searching for keywords 'arthroplasty', 'total', 'THA' (i.e., Total Hip Arthroplasty), 'TKA' (i.e., Total Knee Arthroplasty), and 'TSA' (i.e., Total Shoulder Arthroplasty). During this filtering process, a total of 3,420 procedures were excluded because they were identified as non-TJR procedures, (e.g., arthroscopic procedures, reductions, nailing hip). A total of 82 TJR procedures were also excluded from the analysis because they were either duplicate records (n = 1) or missing key outcomes and demographic values (n = 81) of the patients.

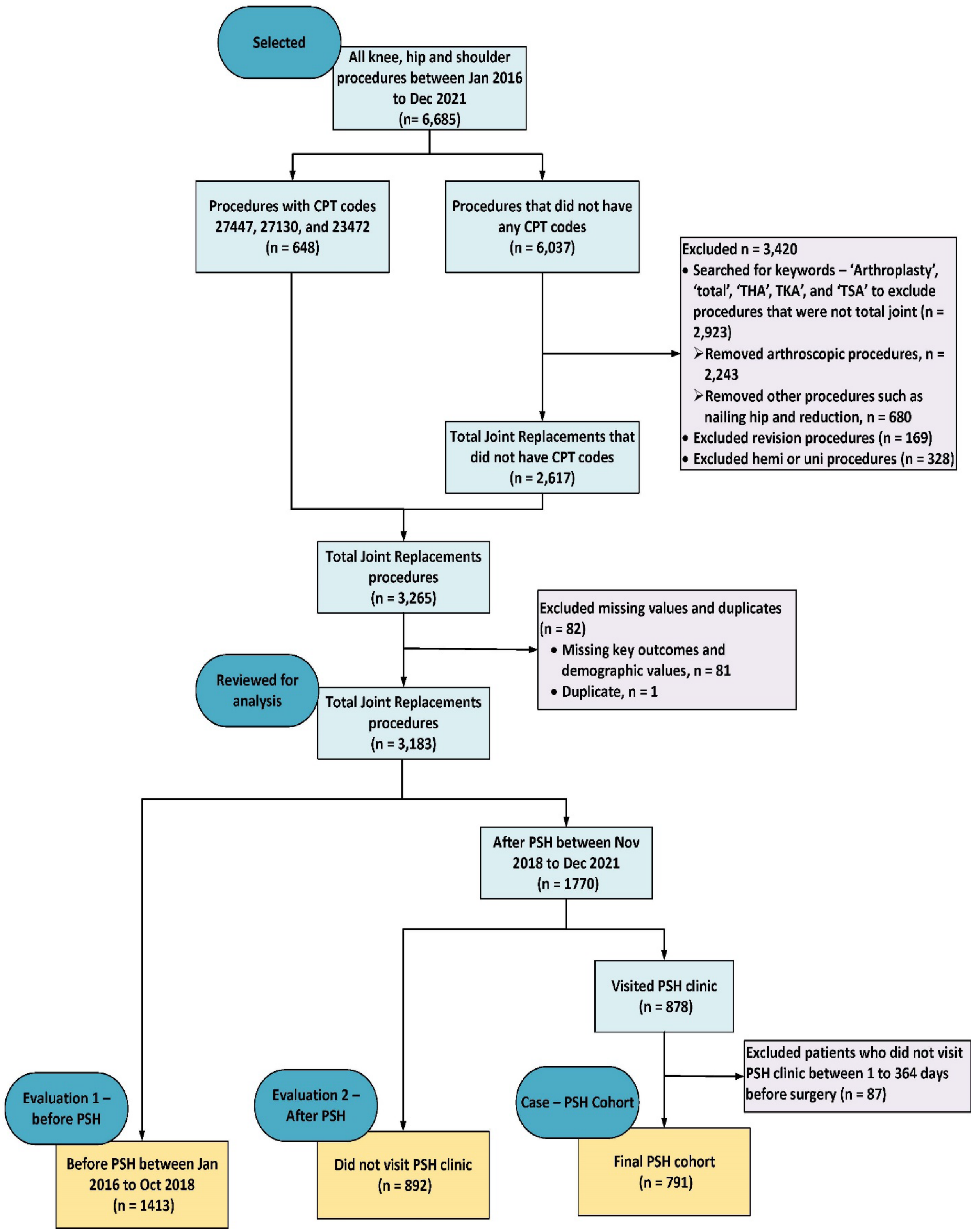

Figure 4.2 CONSORT diagram for PSH case-control study

A total of 3,183 TJR procedures were considered for the analysis and were categorized into: the PSH cohort (case) and non-PSH cohort (control). The PSH pathway begins with visiting PSH clinic for preoperative assessment. Most patients visited the PSH clinic between 30 to 60 days before surgery for their preoperative assessment. A very few medically complicated patients needed more time for optimization and postponed their surgery 6-9 months (not more than a year) after their preoperative assessment. Therefore, the inclusion criteria for the PSH cohort (n = 791) included if the patient visited the PSH clinic for optimization between 1 and 364 days before surgery. Those patients who visited the PSH clinic but failed to meet the inclusion criteria (i.e., visited the PSH clinic a year before their surgery or after their surgery), were excluded from the analysis (n = 87). The inclusion criteria for the non-PSH cohort included the patients who did not visit the PSH clinic during their surgical process at all. The non-PSH cohort was further subcategorized based on the timeframes: *Control-1 PSH cohort* (before PSH implementation between January 2016 and October 2018, n = 1,413) and *Control-2 PSH cohort* (after PSH implementation between November 2018 and December 2021, n = 892).

The study utilized two control cohorts to evaluate the importance of the PSH system in two timeframes – before and after PSH implementation. In the first evaluation, the PSH cohort was compared with Control-1 PSH cohort (C1-PSH). In the second evaluation, the PSH cohort was compared with Control-2 PSH cohort (C2-PSH). The baseline characteristics were compared with variables including patient age, gender, Body Mass Index (BMI), American Society of Anesthesiologist (ASA) score (Class 1, 2, 3, or 4), procedure type (THA, TKA, and TSA) and insurance type (private or public payer). These variables were included in the baseline characteristics and in the analysis, as they were found to be potential confounders at PSH implemented hospitals with the surgical outcomes LOS, discharge disposition, and 90-day readmission (Alvis et al., 2021; Duplantier et al., 2015; Kim et al., 2019; Leahy et al., 2019; Qiu et al., 2016).

Statistical Analysis:

Either the Fischer's exact test or Chi-square test for association were used to compare the categorical variables between non-PSH and PSH cohorts. The continuous variables between two cohorts were analyzed using the Mann-Whitney test or Student's t-test, as appropriate. The LOS was found to be right skewed and was not normally distributed using the Shapiro-Wilk test (P-value < 0.01). Therefore, a Poisson regression was performed to fit an adjusted model (Carter & Potts, 2014; Qiu et al., 2016). For dichotomous variables, i.e., discharge disposition and 90-day readmission, the binomial logistic regression was used to fit an adjusted model. All data handling, visualization, and statistical analyses were performed using R (V4.0.3, Vienna, Austria). The statistical analyses were performed with an alpha (α) value of 0.05. All data were encrypted and were accessed only by the authors and clinicians working at the hospital.

Results

Evaluation 1: Comparison of C1-PSH Cohort and PSH Cohort

There were no significant differences observed in the baseline characteristics for the variables gender, BMI, and procedure type (P-value > 0.05) (Table 4.1). However, a difference was observed between cohorts for the variables age, ASA class, and insurance type (P-value < 0.05). On average, patients in the PSH cohort were two years older than in the C1-PSH cohort. The PSH cohort also included more medically complex patients with a higher proportion of ASA class 3 (42%) compared to the C1-PSH cohort (36%). For insurance, there were more public insurance payers in the PSH cohort (82%) compared to the C1-PSH cohort (71%).

Table 4.1 Comparison of baseline characteristics between C1-PSH and PSH cohorts

Characteristics	C1-PSH (n= 1413) Mean (SD) [Min, Max] or n(%)	PSH (n= 791) Mean (SD) [Min, Max] or n(%)	P-value
Age	67.3 (10) [18, 95]	69.2 (8.6) [31, 90]	<0.01[1]
Gender			0.19[2]
Male	629 (45%)	379 (47.5%)	
BMI	29.7 (6.2) [17.3, 68.5]	29 (6.09) [14.67, 55.3]	0.86[1]
ASA			
Class 1	67 (4.7%)	20 (2.5%)	
Class 2	817 (57.8%)	434 (54.9%)	0.009[3]
Class 3	517 (36.6%)	332 (42%)	
Class 4	12 (0.8%)	5 (0.6%)	
Procedure			
THA	489 (35%)	311 (39.3%)	0.08[2]
TKA	686 (49%)	356 (45%)	
TSA	238 (17%)	124 (15.7%)	
Insurance			
Private	415 (29%)	145 (18%)	<0.01[2]
Public	998 (71%)	646 (82%)	

[1]Mann-Whitney Test. [2]Chi-Square Test. [3]Ficher's Exact Test

The LOS was lower in the PSH cohort compared to the C1-PSH cohort (median 34 vs 53 hours, P-value < 0.01) (Figure 4.3). Based on the Poisson regression results, the PSH clinic had a positive effect on LOS (P-value < 0.01). On average, the LOS was 10% shorter in the PSH cohort compared to the C1-PSH cohort (Table 4.1). Other variables that also had a significant effect on patients' LOS were age, gender, BMI, procedure type, and insurance type (P-value < 0.05) (Appendix Table B.1).

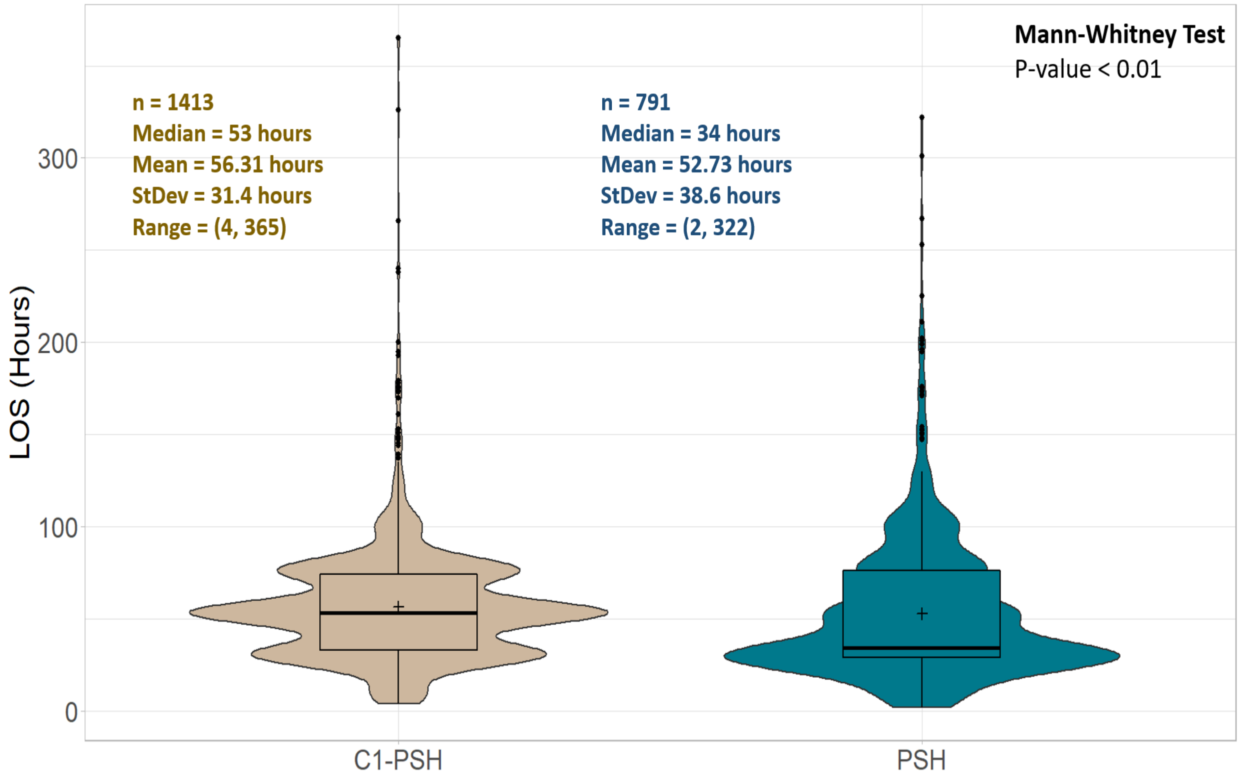

Figure 4.3 LOS distributional difference between the C1-PSH and PSH cohort

Discharge disposition was classified into two types: patient discharged to home or discharged to other facilities such as skilled nurse facilities (SNF), inpatient rehabilitation facilities (IRF), or other hospitals' swing beds. Discharge disposition was significantly different between the PSH and C1-PSH cohort ($\chi^2 = 72$, P-value < 0.01) (Figure 4.4). The unadjusted odds for the PSH cohort discharged to other facilities was 80% lower than the C1-PSH cohort (P-value < 0.01) (Table 4.2). Using logistic regression, the adjusted odds for the PSH cohort discharged to other facilities were 91% lower than the C1-PSH cohort (P-value < 0.01) (Table 4.2). Age, gender, procedure type, insurance type, and LOS were also associated with the patient's discharge type (P-value < 0.05) (Appendix Table B.1).

Table 4.2 - Surgical outcomes of PSH cohort relative to C1-PSH cohort

Outcomes	**Unadjusted Odds Ratio (95% Confidence Interval)**	**Unadjusted P-value**	**Adjusted Risk (95% Confidence Interval)**	**Adjusted P-Value**
Length of Stay	-	-	0.90 (0.88, 0.91)[1]	<0.01
Discharge Disposition	0.20 (0.13, 0.30)	<0.01	0.09 (0.05, 0.14)[2]	<0.01
Readmission	0.76 (0.51, 1.12)	0.17	0.72 (0.47, 1.09)[3]	0.11

[1]Poisson regression adjusted with age, gender, BMI, ASA, procedure type, and insurance type [2]Binomial logistic regression adjusted with LOS, age, gender, BMI, ASA, procedure type, and insurance type [3]Binomial logistic regression adjusted with LOS, discharge disposition, age, gender, BMI, ASA, procedure type, and insurance type

Readmission was categorized by if a patient was readmitted to any inpatient within 90 days post-surgery or not. The Chi-square test had no strong evidence for a difference in the readmission rates between the PSH and C1-PSH cohort (χ^2 = 1.65, P-value = 0.2) (Figure 4.4). The unadjusted odds for the PSH cohort readmitted after surgery was 24% lower than the C1-PSH cohort (P-value = 0.17) (Table 4.2). The adjusted odds for the PSH cohort readmitted after surgery was 28% lower than the C1-PSH cohort (P-value = 0.17) (Table 4.2). In this adjusted analysis, no variable had a significant effect on patient readmission (Appendix Table B.1).

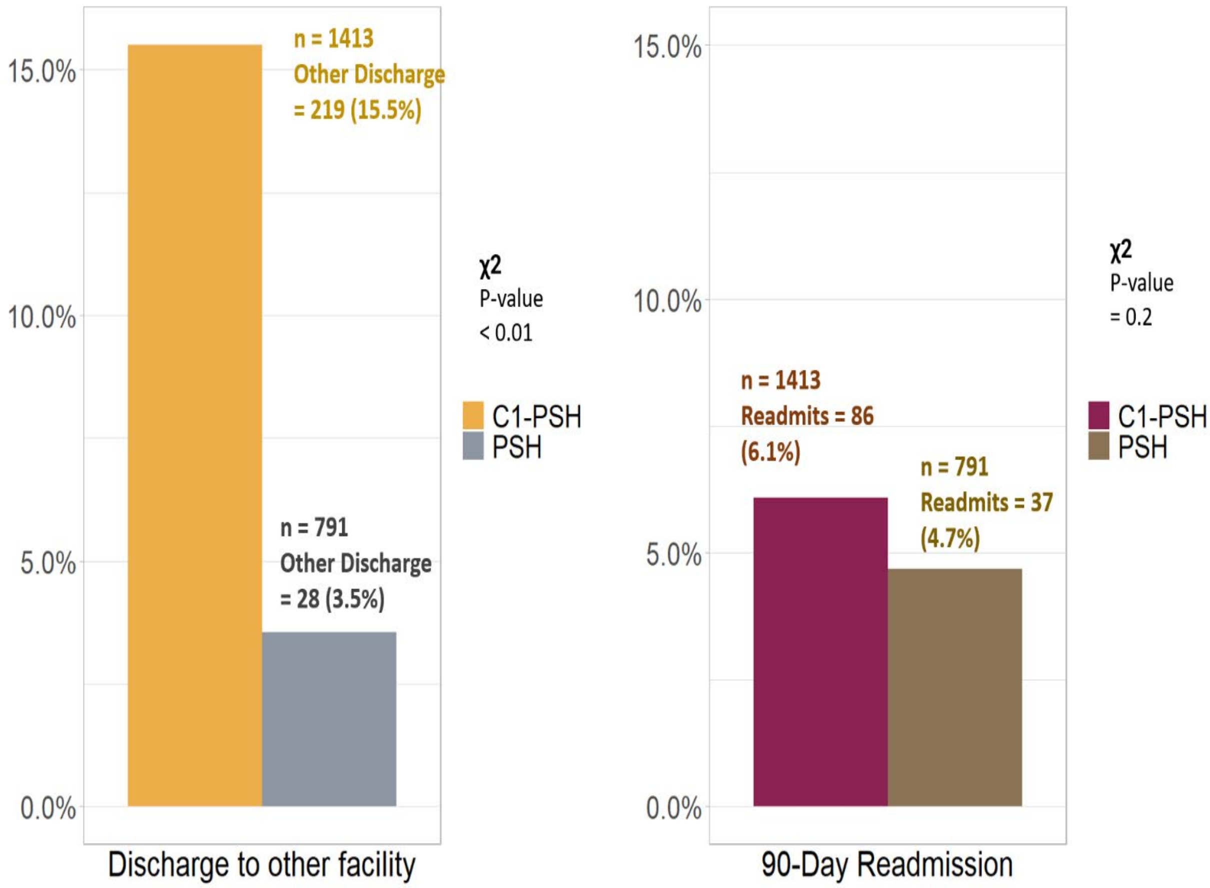

Figure 4.4 Discharge disposition and readmission between the C1-PSH cohort and PSH cohort

Evaluation 2: Comparison of PSH Cohort and C2-PSH Cohort

Except for variables ASA and procedure type, there was no significant difference observed between cohorts in the baseline characteristics (P-value = 0.046) (Table 4.3). Similar to evaluation 1, the PSH cohort had more medically complex patients with a higher proportion of ASA class 3 (42%) compared to the C2-PSH cohort (36%). For procedure types, there were more knee procedures in the PSH cohort and there were more hip and shoulder procedures in the C2-PSH cohort.

Table 4.3 – Comparison of baseline characteristics between the C2-PSH and PSH cohorts

Characteristics	C2-PSH (n= 892) Mean (SD) [Min, Max] or n(%)	PSH (n= 791) Mean (SD) [Min, Max] or n(%)	P-value
Age	69 (8.5) [37, 98]	69.2 (8.6) [31, 90]	0.2[1]
Gender			
Male	439 (49.2%)	376 (47.5%)	0.52[2]
	30 (6.2) [17, 57.8]	30 (6.1) [14.67, 55.3]	0.76[1]
ASA			
Class 1	24 (2.7%)	16 (3.4%)	
Class 2	546 (61.2%)	434 (54.9%)	0.046[3]
Class 3	319 (35.8%)	332 (42%)	
Class 4	3 (0.3%)	5 (0.6%)	
Procedure			
THA	294 (33%)	311 (39.3%)	
TKA	355 (39.8%)	356 (45%)	<0.01[2]
TSA	243 (27.2%)	124 (15.7%)	
Insurance			
Private	179 (20%)	145 (18%)	0.4[2]
Public	713 (80%)	646 (82%)	

[1]Mann-Whitney Test. [2]Chi-Square Test. [3]Ficher's Exact Test

There was no significant difference between LOS in the PSH cohort and C2-PSH cohort in the un-adjusted analysis (median 34 vs 35 hours, P-value = 0.5) (Figure 4.5). However, in the adjusted analysis using Poisson regression, the LOS was found to be lower in the PSH cohort compared to the C2-PSH cohort (P-value < 0.01). On average, the LOS was 10% shorter in the PSH cohort compared to the C2-PSH cohort (Table 4.4). Other variables that also had significant effect on patients' LOS were age, gender, BMI, procedure type, and insurance type (P-value < 0.05) (Appendix Table B.2).

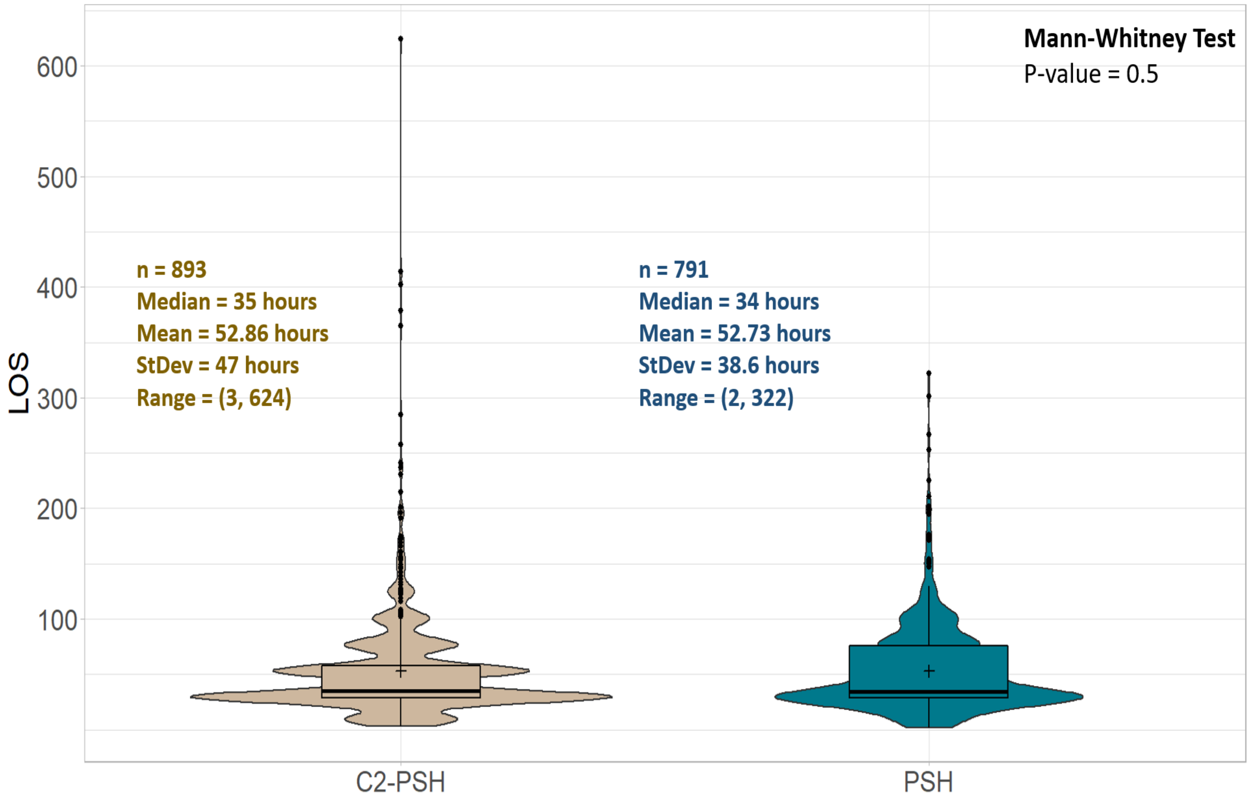

Figure 4.5 LOS distributional difference between C2-PSH and PSH cohort

Similar to evaluation 1, the discharge disposition was found to be significantly different between the PSH and C2-PSH cohorts ($\chi^2 = 8$, P-value < 0.01) (Figure 4.6). The unadjusted odds for the PSH cohort discharged to other facilities was 49% lower than the C2-PSH cohort (P-value < 0.01) (Table 4.4). Using logistic regression, the adjusted odds for the PSH cohort discharged to other facilities was 62% lower than the C2-PSH cohort (P-value < 0.01) (Table 4.4). Age, gender, procedure type, insurance type, and LOS were also associated with patient discharge type (P-value < 0.05) (Appendix Table B.2).

Table 4.4 - Surgical outcomes of PSH cohort relative to C2-PSH cohort

Outcomes	**Unadjusted Odds Ratio (95% Confidence Interval)**	**Unadjusted P-value**	**Adjusted Risk (95% Confidence Interval)**	**Adjusted P-Value**
Length of Stay	-	-	0.91 (.90, .94)[1]	<0.01
Discharge Disposition	0.51 (.32, .80)	<0.01	0.38 (.17, .77)[2]	<0.01
Readmission	0.48 (.22, .99)	0.04	0.43 (.21, .93)[3]	0.03

[1]Poisson regression adjusted with age, gender, BMI, ASA, procedure type, and insurance type [2]Binomial logistic regression adjusted with LOS, age, gender, BMI, ASA, procedure type, and insurance type [3]Binomial logistic regression adjusted with LOS, discharge disposition, age, gender, BMI, ASA, procedure type, and insurance type

Similar to evaluation 1, the Chi-square test had no strong evidence for a difference in the readmission rates between the PSH and C2-PSH cohort ($\chi^2 = 1$, P-value = 0.31) (Figure 4.6). However, atypical results were observed in the unadjusted analysis, where the odds of the PSH cohort readmitted after surgery was 31% higher than the C2-PSH cohort (P-value = 0.26) (Table 4). Atypical results were also observed in the adjusted analysis, where the odds for the PSH cohort readmitted after surgery was 29% higher than the C2-PSH cohort (P-value = 0.26) (Table 4.4). In the adjusted analysis, no variable had a significant effect on patient readmission (P-value > 0.05) (Appendix Table B.2).

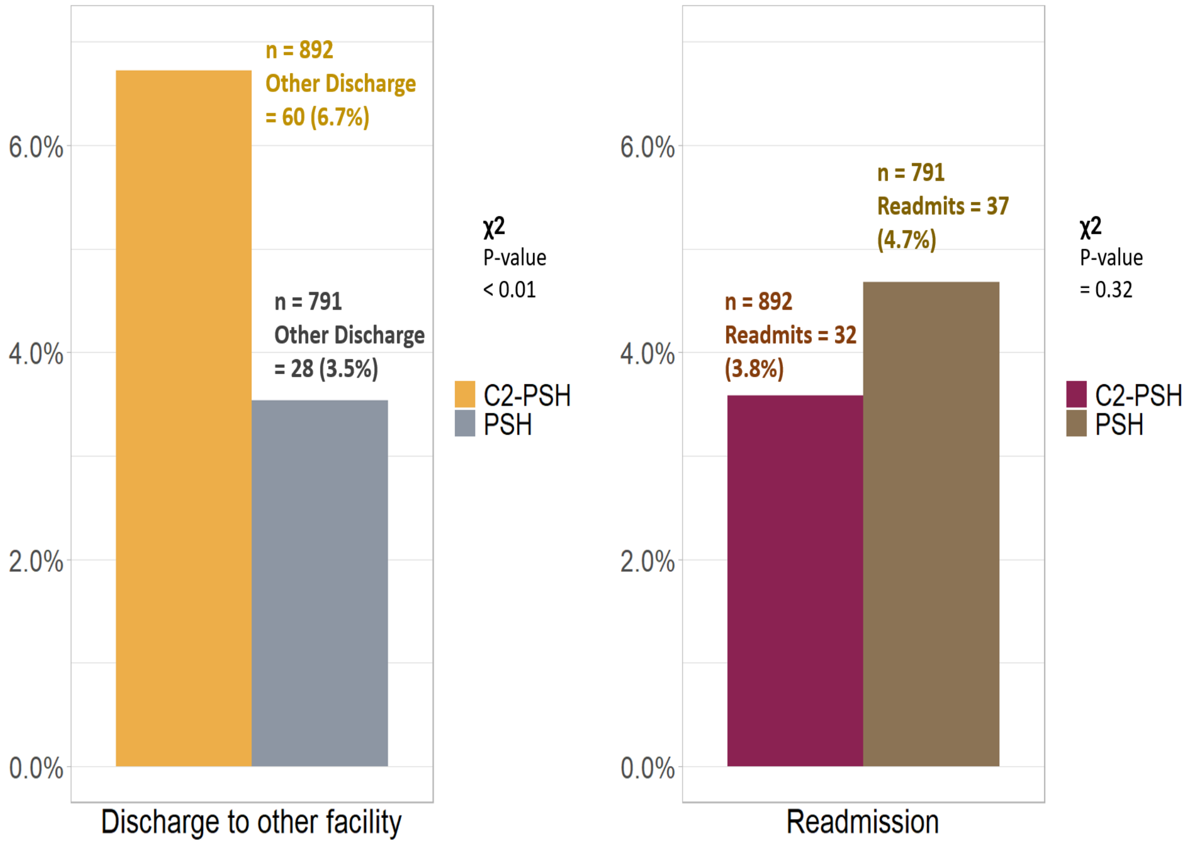

Figure 4.6 Discharge disposition and readmission between the C2-PSH cohort and PSH cohort

Discussion

This study evaluated the importance of PSH at a rural community hospital by comparing the PSH cohort with two control cohorts. In the first evaluation, the PSH cohort was compared with the C1-PSH cohort and for the second evaluation, the PSH cohort was compared with the C2-PSH cohort. The C1-PSH cohort included patients who had TJR surgeries before the PSH was implemented. The C2-PSH cohort consists of patients, who had TJR surgeries after PSH was implemented but did not visit the PSH clinic or followed the PSH-pathway.

In both evaluations, the LOS was shorter in the PSH cohort compared to the control cohorts (median PSH = 34 hours, C1-PSH = 53 hours, C2-PSH = 35 hours) (Alvis et al., 2021; Duplantier et al., 2015; Qiu et al., 2016). Although there was no statistical difference in LOS between the PSH and the C2-PSH cohort in the unadjusted analysis, the LOS was significantly shorter in the PSH cohort (10% shorter) in the adjusted analysis. This is because the PSH cohort had older and more medically complicated patients than the control cohorts. Therefore, when adjusted for the variables age, BMI, ASA, etc., the PSH had a significant effect in reducing LOS. Correspondingly, the PSH cohort had lower percentage of discharges to other facilities compared to the control cohorts (PSH = 3.5%, C1-PSH = 15.5%, C2-PSH = 6.7%). Even with medically complicated patients, there was an average decrease in discharge to other facilities in the PSH cohort of 7.6%.

There was no statistical significance in adjusted and unadjusted analysis for 90-day readmission. The readmission percentage was lower in the PSH cohort (4.7%) than the C1-PSH cohort (6.1%). Conversely, the PSH cohort (4.7%) had slightly higher percentage of 90-day readmission than the C2-PSH cohort (3.6%). Despite a marginal increase in the PSH cohort, the 90-day readmission percentage was still lower than the national average 30-day readmission which is 5.5% (Alem et al., 2016; Chand et al., 2018; Ramkumar et al., 2015). Past studies also demonstrated similar results where despite no statistical significance, the implementation of PSH helped to lower the readmission rates after surgery (Alem et al., 2016; Alvis et al., 2021; Couch et al., 2022).

Akin to other studies of urban health systems (Cline et al., 2020; B. Kash et al., 2014), implementing PSH at a community hospital helped to improve the TJR surgical outcomes. With only limited resources and siloed supporting microsystems, physician co-management was vital to effectively establish the PSH system at the rural community hospital. The PSH preoperative process utilized patient assessment and patient education approximately 30 days before surgery. The assessment helped clinicians identify patients with high-risk factors such as diabetes, high or low blood pressure, sleep apnea, obesity, and heart or respiratory complications (Duncan, 2019; Vetter et al., 2013). Based on these risks, the patients were 'optimized' and received treatment to improve the overall care by minimizing existing conditions or controlling undiagnosed conditions. In addition, the total joint education class hosted by the PSH clinicians educated patients on how to prepare for surgery, manage pain, plan for postoperative discharge, and reach clinicians for postoperative assistance (B. Kash et al., 2014; Yoon et al., 2010). Finally, a digital platform was initiated in the recovery phase to improve patient-clinician coordination and communication after surgery. The digital platform was used to engage and assess longitudinal patient-reported outcomes (post and pre-surgical pain, satisfaction, sleep, etc.) from 30 days preoperative to 90 days postoperative. These factors were conducive to improving patient satisfaction, shortening the LOS, increasing discharge to home, and reducing readmission after the surgery (B. Kash et al., 2014; Leahy et al., 2019; Lesher et al., 2021).

As mentioned before, the PSH clinic majorly saw patients who were high risk (older, high ASA score, high BMI, one or more medical complications such as diabetes, hypertension), which left the C2-PSH cohort with low to medium risk patients. This explained why the C2-PSH had improved surgical outcomes for LOS, discharge disposition, and 90-readmission compared to the C1-PSH cohort. The PSH system was effective in optimizing medically complicated patients, delivering similar or improved surgical outcomes compared to the C2-PSH cohort. The results from this study support that more patients (especially high and medium risk) should follow the PSH-pathway for an effective and improved surgical experience. The limitations of this study include being a retrospective which may contain data collection biases that could alter the results and key findings (Hess, 2004). Instead, a prospective clinical trial study can minimize these biases and provide better evidence-based results (Euser et al., 2009). Second, this study was performed at a community hospital located in a rural micro-statistical area (with a population size less than 50,000). The results from this study may not be generalizable to more rural places (e.g., with a population of less than 5,000).

Conclusion

To the author's knowledge, this study is first of its kind to evaluate the effectiveness of a PSH in a rural surgical system using a case-control study design. Implementing PSH at a community hospital was primarily successful because of patient-centric physician co-management to ensure continuity of care across all perioperative surgical phases. The PSH elements including preoperative assessment, patient education, and longitudinal digital engagement were imperative for improving the TJR surgical outcomes at the community hospital. Future research should include analysis of outcomes including same-day surgery cancellation, surgical cost, postoperative recovery measures, and postoperative opioid consumption. Other future research should also include advanced analytics and predictive modeling such as machine learning and deep learning to predict patient risk and improve the performance of surgical systems at rural and frontier hospitals.

CHAPTER FIVE

PREDICTING LENGH OF STAY USING MACHINE LEARNING FOR TOTAL JOINT REPLACEMENT PERFORMED AT A RURAL COMMUNITY HOSPITAL

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Contribution: Funding Acquisition, Project Administration, Supervision, Validation, Review and Editing

Manuscript Information

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PLOS ONE

Status of Manuscript: [Put an x in one of the options below, delete this]

_________Prepared for submission to a peer-reviewed journal

_________Officially submitted to a peer-reviewed journal

_________Accepted by a peer-reviewed journal

___☑___Published in a peer-reviewed journal

PLoS

April 30th, 2022

November 10th, 2022

https://doi.org/10.1371/journal.pone.0277479

Abstract

Background: Predicting patient's Length of Stay (LOS) before total joint replacement (TJR) surgery is vital for hospitals to optimally manage costs and resources. Many hospitals including in rural areas use publicly available models such as National Surgical Quality Improvement Program (NSQIP) calculator which, unfortunately, performs suboptimally when predicting LOS for TJR procedures.

Objective: The objective of this research was to develop a Machine Learning (ML) model to predict LOS for TJR procedures performed at a Perioperative Surgical Home implemented rural community hospital for better accuracy and interpretation than the NSQIP calculator. Methods: A total of 158 TJR patients were collected and analyzed from a rural community hospital located in Montana. A random forest (RF) model was used to predict patient's LOS. For interpretation, permuted feature importance and partial dependence plot methods were used to identify the important variables and their relationship with the LOS.

Results: The root mean square error for the RF model (0.7) was lower than the NSQIP calculator (1.21). The five most important variables for predicting LOS were BMI, Duke Activity Status-Index, diabetes, patient's household income, and patient's age.

Conclusion: This study is the first of its kind to develop an ML model to predict LOS for TJR procedures that were performed at a small-scale rural community hospital. This study contributes an approach for rural hospitals, making them more independent by developing their own predictions instead of relying on public models.

Introduction

With increasing rates of Total Joint Procedures (TJR) in the United States (US), predicting length of stay (LOS) is vital for hospitals to control costs, manage resources, and prevent postoperative complications (Li et al., 2019; Ong & Pua, 2013; Singh et al., 2019). LOS is the period between the time when the patient is admitted after the surgery to the time when the patient is discharged from the hospital. A longer LOS has been shown to negatively affect the quality of care and patient satisfaction (Alper et al., 2017; Tsai et al., 2015). Specifically, patients with longer LOS drastically increases surgical expenses due to the high average inpatient costs at hospitals, which is $2,000 to $3,000 per day (Candrilli & Mauskopf, 2006; Carr et al., 2021; Weiss & Elixhauser, 2014). Moreover, past studies have demonstrated that patients with longer LOS have higher chances of experiencing poor postoperative surgical outcomes such as readmission and discharge to nursing or rehabilitation facility (London et al., 2016; Rachoin et al., 2020).

To better manage surgical costs, allocate resources, and improve patient satisfaction, researchers have identified factors responsible for longer LOS using various analytic tools, including statistical and machine learning (ML) models (Johnson et al., 2020; Kugelman et al., 2021; Li et al., 2019; Li et al., 2020). However, limited work has been done to predict LOS at community hospitals located in rural areas. It is more challenging to predict patients' LOS in rural than urban areas because community hospitals located in rural areas often lack adequate resources – such as data, staff, and expertise – needed to develop an accurate predictive model (Cecchetti, 2018). Instead, many hospitals use publicly available models that were developed to quantify patient risk before surgery (Merrill et al., 2020).

One such available model is the National Surgical Quality Improvement Program (NSQIP) risk calculator. The NSQIP risk calculator is widely used by hospitals to predict risks for TJR procedures performed on knees, hips, and shoulders (Merrill et al., 2020). At a single hospital or institution, the NSQIP risk calculator can be useful for surgeons to assess patient risk, but it has been found to be suboptimal when predicting LOS for TJR procedures (Carr et al., 2021; Goltz et al., 2018; Merrill et al., 2020). Interpretability is also a concern for the NSQIP risk calculator. In NSQIP, the risk factors are not quantified (i.e., it does not let the clinicians know which risk factor is most associated with a particular outcome). NSQIP's lack of factors quantification demonstrates that this predictive tool may not be suitable for evidence-based decision-making patient optimization in PSH care models. Predicting LOS has become more vital for orthopedic clinicians since recently the Center for Medicare and Medicaid services (CMS) removed knee and hip arthroplasty from the inpatient list (Iorio et al., 2020; Medicare & Services, 2020). Knowing the risk factors and which patient will stay longer in the hospital after surgery are pertinent metrics for clinicians, administrators, and payers to correctly evaluate resource utilization, cost, and severity of illness (Stone et al., 2022).

Recent research has explored a promising application of ML for predicting surgical outcomes (Ogink et al., 2021). ML is a part of Artificial Intelligence (AI) which uses algorithms to recognize patterns in data to make predictions (Carbonell et al., 1983). In the past decade, the application of ML in healthcare increased drastically due to wider usage of Electronic Medical Record (EMR) systems, which enabled the generation of 'big data' (Bhardwaj et al., 2017; Callahan & Shah, 2017; Galetsi & Katsaliaki, 2020; Srinivasan, 2019). Big data has motivated many researchers and clinicians to apply ML and predict various health outcomes to improve patient treatment and quality of care (Khanra et al., 2020; Shafqat et al., 2020). Proportionally, the role of ML surged in the orthopedic field as well (Lalehzarian et al., 2021; Maffulli et al., 2020; Ogink et al., 2021).

For example, Ramkumar et al (Ramkumar, Navarro, et al., 2019) developed an ML using a naïve Bayesian model to forecast LOS and payments for total hip arthroplasty (THA). The authors used it as a classification problem by grouping the inpatient payments to <$12000, $12100-$24000, and >$24000, and LOS to 1-2, 3-5, and 6+days. The ML model was found valid, reliable, and accurate in its predictions with AUC of 0.87 and 0.71 for LOS and payment respectively. Similarly, Li et al (Li et al., 2020) developed an ML model which accurately predicted the LOS for total knee arthroplasty (TKA) procedure with an AUC greater than 0.73. Gabriel et al (Gabriel et al., 2019) predicted LOS using ML methods to determine patients who do not require prolonged LOS. The developed model was reliable with AUC of more than 0.7 and helped hospital administrators to plan resources to avoid both overcrowding and underutilization of TJR patients. Relatedly, Han et al (Han et al., 2021) predicted LOS for knee patients in China and identified that Random Forest model predicted more accurately than other ML models with AUC of 0.7. Aazad et al (Abbas et al., 2021) utilized various ML methods to predict the duration of surgery and LOS which significantly contributed to an increase in surgical cost. The study found that PyTorch MLP performed better among other ML models with least Mean Square Error of 0.89 and 0.69 for duration of surgery and LOS, respectively. Klemt et al (Klemt et al., 2022) used three ML methods to predict LOS for knee revision patients. The authors observed all three ML models performed well with AUC more than 0.8 and decision curve analysis with P-value <0.01. In addition, the authors identified that patients’ age, Charles comorbidity index, and body mass index, were strong predictors for predicting LOS. The above examples are some of the recent studies that used ML methods to predict LOS for TJR procedures. Several studies were also performed in predicting TJR outcomes including surgical site infection, readmission, discharge disposition, and other adverse events (Lopez, Gazgalis, et al., 2021; Ogink et al., 2021).

Yet, limited research has been performed with ML in rural hospitals. In addition, to the authors' knowledge, no research has been performed in predicting surgical outcomes at a rural hospital that adopted newly emerging coordinated surgical system in orthopedics - the Perioperative Surgical Home (PSH) (Cecchetti, 2018). The PSH model of care was created by the leaders within the American Society of Anesthesiologists (ASA) to improve surgical outcomes and patient experience (Cline et al., 2020; B. Kash et al., 2014; Vetter et al., 2013). Therefore, this research focuses on developing an ML model to predict LOS for TJR procedures performed at a PSH-implemented community hospital. Despite the challenges associated with limited availability of data, this study expects that the developed ML model will perform better in accuracy and interpretation than the NSQIP risk calculator.

Methods

Data Collection and Preprocessing

A rural community hospital formed an integrated PSH outpatient clinic in November 2018. The hospital was an 83-bed, licensed level-III trauma center primarily serving three rural counties, but often sees patients from more than 10 surrounding rural counties which span 9,000 square miles and approximately 136,000 residents. The PSH outpatient clinic was affiliated with the hospital began seeing patients preoperatively for TJR including hip, knee, and shoulder replacements. A written consent was obtained from the patients before their participation in this study. The consent was documented and attached to patient's EMR for reference. The study had no patients who are younger than 18. The scope of this study focused on elective procedures and excluded any revisions. A total of 158 TJR patients were analyzed retrospectively after visiting the PSH clinic during preoperative surgical assessment from August to December 2020. All preoperative surgical assessments were performed within 30 days before surgery.

A total of 28 independent variables were collected for each patient, which included 20 NSQIP preoperative characteristics and eight additional variables. The NSQIP characteristics were collected and entered manually into the risk calculator to determine NSQIP-predicted LOS (Bilimoria et al., 2013). Additional variables were extracted from the Electrical Medical Record (EMR) such as the Duke Activity Status Index (DASI) (Hlatky et al., 1989), living status (whether the patient was living alone or with family), patient's household income, postoperative nausea and vomiting score (PONV) (Shaikh et al., 2016), depression (whether the patient was depressed at the time of the assessment), preoperative preparation period (the number of days between assessment and surgery), distance traveled by the patient (in miles, from their residence to the hospital), and patient primary insurance type (private or public payer). These additional variables were included in the analysis as they were found to be closely associated with risk for poor surgical outcomes in past studies (El Bitar et al., 2015; Jackson et al., 2014; B. Kash et al., 2014; Krampe et al., 2018; Mahajan et al., 2020; Ong & Pua, 2013). After patient's discharge from the hospital, the actual LOS was extracted from the EMR.

Eleven NSQIP categorical variables were excluded as there were no cases observed in those categories: steroid use, ascites, systemic sepsis, ventilator-dependent, emergency case, dissemination of cancer, congestive heart failure, chronic obstructive pulmonary disease, dyspnea, dialysis, and acute renal failure. After exclusion, a total of 17 variables were considered in the analysis (Table 5.1). The variable distance traveled by the patient was produced by calculating the mileage between their zipcode and the hospital on Google Maps (Gibson & Erle, 2006). There were no missing values for the independent variables except for patient's household income. Thirty-six patients (23%) out of 158 declined to provide their household income to clinicians during the assessment. These missing values were imputed using the median income of the patient's zipcode (Erekat et al., 2020). The 2019 US Census Bureau database was used to input the zipcode median income obtained from Montana Demographics by Cubits (Cubits, 2019). Additionally, the independent variables that were classified as ordinal were ranked accordingly for use in the correlation analysis (Table 5.1).

Table 5.1 Variable description

	Variables	Type	Description
Response Variable	Length of Stay (LOS)	Continuous	Length of stay post surgery in hours
NSQIP Variables (Bilimoria et al., 2013)	Procedure	Categorical	Total Knee (TKA), Total Hip (THA), Total Shoulder (TSA) Arthroplasty
	Age	Continuous	Patient age in years
	Sex	Dichotomous	Gender: Male, Female
	Functional Status	Ordinal	Fully Independent (1), Partially independent (2), Fully dependent (3)
	ASA Class	Ordinal	Healthy patient (1), Mild systemic disease (2), Severe systemic disease (3), Severe disease with constant threat to life (4)
	Diabetes	Dichotomous	No (1), Yes (2)

	Hypertension	Dichotomous	No (1), Yes (2)
	Current Smoker within 1 year	Dichotomous	No (1), Yes (2)
	BMI	Continuous	Body Mass Index in Kg/m^2
Additional variables	Duke Activity Status Index (Hlatky et al., 1989)	Continuous	Functional capacity scaled from 2.74 (low functional activity) to 9.89 (high functional activity) in METs
	Living Status (Krampe et al., 2018)	Dichotomous	Patient's primary household status - lives alone, living with another
	Patient's Household Income (El Bitar et al., 2015)	Ordinal	Patient's household income level: <$49K (1), $50-99k (2), $100+k (3)
	Postoperative Nausea and Vomiting Score (PONV) (Shaikh et al., 2016)	Ordinal	To estimate nausea after surgery due to anesthesia, scaled 0 (low chances of nausea) to 4 (high chances of nausea)
	Depression (Ong & Pua, 2013)	Dichotomous	Depression at the time of preoperative assessment: No (1), Yes (2)
	Preoperative Engagement Period (B. A. Kash et al., 2014)	Discrete -Ordinal	Difference in time period (in days)
	Patient Insurance Type (Leahy et al., 2019)	Dichotomous	Patient's payer - Public, Private type
	Distance Travelled by the patient (Jackson et al., 2014)	Continuous	Distance traveled by the patient from their resident to the hospital (in miles)

Feature Selection

Feature selection was performed to identify the most important features, i.e., independent variables to train a novel ML model, improve accuracy, and reduce computation time (Guyon & Elisseeff, 2003). This study used Spearman's rank correlation filter method (Khamis, 2008) and

Boruta wrapper method (Kursa & Rudnicki, 2010) to identify the important independent variables to predict LOS.

Spearman's Rank Correlation Correlation analysis was performed to identify highly correlated variables (correlation value close to 1 or -1). Independent variables that are highly correlated with one another can act as redundant in the analysis as they do not improve the model performance but increase the model complexity and computation time (Hall, 1999). The database in this study consisted of both continuous and ordinal variables and Spearman's rank method was used to perform correlation analysis (Khamis, 2008). No highly correlated (correlation more than 0.7) independent variables were observed (Figure 5.1). Similarly, there were no highly correlated independent variables with dependent variable, LOS. The remaining feature selection was refined using the wrapper method.

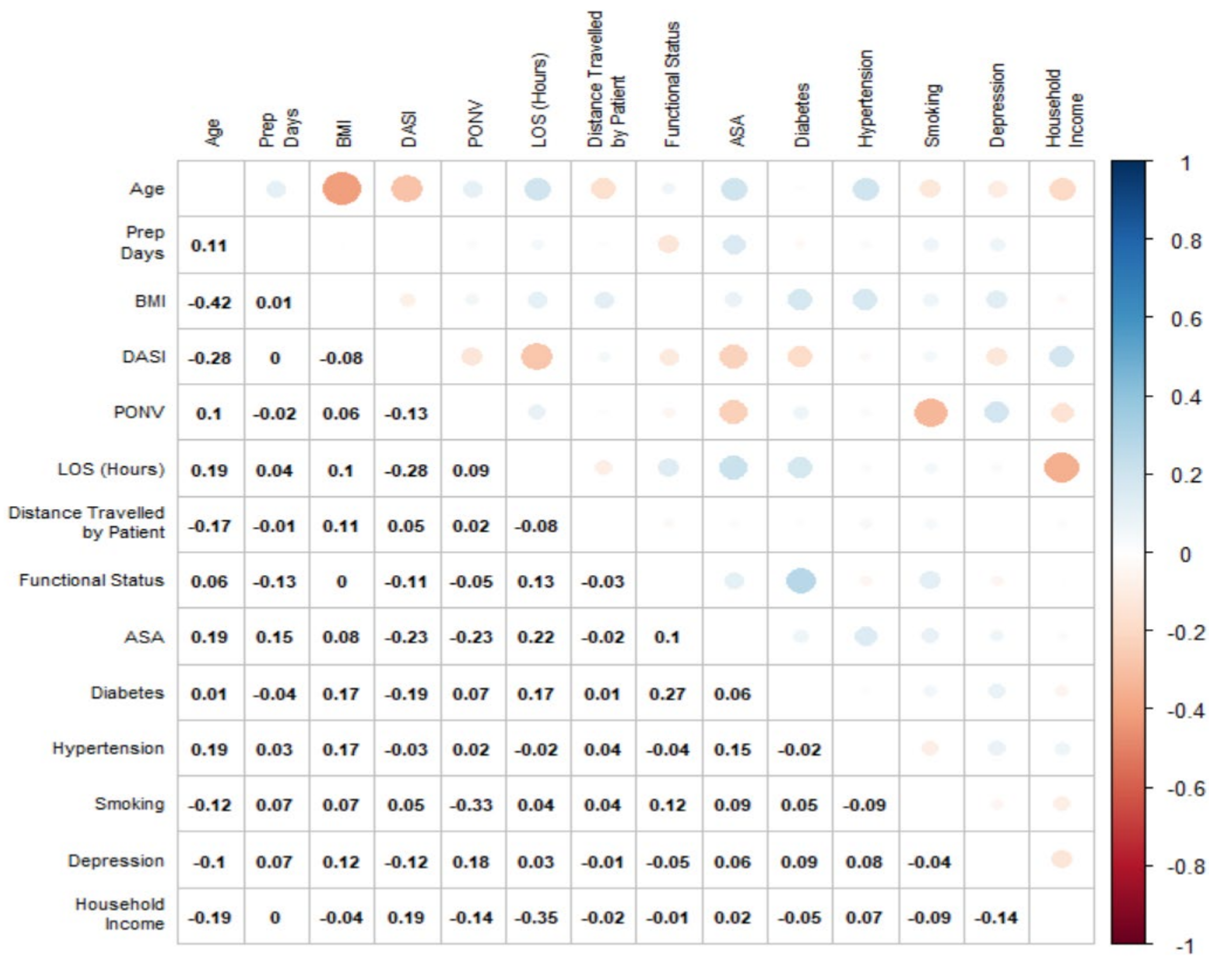

Figure 5.1 Correlation plot

<u>Boruta Feature Selection Method</u> Boruta feature selection is a wrapper method that utilizes the random forest algorithm to rank variable importance (Kursa & Rudnicki, 2010). The Boruta uses shadow variables that are obtained by shuffling the original values across objects (Kursa et al., 2010; Kursa & Rudnicki, 2010). The Boruta ranks variable importance using shadow variables as a reference. Any variable that showed higher importance than shadow variables is considered important (Kursa & Rudnicki, 2010). The Boruta is known to have

comparable, if not superior, ability in independent variable selection than other available feature selection methods (Degenhardt et al., 2019).

This study simulated Boruta for 100 runs to eliminate random errors in the results. The independent variables that were found important and statistically significant in the binomial distribution (P-value < 0.01) were selected for the prediction modeling. The variables that were found important were Insurance Type, Patient's Household Income, DASI, BMI, Functional Status, Diabetes, Living Status, and Age (Figure 5.2). The rest of the independent variables were found not important. This study considered the important and excluded the non-important variables from the ML analysis.

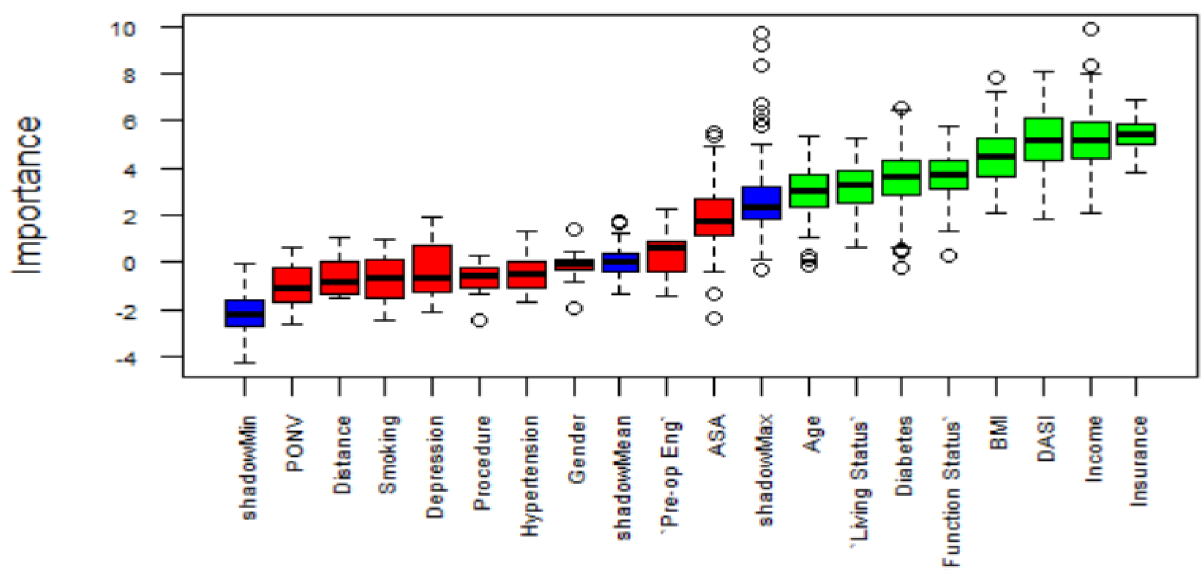

Figure 5.2 Independent variable selection using Boruta (Kursa & Rudnicki, 2010)

Model Selection

The study found no strong linear correlations between dependent and independent variables indicating that the dependent variable and independent variables were non-linearly related. To identify non-linear patterns, Random Forest (RF) method was used. RF is an ensemble learning where the output of multiple decision trees is combined to deliver the final outcome or prediction (Breiman, 2001). Past studies also have exhibited the effectiveness of RF in predicting surgical outcomes with limited data, similar to this study (Bloomfield et al., 2021; Elfanagely et al., 2021). Compared to RF, other commonly known ML methods such as Neural Networks, Boosted Trees, and Support Vector Machines have more tuning parameters and often require more data to train (Kuhn & Johnson, 2013; Kuhn & Silge, 2022; Xu et al., 2021). Due to the very small sample size and RF being one of the most familiar ML methods in predicting orthopedic surgical outcomes (Ogink et al., 2021), this preliminary study used only RF to predict patient LOS after TJR procedures performed at a community hospital. Other ML methods will be considered in the future upon more data availability (n> 2,000).

Data Splitting and Tuning the Parameter:

The data was split into training (80%, n = 127) and testing (20%, n = 31) (Table 5.2). The data splitting and tuning were performed using the CARET package in R software (Kuhn & Johnson, 2013).

Table 5.2 Baseline of training and test sample

Variables		Train data (n = 127) Mean (SD) [Min, Max] or N (%)	Test Data (n = 31) Mean (SD) [Min, Max] or N (%)
Length of Stay (LOS)		41 (29) [3, 195]	36 (16.5) [5, 77.9]
Age		68.6 (9.63) [43, 91]	70.7 (7.43) [54, 84]
Functional Status			
	Independent	128 (98%)	31 (100%)
Diabetes			
	Yes	13 (10%)	2 (6%)
BMI		30.7 (7.25) [17, 58]	29.9 (4.28) [20, 40]
Duke Activity Score Index (DASI)		7.5 (1.67) [4.4, 9.89]	7.29 (1.5) [4.64, 9.89]
Living Status			
	Alone	26 (20%)	9 (29%)
Patient's Household Income			
	<40K	50 (39%)	14 (45%)
	50-99k	56 (44%)	12 (39%)
Patient Insurance Type			
	Private	34 (27%)	5 (16%)

The RF has two main tuning parameters, which are the number of trees in the forest (n_{tree}) and the number of variables randomly sampled as candidates at each split (m_{try}). One thousand trees (n_{tree}) were used in the forest, as recommended by past researchers (Breiman, 2001; Kuhn & Johnson, 2013). Having more trees in the RF does not affect the performance of the prediction negatively, but it can increase computation time (Probst & Boulesteix, 2017). The study expects no significant increase in computation time by using 1000 trees as compared to fewer trees (100 to 500 trees) because there were only 127 data points in the analysis. Leave One Out Cross Validation (LOOCV) was used to find the optimal number of variables available for splitting at each tree node – m_{try} (Berrar, 2019) (Figure 5.3). The study chose LOOCV as it was more appropriate to use in smaller datasets (Kuhn & Johnson, 2013; Wong, 2015).

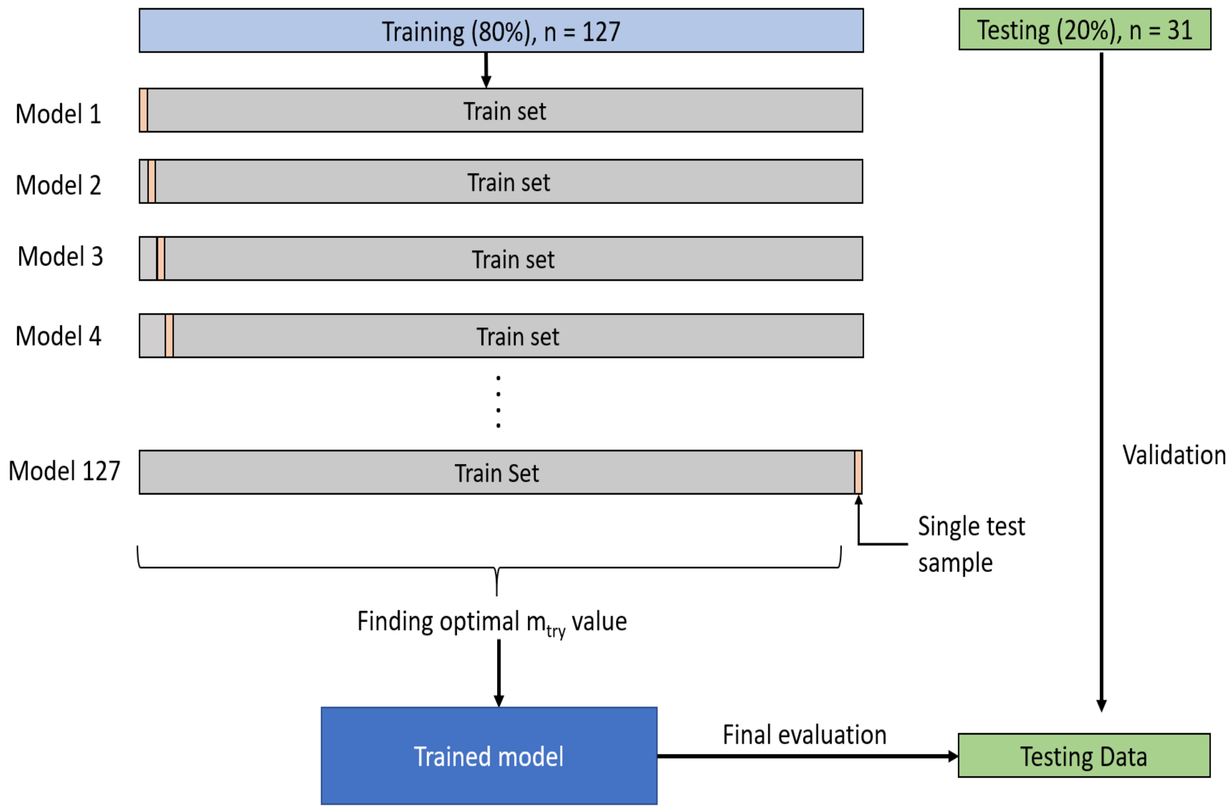

Figure 5.3 Leave One Out Cross Validation

Model Validation

The NSQIP predicted LOS in days, segmented into half-day intervals. For appropriate comparison, the actual LOS and RF-predicted LOS, which were in hours, were converted to days. Conversion was performed in 12 hour-intervals, such that LOS less than or equal to 12 hours was considered 0.5 days, LOS less than or equal to 24 hours was considered 1 day, and LOS less than and equal to 36 hours was considered 1.5 days, and so on. The study was a regression problem as the response variable LOS was numeric and continuous. Therefore, the Root Mean Square Error (RMSE) was used as the cost function to validate the model's prediction performance i.e., the lower the RMSE value, the better the model is performing (Kuhn & Johnson, 2019). Pearson's correlation was also performed to determine the linear relationship between predicted LOS and actual LOS i.e., high correlation demonstrates better model performance. This study expects the developed RF model to have a lower RMSE and higher correlation than NSQIP.

Model Interpretation

RF is an ensemble ML model that aggregates many independent decision trees to make a prediction. Though it greatly helps the accuracy of the prediction, the model acts as a black box and the interpretation is complex. In RF, each tree has a different structure as they are built based on the subset of predictors or independent variables that were randomly selected (Breiman, 2001). To understand and explain each tree in the forest is complex and nearly impossible, which makes the interpretability of a RF model difficult. However, past researchers have been able to interpret ML models (such as RF) substantially, if not completely, using different model-agnostic approaches (Haddouchi & Berrado, 2019; Molnar, 2020). In ML, unlike model-specific methods, model-agnostic methods can be applied to any ML model for interpretation. This makes the model agnostic approaches more flexible and reliable than model-specific when interpreting different ML models (Molnar, 2020). This study applied two widely used model-agnostic methods; permutation feature importance and partial dependence plots for interpreting and explicating the relationship of the variables in the RF model (Boehmke & Greenwell, 2019).

Permutation Feature Importance Permutation Feature Importance (PFI) method measures importance by calculating the increase in prediction error after permuting the independent variable (Fisher et al., 2019). In other words, the independent variable in the data set is randomly permuted which degrades the relationship between that independent variable and the response variable. The importance of a variable is measured based on the difference in cost function before and after the variable is permuted (Molnar, 2020). The PFI approach uses randomness in the procedure to evaluate the importance. Thus, this study simulated this method for 100 times to minimize random errors and ranked the important variables based on the average value. The PFI algorithm used in this study adapted from (Greenwell et al., 2020) and (Molnar, 2020):

Let j be the total number of independent variables

Let X be the independent variable

Let E be the baseline RMSE value for the trained model

Let F be a two-dimensional matrix of RMSE values after a feature is permuted in the training data

For k = 1, 2, 3, ….100: (for simulating 100 times)

For i = 1, 2, 3, …..j:

Permute the values of variable X_i in the training data.

Recompute the RMSE value on the permuted data – F_{ki}.

For i = 1, 2, 3, …..j:

Compute average importance for each variable, $Imp_i = \frac{1}{100}\sum_{k=1}^{100}(E - F_{ki})$

Sort the average importance (Imp_i) by descending order.

Partial Dependence Plot The Partial Dependence Plot (PDP) is an another agnostic method that helps to understand the marginal effect of a variable on the predicted outcome of an ML model (Friedman, 2001). The PDP shows the relationship between a response variable and an independent variable whether they are linear, monotonic, or complex (Molnar, 2020). This demonstrates how the response variable changes as the value of an independent variable while considering the average effect of all the other independent variables in the model (Boehmke & Greenwell, 2019). The biggest disadvantage of PDP is that it is effective when the variables are not correlated. However, this study had no strong correlation between any independent variables. Therefore, the PDP approach was more ideal method as they were easy to implement and more importantly, simple to interpret. In Equation 5.1, f_S was the partial function which was estimated by calculating the average value in the training data. The x_S was the independent variable that was being plotted in the PDP where $S \subset (1, 2, \ldots j)$. The $x_C^{(i)}$ were the rest of the independent variables in the training data where C was complement of S. The variable n was the total number of data points in the training data which was 127.

$$f_S(x_S) = \frac{1}{n}\sum_{i=1}^{n} f(x_S, x_C^{(i)}) \qquad \text{(5.1) (Molnar, 2020)}$$

All data handling, visualizations, statistical analysis, ML modeling and interpretations were performed using R (V 4.0.3, Vienna, Austria). The data were recorded and secured in an encrypted database and were accessed only by the authors and the clinicians. The research study was conducted at a single rural community hospital and was approved by Montana State University Institute Review Board (approval number – BM050819 (EX))

Results

Model Performance

The m_{try} with the lowest RMSE value was found at 2. The RMSE of RF for the train data (n = 127) and test data (n = 31) were 0.71 and 0.61, respectively. The RMSE of RF for the whole data (n = 158) was 0.7, which was lower than NSQIP which was 1.21 (Figure 5.4). The Pearson's correlation between predicted and actual for NSQIP and RF were 0.22 and 0.82 (Figure 5.5). Compared to NSQIP, the RF model had lower RMSE and higher Pearson's correlation, making it a better model for predicting patient LOS after the TJR procedure.

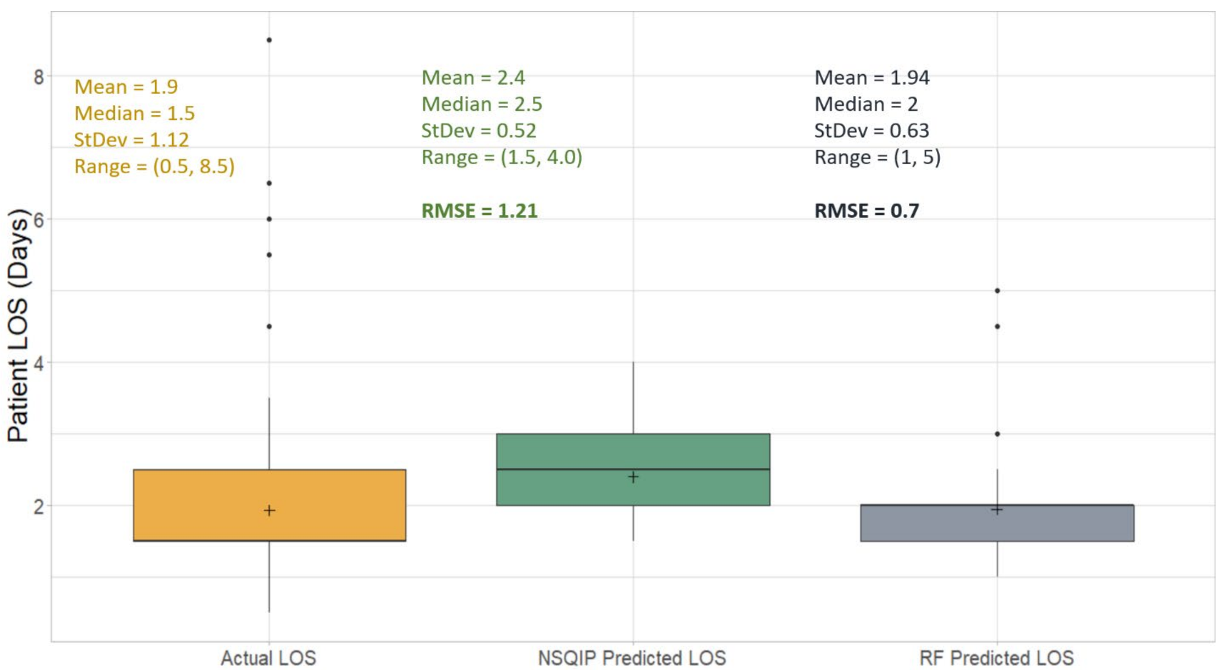

Figure 5.4 Comparison of NSQIP and Random Forest (RF)

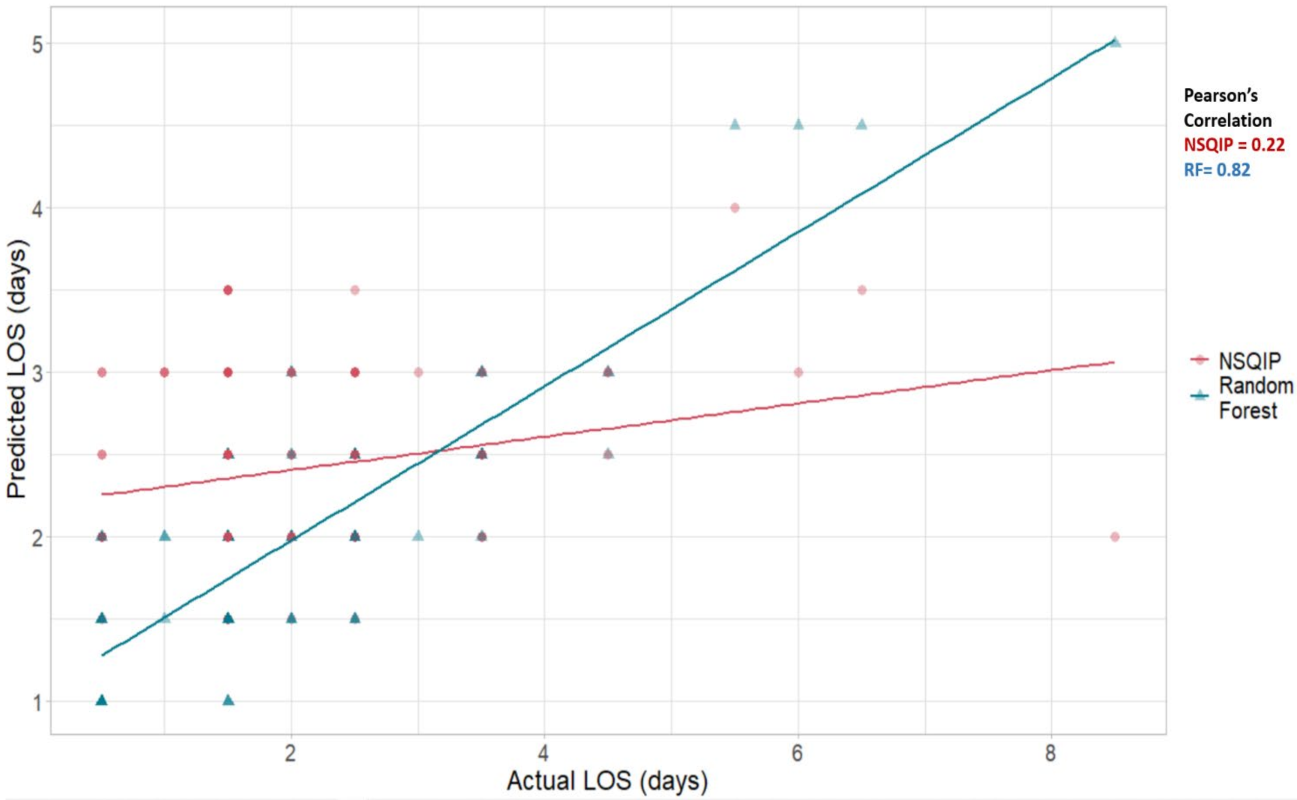

Figure 5.5 Pearson's correlation for NSQIP and random forest

<u>Model Interpretation</u>

The PFI ranked independent variables based on their contributions to an accurate estimation of LOS using the RF training model. For example, BMI contributes most towards accurate prediction of LOS such that, if the values in BMI were randomly permuted, there will be an increase in overall RMSE by 5.1 (Figure 5.6). Similarly, the variables diabetes, DASI, living status, household income, ASA class, age, insurance type, and functional status were ranked most important to least important based on their average increase in RMSE after permutation (Figure 5.6). The PDP plots show the relationship between independent variables and the response variable (LOS) (Figure 5.7). More detailed explanation on their relationship is delineated in the discussion section of this paper.

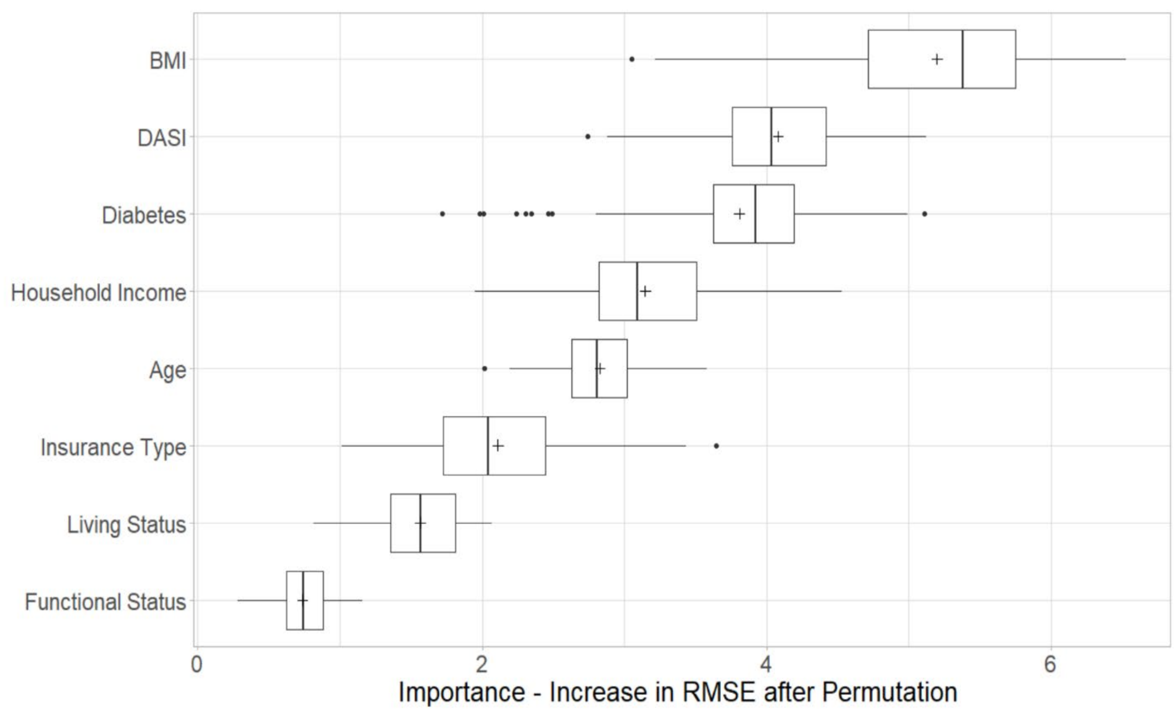

Figure 5.6 Variable importance using Permuted Feature Importance (PFI) method

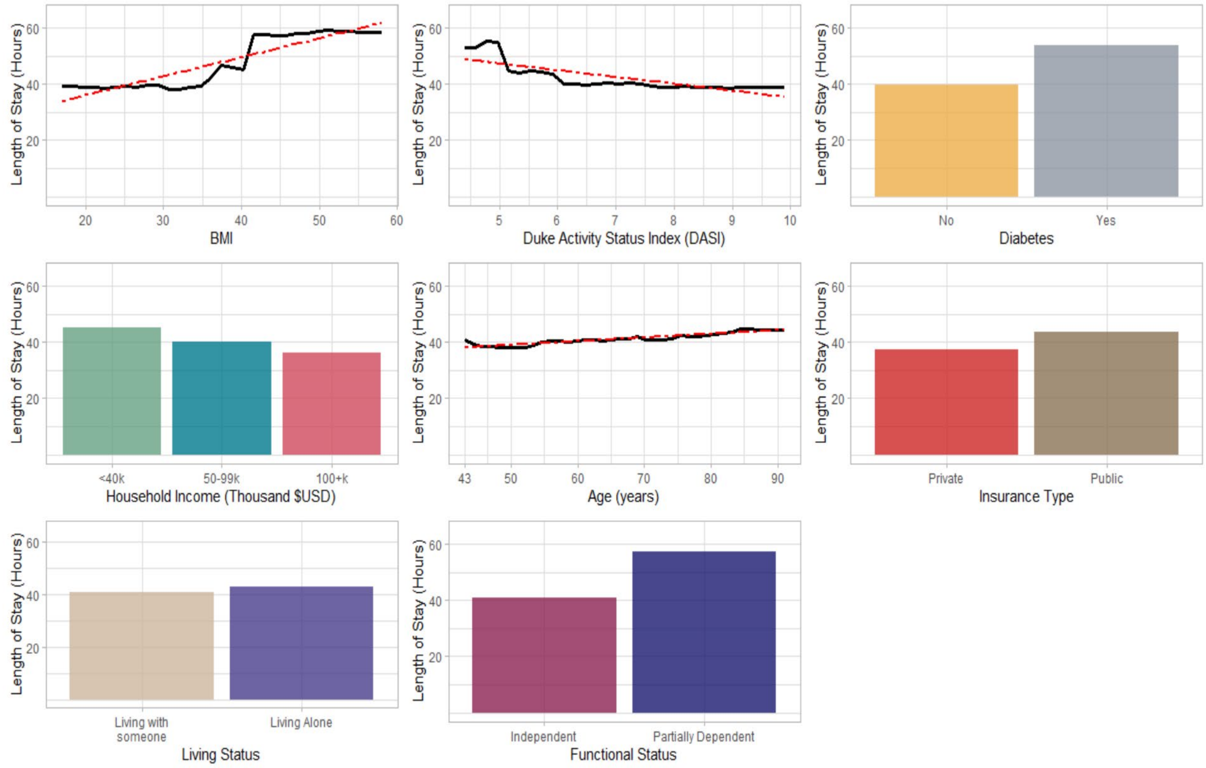

Figure 5.7 Partial Dependence plot of independent variables against Length of Stay (LOS)

Discussion

The study developed an ML model to predict LOS for TJR procedures that were performed at a small-scale community hospital (bed size less than 100) located in a rural area. The developed model predicted LOS (RMSE = 0.7) more accurately than the NSQIP risk calculator (RMSE = 1.21). The NSQIP was developed using a cohort of 1.4 million patient data, which were taken from 393 health institutions in the US (Bilimoria et al., 2013). Sixty-nine percent of the cohort were collected from a teaching or academic affiliation and 43% of the cohort were collected from large hospitals (i.e., bed size more than 500) (Bilimoria et al., 2013; Edelstein et al., 2015). The inaccuracy in patient risk assessment is due to the vast differences between NSQIP cohort and the population (collected from a single hospital) on which NSQIP is used (Merrill et al., 2020). For instance, the TJR patients collected from a rural community hospital may be vastly different from the NSQIP cohort that was used to build the risk calculator.

Moreover, the NSQIP includes insufficient numbers of orthopedic data i.e., only 12% of orthopedic patient data contribute to the analysis (Edelstein et al., 2015). These factors contribute to the NSQIP's suboptimal performance when predicting LOS for TJR procedures especially those performed at a community hospital. Another difficulty to why NSQIP poorly predicted LOS was the adoption of the PSH system (Cline et al., 2020). Past studies have demonstrated that the implementation of PSH has led to a reduction in hospital LOS for TJR procedures (Alvis et al., 2017; Cline et al., 2020; Qiu et al., 2016). Thus, similar to another study, it was observed that the NSQIP predicted LOS much higher than the actual LOS for TJR procedures performed at the PSH implemented community hospital (Carr et al., 2021).

To the authors' knowledge, this study is the first of its kind to develop an ML model that exceeds NSQIP risk calculator in predicting a TJR surgical outcome at a community hospital and the first to predict rural patients only. The developed ML model also provides a clearer interpretation compared to the NSQIP risk calculator. The model agnostic methods, PFI and PDP plots, revealed important independent variables and their relationship with LOS. The PFI model agnostic method ranked independent variables that most contributed toward accurate prediction of LOS (Fig 5). Through this, clinicians can prioritize those factors they should address first and design a suitable intervention in the preoperative phase to optimize patients, given the severity of the condition, surgery timing, and comorbidities.

The PDP model agnostic method illustrated the relationship between the independent variables and the response variable (Figure 5.7). The PDP for BMI indicated that patients with higher BMI (specially more than 40 Kg/m^2) were more likely to stay longer at the hospital after the surgery compared to patients with lower BMI (Jonas et al., 2013; Prohaska et al., 2017). For DASI, the LOS was found decreasing with an increase in DASI score. DASI assesses patient's heart condition and functional capacity using likert scale questionnaires on daily activities, personal care, and recreation (Hlatky et al., 1989). Patients with a higher DASI score represent they are healthier and more active. Thus, in this study, it was reasonable to observe that patients with lower DASI scores (especially less than 5 METs) had longer LOS compared to patients with higher DASI scores. The PDP for diabetes showed that on average, patients with diabetes had 14 hours longer LOS compared to the patients with no diabetes (Akiboye & Rayman, 2017). The income levels in the PDP plot of household income revealed that patients with lower household income were more likely to have longer LOS than patients with higher household income (100k+). Patients with lower household income (<40K) often delay their pre-operative treatments or even postpone their surgical procedures due to their financial barriers and cost of undergoing TJR procedures. These delays increase the complications at the time of surgery requiring a longer LOS to stabilize them before discharge (El Bitar et al., 2015).

Concerning age, like most studies, it was observed that the LOS was higher with an increase in age (Johnson et al., 2020; Newman et al., 2017; Rozell et al., 2017). The PDP plot for insurance type showed that on average, patients who had public insurance as their payer had six hours longer LOS than patients who had private insurance. The public insurance payers in this study were Medicare and Medicaid. Compared to private insurance patients, Medicare patients are older (aged more than 65) with increased chances of having one or two medical complications (El Bitar et al., 2015). The Medicaid patients are US citizens or legal permanent residents who are mostly from a low-income background with certain disabilities, behavioral health problems, or other complications (Casalino, 2013). Therefore, patients with public insurance are often more medically complicated which results in them staying longer at the hospital (El Bitar et al., 2015).

For living status, patients who were living alone, on average stayed three hours longer than patients who were living with someone (spouse, friends, or family). This was because a majority of the patients who lived alone had lower social support causing mental health problems (such as loneliness and sadness) which influenced them to stay longer at the hospital after surgery (Krampe et al., 2018). Another reason was most patients who lived alone had to rely on the hospital to arrange for a ride before discharge. This often takes longer than patients who get picked up by their family or friends during the discharge. Finally, for functional status, despite the limited sample size in the partially dependent category (less than 3%, Table 5.2), it was observed that on average, partially dependent patients had 17 hours longer LOS than fully independent patients.

Akin to many studies, variables BMI (Jonas et al., 2013; Prohaska et al., 2017; Sephton et al., 2020), age (Johnson et al., 2020; Matsen III et al., 2015; Newman et al., 2017; Oh et al., 2020; Rozell et al., 2017), and insurance type (El Bitar et al., 2015; Matsen III et al., 2015; Oh et al., 2020) were found as important predictors in this study well. Conversely, unlike many studies, the variable DASI was used in this study and was found as an important predictor of LOS. The researchers have used DASI as a preoperative assessment metric to evaluate postoperative risks, especially in colorectal surgeries (El-Kefraoui et al., 2021; Pook et al., 2022). To the authors' knowledge, the DASI has not been used in the past TJR studies to predict or measure its association with LOS. It was also observed that the ASA had no relationship in predicting LOS in this study which in contrast, had a significant effect on LOS in other TJR studies (Jonas et al., 2013; Li et al., 2019; Sephton et al., 2020). Along with the ASA, other clinical variables such as smoking, depression, and hypertension that were found important in other studies did not contribute to predicting LOS in this study (Johnson et al., 2020; Oh et al., 2020). Instead, demographic variables household income and living status were found more important. This could be due to the implementation of the PSH system which included preoperative assessment and patient education, that helped clinicians to optimize patients with higher ASA, smoking, and hypertension complications (B. Kash et al., 2014; McCrory et al., 2019). Differences in demographics and factors related to rural Montana location could be another reason for finding demographic variables household income, living status more important than clinical variables ASA, smoking, and hypertension, for predicting LOS.

The need for prediction such as ML is ever more necessary in rural healthcare systems as they do not receive the same attention as urban areas (Cecchetti, 2018). This research addresses that gap by introducing ML at a rural community hospital and making the community hospital more independent instead of relying on publicly available models/methods. This study is also unique by using global agnostic methods at the rural community hospital for interpretation instead of using traditional interpretable prediction models such as general linear models and decision tree (Molnar, 2020). Future research built from this study should focus on predicting other surgical outcomes such as discharge disposition and 90-days readmission rate (Alper et al., 2017). Also, with Medicare's recent removal of TJR surgeries from the inpatient list, future research from this study should focus on developing a LOS prediction model to determine "inpatient" vs "outpatient" status for TJRs performed at rural hospitals (Kugelman et al., 2021).

Limitations in this study include using only the RF model for prediction. Further research is on the way to applying different ML models such as Neural Networks, Boosted Trees, and Support Vector Machine (SVM) to discover how well they perform on these surgical data sets compared to RF. Second, the study used only a five-month duration (from August 2020 to December 2020) data with a very small sample size for the ML modeling. Yearly data with a high sample size (n > 1000) could have accounted for a better prediction, validation, and more robust interpretation. Third, the study was retrospective which may contain data collection biases that could alter the results and key findings (Hess, 2004). Fourth, the testing data contained only 31 patients. More testing and validation data is required to confirm the developed model's validity. Finally, this study was performed at a community hospital located in a micro-statistical area (with a population size less than 50,000). The results from this study may not be generalizable to more rural places (e.g., with a population of less than 10,000)

Conclusion

Delivering quality surgical care to TJR patients is a challenge to many US hospitals located in rural areas. Predicting LOS in surgery is an important factor as it helps rural hospitals deliver quality surgical service, ensure patient safety, and plan for resources such as inpatient beds. This research explored how a publicly available model (NSQIP) was not an ideal model to predict LOS after a TJR procedure performed at PSH implemented community hospital. Instead, a customized machine learning model – random forest – delivered more accurate LOS predictions despite the limited data available in rural surgical systems. Further, the random forest model also provided a better interpretation by ranking the important independent variables and illustrating its relationship against LOS. The study is first of its kind to use ML at PSH incorporated rural surgical system to predict patient LOS. Results from this study will contribute to helping rural surgical care by reducing LOS while improving patient satisfaction.

CHAPTER SIX

GENERAL DISCUSSION AND CONCLUSION

The PSH system has grown popular in recent years, due to its state-of-the-art clinician coordination and resulting improved surgical care delivery to patients. To successfully facilitate PSH system in an institution or a hospital, past researchers have described the importance of organizational designs, management techniques (such as lean six-sigma), clinician's role in surgical care, and acquired medical resources (Desebbe et al., 2016; Mahajan et al., 2021; Vetter et al., 2013). This incentivized many surgical organizations to successfully implemented PSH system in their institutions or hospitals (primarily located in urban areas) to enhance surgical care (Cline et al., 2020). However, limited to no research has been performed in augmenting the PSH surgical care using healthcare analytics. The central purpose of this research was to incorporate a novel analytical framework in the PSH system to improve surgical outcomes and experiences for both patients and clinicians. The analytic framework exhibits the importance of patient data in surgical care, such that it delineates from data collection to decision-making process. The key highlights in the framework are:

1) Collect more longitudinal (~120 days) patient data (such as physiological, behavioral, and psychological) using sensors and digital platforms, beyond what is collected during patient assessments and consultations.
2) The data should be digitally stored in a cloud-based format for easy accessibility for clinicians and researchers.
3) The PSH system should include a data science team to perform various processes including exploring, evaluating, and estimating to make data-driven decisions.

In general, the utilization of healthcare analytics is more observed in urban institutions compared to rural community hospitals (Cecchetti, 2018). Conversely, in this research, healthcare analytics was incorporated at a rural community hospital. Therefore, it is envisioned that the developed PSH analytical framework is inclusive and can be incorporated in both small rural hospitals and large urban hospitals.

There are three objectives in this study. The objective 1 in chapter 3 focused on adopting the digital platform to collect patient PROM data during the longitudinal perioperative period (Figure 6.1). The study contributed to improving the surgery experience and satisfaction for rural patients by identifying barriers and best practices for perioperative engagement. The results from chapter 3 illustrate the effectiveness of the digital platform and how it can be initialized in rural Montana to monitor and guide patients during their perioperative period. ***The study supports the hypothesis that the digital platform is successful for longitudinal perioperative engagement performed at a community hospital located in rural Montana.***

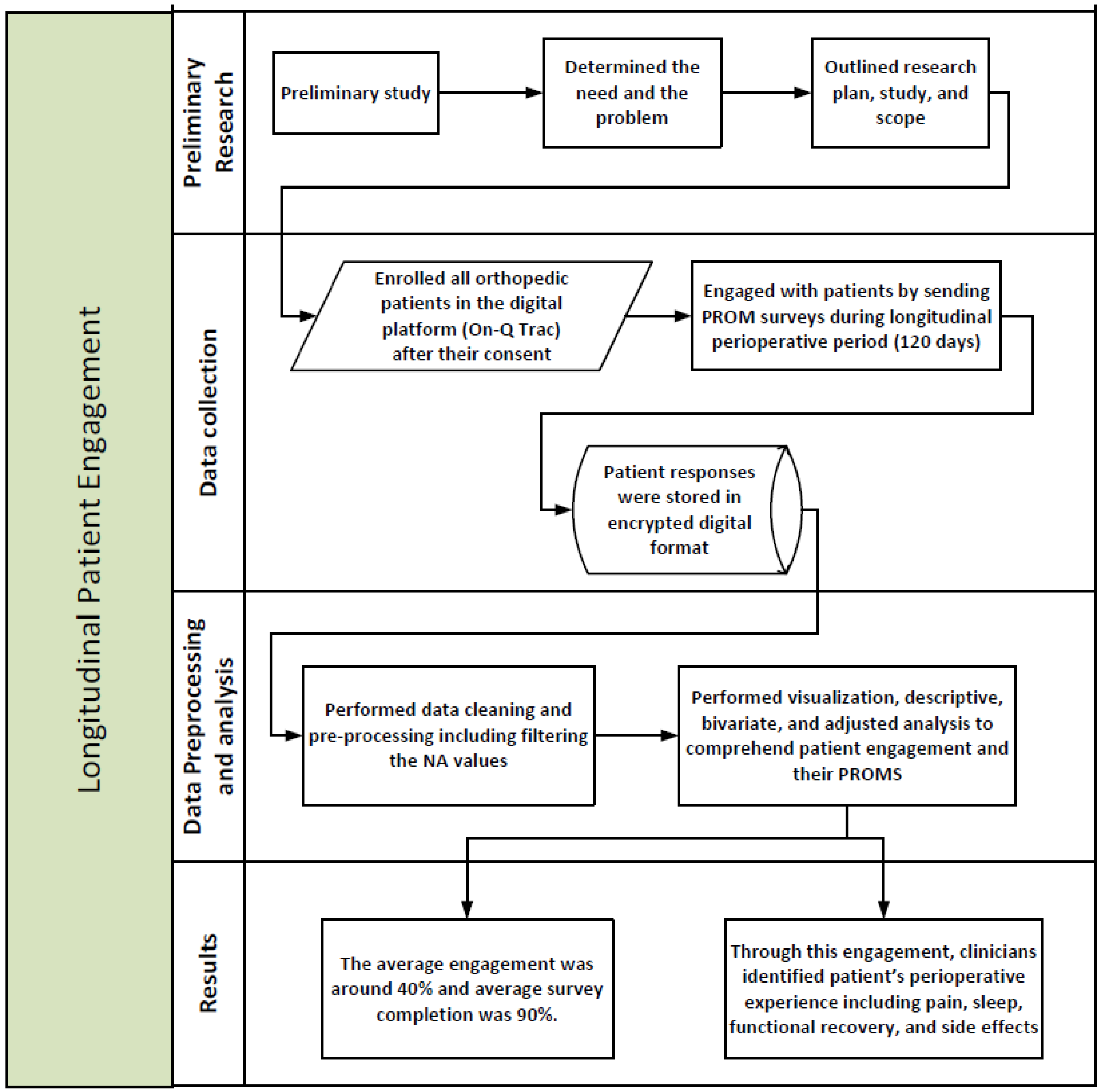

Figure 6.1 Objective 1 conceptual model

Chapter 3 concentrated on exploring the patient's response rate when longitudinally engaged using the digital platform. A preliminary analysis of this study has demonstrated that knee patients experienced more pain than hip patients in the postoperative period, especially on day seven (Appendix Table C.1). Past studies have also delineated knee arthroplasties as being more painful compared to hip arthroplasties postoperatively (Beswick et al., 2012; Kuklinski et al., 2020; Ranawat & Ranawat, 2007). It will be worthwhile to know what covariates such as: age, gender, depression, range of motion, and pain medication have significant influence on postoperative pain after hip and knee procedures (Noiseux et al., 2014; Rakel et al., 2012; Sayers et al., 2016; Yang et al., 2019).

The future research should include using advance sensors and wearables at rural community hospitals to remotely collect various patient data. The pressing interest would be collecting patient's step count data which has shown promising results for clinicians in monitoring and measuring TJR patients' recovery after surgery (Bahadori et al., 2018; Crizer et al., 2017; Höll et al., 2018; Lyman et al., 2020; Ramkumar, Haeberle, et al., 2019; Schotanus et al., 2017; Stienen et al., 2020; Van der Walt et al., 2018; Yang et al., 2018). Additionally, the future research should also focus on studying and evaluating patient culture when incorporating modern technology such as sensors and wearables on patients during the perioperative period.

The objective 2 in chapter 4 evaluated the PSH system intervention on TJR patients' surgical outcomes at a rural community hospital (Figure 6.2). The study contributed to understanding the importance of PSH system at a rural community by improving TJR surgical outcomes. ***The study supports the hypothesis that implementing PSH at a community hospital will lead to shorter LOS, reduced 90-day readmissions, and increased rate of home discharge.***

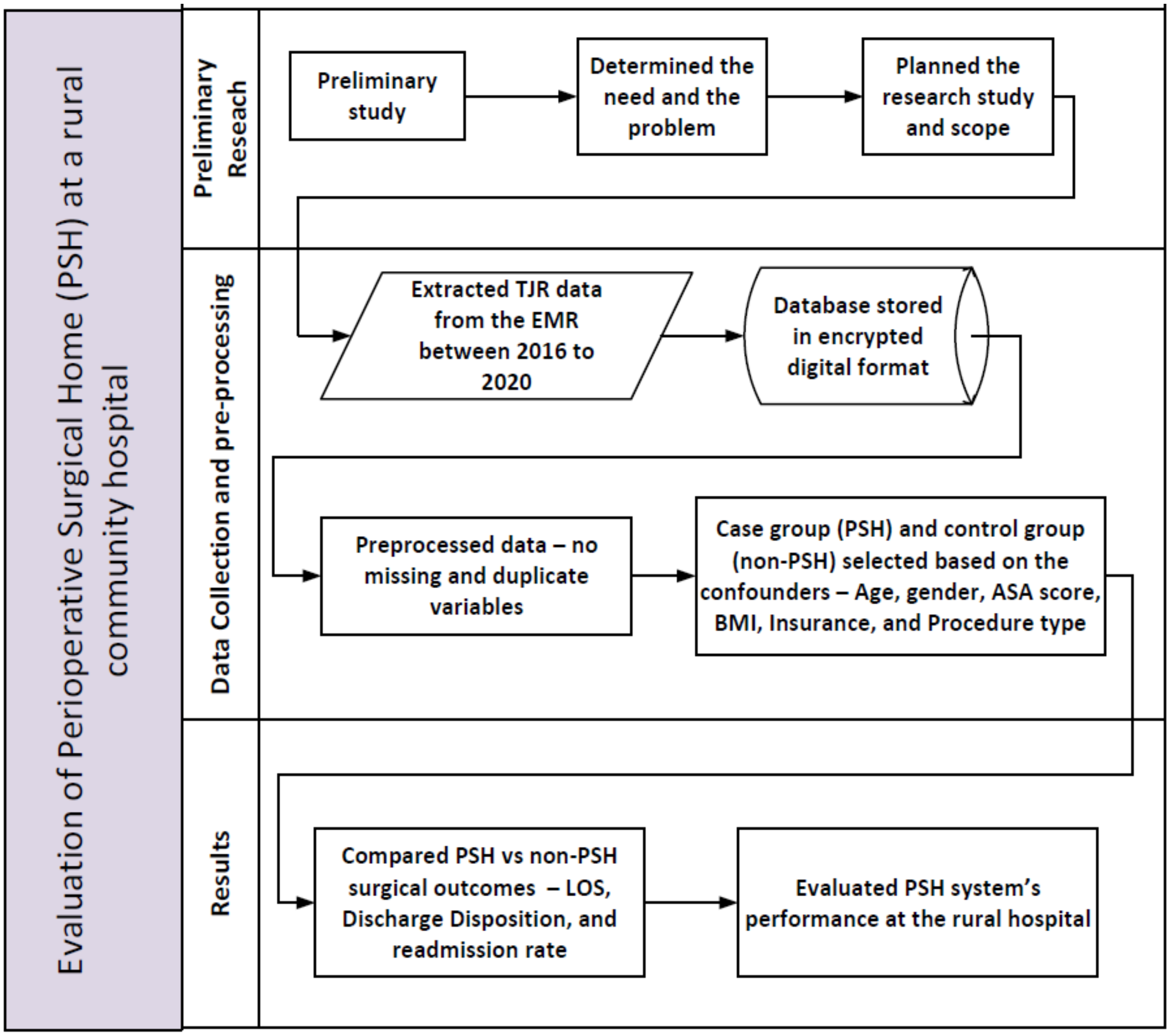

Figure 6.2 Objective 2 conceptual model

The prospects of perioperative care are concentrated on delivering personalized care to patients and the future research built from this study should focus on utilizing n-of-1 clinical trials to evaluate the interventions or drug instituted on the patients (Nirvik & Kertai, 2022; Pal & Kertai, 2020). Compared to the randomized control trial, the n-of-1 trial just uses a single subject to determine suitable intervention using objective data-driven criteria (Lillie et al., 2011).

The use of a single-subject clinical trial will enhance the personalized surgical care, such that factors related to patient diversity, equity, and inclusion in the population enrolled, will be impervious to evaluate the effectiveness of a drug or an intervention (Nirvik & Kertai, 2022).

Finally, the objective 3 in chapter 5 delineated on developing a custom ML model to predict and identify factors responsible for longer LOS (Figure 6.3). Despite limited data availability, the developed model outperformed the NSQIP risk calculator in both prediction accuracy and interpretation. ***The study supports the hypothesis that the developed ML model is more accurate and reliable than NSQIP for decision-making for TJR procedures performed at a rural community hospital.***

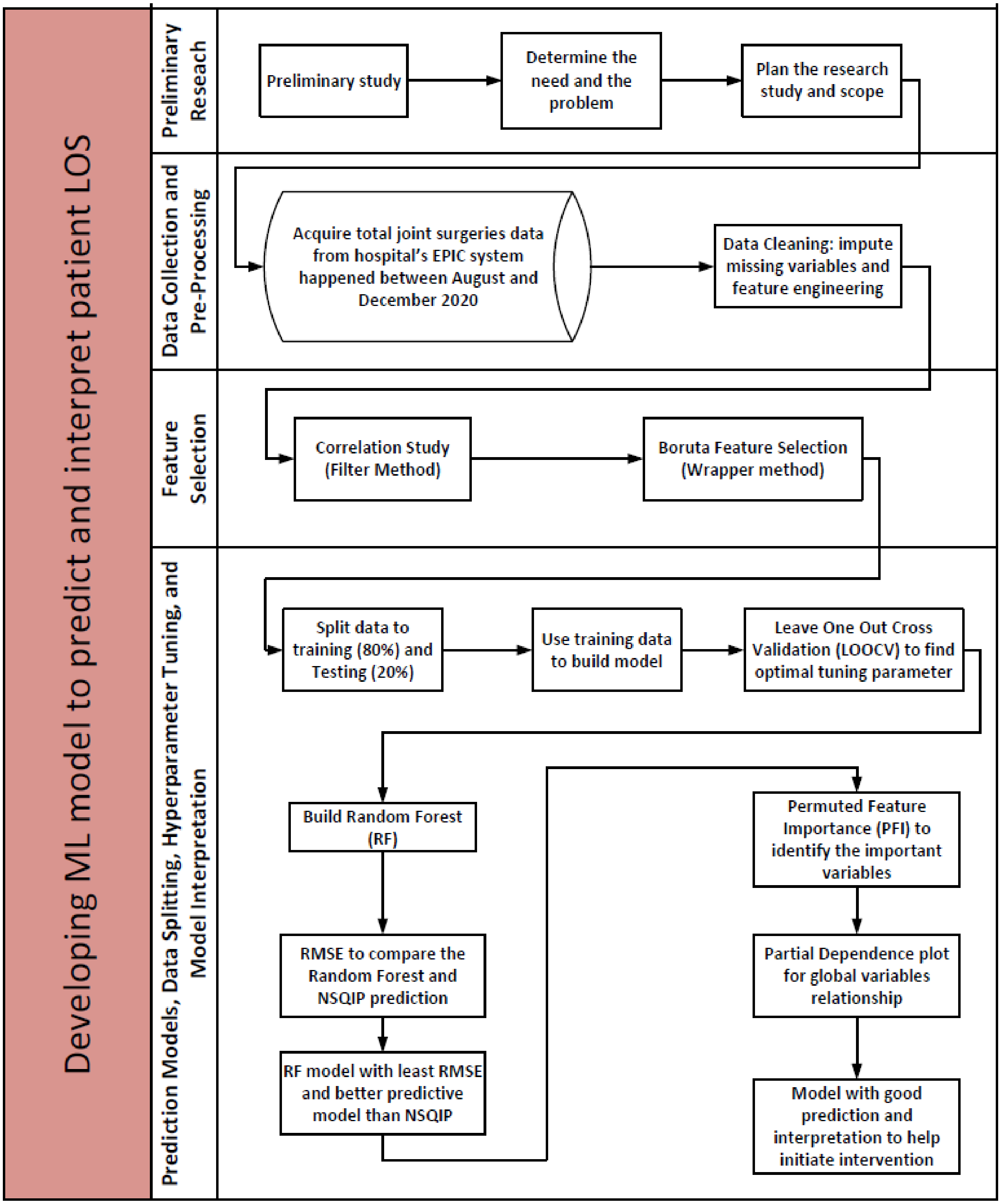

Figure 6.3 Objective 3 conceptual model

In chapter 5, some variables such as patients' living status and depression were extracted from the EHR after manually examining the unstructured clinician's notes. The manual extraction from the unstructured notes was possible in this study, due to very small sample size (n = 158). It will be excessively arduous to perform manually if the volume of the data were high (in thousands or millions). An alternative method would be employing Natural Language Processing (NLP) tools especially in extracting more information and meaning from unstructured clinical notes (Murff et al., 2011; Roy et al., 2021). In the era of modern analytics, extracting patient information from both structured and unstructured data stored in EHR is crucial for clinical researchers to understand and provide better care (Chary et al., 2019; Koleck et al., 2021). Adopting NLP in PSH analytics system, would be an interesting approach to explore its advantages to augment data-driven decisions in PSH surgical care.

Future research built from objective 3 will need to focus on addressing clinician's trust while using advanced analytics (involving AI, i.e., ML) for decision-making. Incorporation of complex ML methods can lead to superior accuracy but in contrast to the traditional statistical methods, ML methods often lack clear definition of the process, functioning, and their explainability on how an output was derived (Ley et al., 2022; Rajula et al., 2020; Siau & Wang, 2018). In addition, the ML methods lack human sense and often struggle to make simple decisions which would be obvious to humans (Asan et al., 2020; St Evans, 2008). These reasons reduce trust for humans, including clinicians, to incorporate ML in their decision-making process (Jermutus et al., 2022; Rossi, 2018).

Trust is a human emotion state which is spread across various disciplines and has many definitions (Adjekum et al., 2017; Jermutus et al., 2022). Trust can be described as a system encompassing three main elements: trustor (a person who trusts), trustee (could be a person or an object; in this case ML), and task or situation (in this case, prediction task performed by ML) (Baier, 1986; Hoff & Bashir, 2015). According to researchers, a person's trust on trustee depends on many factors, including trustee's reliability, and predictability in performing the required task (Jermutus et al., 2022). The characteristics projected by trustee to gain trust from an individual or group (trustor) is called trustworthy (Adjekum et al., 2017; Holm & Nystedt, 2010). The concept of trustworthy is sensitive and critical in healthcare more so than other fields due to involvement of greater risk, i.e., patient safety (Glikson & Woolley, 2020).

Most clinicians solely depend on their experience and knowledge to make decisions for patients due to magnitude of risk and human factors associated in the healthcare field (Asan et al., 2020; Jermutus et al., 2022). Nonetheless, the past studies have demonstrated that if used adequately in the decision-making process, the AI/ML significantly benefit both clinicians and patients in healthcare (Bhbosale et al., 2020; Callahan & Shah, 2017). In that context, researchers have identified that educating clinicians and increasing the transparency of the complex ML models has proven to be the effective approach to improving clinician's trust and appropriate utilization of ML models (Asan et al., 2020; Jermutus et al., 2022; LaRosa & Danks, 2018). One such way to increase the transparency is by interpreting the ML model predictions (ElShawi et al., 2021).

The ML interpretations methods enable users and decision-makers to understand the predictions made by the ML model (Lim et al., 2009). Understanding the prediction of ML provides insights on how the model functions and based on that, users or clinicians can decide where and how the ML model should be used in their decision-making (ElShawi et al., 2021).

The ML interpretation can be classified into two types: local and global. The global methods are used to understand the general distribution of the data (Molnar, 2020). Examples of global interpretation include decision trees, general linear models like linear and logistic regressions. The interpretation from the global methods provides users to identify the relationship between variables such that they can comprehend the entire model behavior (Martens et al., 2008; Stiglic et al., 2020). In contrast to global methods, the local methods explain the prediction for a single point or small region of the prediction model in the dataset (Mi et al., 2020; Molnar, 2020). The local models focus on the specific region (preferably a single point) and explain why and how the model predicted that outcome (Mi et al., 2020). Both global and local methods were widely used in healthcare fields, including in orthopedic surgeries (Ahmad et al., 2018).

In Chapter 5, two global interpretation methods (PFI and PDP) were used to simplify and comprehend the RF predictions. The global method PFI showed what variables are important, and PDP illustrated how each dependent variable is related to independent variables. The global methods in chapter 5 delivered a comprehensive interpretation of model prediction but, failed to explain the interpretation at a local or single point. For instance, in chapter 5, the global interpretations results were derived from observing the entire training cohort (n = 127). These interpretations might not be too valuable to clinicians when assessing a single patient. In other words, the clinicians may not be able to identify what variables are most important and how they are important for a particular patient using the comprehensive interpretation generated by the global methods. In such cases, local methods are more useful as they address the local region to produce interpretations for a single patient (Zhang et al., 2019). Yet, the local methods have disadvantages. The local models, that are perturbation based, have the biggest drawback of being inconsistent and unstable due to randomness (Krishna et al., 2022; Visani et al., 2020; Zafar & Khan, 2021).

In response to these limitations mentioned above, the future research should focus on using both global and local methods for ML interpretation (especially in a smaller data set where n < 50,000) (Konstantinov & Utkin, 2021). Using local methods interpretations, clinicians can identify what variables are specifically important for a particular patient (Stiglic et al., 2020). The local interpretation can be validated by comparing it with the global methods. The interpretations can be considered definitive if both global and local have similar interpretation results. Disagreement between the local and global results indicate there is an error in local or global or in both interpretation methods. This can help in building trust, as clinicians may find it more convincing to accept the predictions of ML model when interpretation from both local and global methods deliver similar and desirable results (Asan et al., 2020; Krishna et al., 2022).

Conclusion

To the author's knowledge, this research study is the first of its kind to develop an analytical framework for the PSH system. The developed framework emphasizes how to utilize data analytics effectively for delivering improved and personalized care to patients. The research contributes to addressing following knowledge gaps 1) Data analytics including descriptive, diagnostic, predictive analytics are not only limited to large urban and academic institutions, but also feasible in small rural community hospitals for providing surgical care, despite the limited data availability 2) Utilizing digital platforms and sensors has potential to benefit rural surgeries, by improving patient experience and satisfaction in perioperative care 3) The PSH system is effective in rural community hospitals to improve TJR surgical outcomes, (i.e., shorter LOS, reduced 90-day readmissions, and increased rate of home discharge), especially for high-risk patients who are older and have one or more medical complications 4) Publicly available risk models are not ideal risk models for community hospitals serving rural patients. Instead, a customized ML model can outperform in both prediction and interpretation making the rural hospitals more effective and independent instead of relying on publicly available models.

In the long term, this research study will contribute to reducing socio-economic and socio-demographic differences for delivering high-quality surgical care to patients in the United States (US). This cross-disciplinary research project, combining both engineering and clinical medicine will enhance rural surgical care and improve patient safety, quality of service, and patient satisfaction. The central limitation of this research is that the entire study was performed at a single community hospital located in rural Montana, which affects the generalizability. To increase the generalizability and the effectiveness of these research findings, concepts of this study should be employed in different hospitals, especially in small-scale hospitals (bed size less than 200) in the US.

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APPENDICES

APPENDIX A

Appendix Table A.1 Survey questions at each time point

	Preop	Day 0	Day 1	Day 2	Day 3	Day 7	Day 30	Day 60	Day 90	Question Frequency
Resting Pain	☑	☑	☑	☑	☑	☑	☑	☑	☑	**9**
Active Pain	☑	☑	☑	☑	☑	☑	☑	☑	☑	**9**
Pain Compared to Expected			☑		☑	☑				**3**
Functional Recovery - Daily Activities	☑	☑			☑	☑	☑	☑	☑	**7**
Functional Recovery - Standing	☑	☑			☑	☑	☑	☑	☑	**7**
Functional Recovery - Walking	☑	☑			☑	☑	☑	☑	☑	**7**
Side Effects			☑	☑	☑	☑				**4**
Sleep Interruption			☑	☑	☑	☑	☑			**5**
Patient Satisfaction on Pain Management							☑	☑	☑	**3**
Patient Satisfaction on Surgery							☑	☑	☑	**3**
Total Questions	**5**	**5**	**5**	**4**	**8**	**8**	**8**	**7**	**7**	**57**

Appendix Table A.2 Association between surgeon and service modality variables

	Inpatient (n = 246)	Outpatient (n = 55)	P-Value (Fischer Exact Test)
Surgeon A	203 (86%)	45 (82%)	0.6
Surgeon B	11 (4%)	3 (5%)	
Surgeon C	19 (8%)	6 (11%)	
Surgeon D	13 (5%)	1 (2%)	

Appendix Table A.3 Survey completion by patients

	Preop (n = 147)	**Day 0 (n = 106)**	**Day 1 (n = 93)**	**Day 2 (n = 105)**	**Day 3 (n = 125)**	**Day 7 (n = 112)**	**Day 30 (n = 140)**	**Day 60 (n = 89)**	**Day 90 (n = 76)**	**Average Question Completion Percentage**
Resting Pain	145 (99%)	105 (99%)	85 (91%)	100 (95%)	117 (94%)	106 (95%)	128 (91%)	87 (98%)	75 (99%)	**96%**
Active Pain	141 (96%)	105 (99%)	87 (94%)	100 (95%)	114 (91%)	107 (96%)	127 (91%)	87 (98%)	73 (96%)	**95%**
Pain Compared to Expected			88 (95%)		114 (91%)	108 (96%)				**94%**
Functional Recovery - Daily Activities	115 (78%)	79 (75%)			86 (69%)	82 (73%)	105 (75%)	73 (82%)	63 (83%)	**76%**
Functional Recovery - Standing	129 (88%)	96 (91%)			106 (85%)	104 (93%)	124 (89%)	84 (94%)	70 (92%)	**90%**
Functional Recovery - Walking	124 (84%)	96 (91%)			107 (92%)	103 (92%)	117 (84%)	82 (92%)	68 (89%)	**88%**
Side Effects			90 (97%)	96 (91%)	115 (95%)	106 (95%)				**94%**
Sleep Interruption			79 (85%)	91 (87%)	108 (86%)	97 (87%)	109 (78%)			**84%**
Patient Satisfaction on Pain Management							127 (91%)	85 (96%)	72 (95%)	**94%**
Patient Satisfaction on Surgery							127 (91%)	85 (96%)	72 (95%)	**94%**
Average Survey completion	**130.8 (89%)**	**96.2 (91%)**	**85.8 (92%)**	**96.75 (92%)**	**108.4 (87%)**	**101.6 (91%)**	**120.5 (86%)**	**83.3 (94%)**	**70.4 (93%)**	**90%**

*n here is the number of patients responded on that particular time point

APPENDIX B

Variable description:

1. Age - Patient's age
2. Gender
    a. F (as reference) - Female
    b. M - Male
3. BMI - Body Mass Index
4. ASA - American Society of Anesthesiologist score
    a. Class 1 (as reference)
    b. Class 2
    c. Class 3
    d. Class 4
5. Procedure
    a) TKA (as reference) - Total Knee Arthroplasty
    b) THA - Total Hip Arthroplasty
    c) TSA - Total Shoulder Arthroplasty
6. PSH
    a. No (as reference) - Did not visit PSH clinic or followed the PSH system pathway
    b. Yes - Visited PSH clinic before the surgery and followed the PSH system pathway
7. Insurance
    a. Public (as reference) - Patients who had public insurance as their payer
    b. Private - Patients who had private insurance as their payer
8. LOS - Length of Stay
9. Discharge Disposition
    a. No (as reference) - Discharged to home
    b. Yes - Discharged to other facility

Appendix Table B.1 Adjusted analysis of PSH and C1-PSH

Variables	Length of Stay			Discharge Disposition			90-Day Readmission		
	Estimated risk (95% CI)	Z-value	P-Value	Estimated risk (95% CI)	Z-value	P-Value	Estimated risk (95% CI)	Z-value	P-Value
Age	1.01 (1, 1.02)	31.46	<0.01	1.08 (1.05, 1.10)	6.96	<0.01	0.99 (0.97, 1.01)	-0.82	0.41
Gender, M	0.85 (0.84, 0.86)	-27.03	<0.01	0.50 (0.35, 0.70)	-3.95	<0.01	1.26 (0.87, 1.83)	1.24	0.22
BMI	1.01 (1, 1.02)	8.50	<0.01	1.02 (0.98, 1.04)	1.07	0.28	0.99 (0.96, 1.02)	-0.55	0.58
ASA, Class 2	1.06 (1.03, 1.10)	3.76	<0.01	3.50 (0.46, 26.2)	1.22	0.22	1.30 (0.39, 4.32)	0.43	0.67
ASA, Class 3	1.26 (1.21, 1.30)	13.16	<0.01	5.67 (0.74, 42.8)	1.68	0.09	2.05 (0.60, 6.99)	1.15	0.25
ASA, Class 4	1.78 (1.67, 1.89)	18.68	<0.01	8.34 (0.74, 93.7)	1.72	0.08	4.92 (0.86, 28.3)	1.78	0.07
Procedure, Hip	1.14 (1.12, 1.15)	20.28	<0.01	1.06 (0.74, 1.50)	0.34	0.73	0.71 (0.46, 1.09)	-1.58	0.11
Procedure, Shoulder	1.17 (1.15, 1.19)	19.63	<0.01	0.43 (0.26, 0.71)	-3.30	<0.01	0.88 (0.53, 1.47)	-0.49	0.62
PSH, Yes	***0.90 (0.88, 0.91)***	***-17.43***	***<0.01***	***0.089 (0.05, 0.14)***	***-9.26***	***<0.01***	***0.72 (0.48, 1.09)***	***-1.57***	***1.09***
Insurance, Private	0.87 (0.88, 0.90)	-16.40	<0.01	0.51 (0.28,0.92)	-2.21	0.03	0.73 (0.43, 1.23)	-1.19	0.24
LOS	-	-	-	1.02 (1.01, 1.03)	10.46	<0.01	1.00 (1.01, 1.02)	1.91	0.06
Discharge, Yes	-	-	-	-	-	-	0.84 (0.45, 1.55)	-0.57	0.57

Appendix Table B.2 Adjusted analysis of PSH and C2-PSH

Variables	Length of Stay			Discharge Disposition			90-Day Readmission		
	Estimated risk (95% CI)	**Z-value**	**P-Value**	**Estimated risk (95% CI)**	**Z-value**	**P-Value**	**Estimated risk (95% CI)**	**Z-value**	**P-Value**
Age	1.01 (1.0, 1.02)	21.04	<0.01	1.12 (1.07, 1.17)	4.59	<0.01	0.99 (0.95, 1.03)	-0.51	0.61
Gender, M	0.83 (0.81, 0.84)	-23.26	<0.01	0.94 (0.51, 1.76)	-0.19	0.85	1.76 (0.95, 3.27)	1.80	0.07
BMI	1.01 (1, 1.02)	18.33	<0.01	1.05 (0.99, 1.11)	1.65	0.10	1.00 (0.95, 1.06)	0.01	0.99
ASA, Class 2	0.88 (0.84, 0.92)	-4.96	<0.01	0.38 (0.06, 2.33)	-1.04	0.30	1236211 (0, Inf)	0.02	0.98
ASA, Class 3	1.09 (1.03, 1.15)	3.20	<0.01	0.56 (0.09, 3.40)	-0.63	0.53	1850634 (0, Inf)	0.02	0.98
ASA, Class 4	1.61 (1.44, 1.79)	8.53	<0.01	5.23 (0.28, 97.2)	1.11	0.27	0.85 (0, Inf)	0.00	1.00
Procedure, Shoulder	1.47 (1.44, 1.50)	37.99	<0.01	1.03 (0.45, 2.36)	0.07	0.94	0.61 (0.26, 1.43)	-1.13	0.26
Procedure, Hip	1.32 (1.30, 1.35)	28.71	<0.01	2.61 (1.29, 5.27)	2.67	0.01	0.96 (0.48, 1.93)	-0.10	0.92
PSH, Yes	***0.91 (0.89, 0.92)***	***-11.34***	***<0.01***	***0.38 (0.18, 0.80)***	***-2.54***	***0.01***	***1.29 (0.70, 2.39)***	***0.83***	***0.41***
Insurance, Private	0.85 (0.82, 0.87)	-13.12	<0.01	0.65 (0.14, 2.99)	-0.56	0.58	0.50 (0.18, 1.40)	-1.32	0.19
LOS	-	-	-	1.03 (1.02, 1.03)	7.33	<0.01	1.00 (1, 1.01)	0.81	0.42
Discharge, Yes	-	-	-	-	-	-	1.09 (0.27, 4.43)	0.13	0.90

APPENDIX C

Appendix Table C.1 Post-operative pain comparison using a 10-point visually anchored pain scale, Mean ± Standard Deviation

						Hip Vs Knee[4]			
	Time Point	Total[3] *n=216*	Hip *n=134*	Knee *n=147*	Shoulder *n=20*	H-Statistic (df = 1)[5]	P-Value[6]	Odds Ratio (OR)[7]	OR P-Value[8]
Resting Pain Level[1]	Pre-Operative	3.2 ± 2.6	3.6 ± 2.7	2.7 ± 2.5	2.4 ± 1.5	4.3	0. 03	0.45	0.04
Active Pain Level[2]	Pre-Operative	4.7 ± 3.0	5.0 ± 3.2	4.3 ± 3.0	4.0 ± 1.7	1.6	0.22	0.81	0.57
	Day 1	3.7 ± 2.7	3.3 ± 2.5	4.1 ± 2.8	2.0 ± 2.3	2.2	0.12	4.03	< 0.01
	Day 2	3.8 ± 2.6	3.0 ± 2.4	4.4 ± 2.6	2.3 ± 2.5	7.0	< 0.01	2.17	0.07
	Day 3	3.3 ± 2.1	2.8 ± 1.8	3.7 ± 2.3	2.0 ± 2.4	5.9	0.01	2.63	0.02
	Day 7	2.8 ± 2.0	2.2 ± 1.8	3.4 ± 2.3	2.3 ± 1.6	9.3	< 0.01	5.24	< 0.01
	Day 30	2.1 ± 2.0	1.5 ± 1.7	2.8 ± 2.0	1.6 ± 1.6	13.7	< 0.01	2.74	0.07
	Day 60	1.2 ± 1.6	0.7 ± 1.1	1.7 ± 1.7	1.0 ± 1.4	7.6	< 0.01	2.44	0.17
	Day 90	1.0 ± 1.7	0.9 ± 1.9	1.2 ± 1.5	2.0 ± 1.9	1.4	0.24	0.9	0.90

[1]Baseline resting pain level was included to provide a basis for the level of pain before surgery even while resting. [2]Active pain levels were included to monitor participant's progress in recovery while active. [3]Average pain level and standard deviation of all procedure types combined (knee, hip, and shoulder). [4]Inferencial statistics of pain levels between procedures hip and knee. [5]H-Statistics value of Kruskal-Wallis test with 1 degree of freedom. [6]P-value of Kruskal-Wallis test. [7]Odds Ratio of knee participant experiencing pain compared to hip with pain levels 0-4 categorized as low and 5-10 categorized as high. [8]P-value of Odds Ratio