Leveraging Overtime Hours to Fit an Additional Arthroplasty Surgery per Day – A Feasibility Study

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Abstract

The COVID-19 pandemic resulted in the cancellation of many hip and knee replacements, creating a backlog of patients on top of an existing long waiting list. To reduce wait lists with no financial burden, we aim to evaluate the possibility of leveraging our previous efficiency-improving work to add an additional case to a typical 4-joint day with no extra cost. To do this, 761 total operation days were analyzed from 2012 to 2019, capturing variables such as case number, success (completion of 4 cases before 3:45pm), and patient out of room time. Linear regression was used on 301 successful days to predict 5th cases, while overtime hours saved were calculated from the remaining unsuccessful days. Different cost distributions were then analyzed for a 77% 4-joint day success rate (our baseline), and a 100% 4-joint day success rate. Our predictions show that increasing performance to a 77% success rate can lead to approximately 35 extra cases per year at our institution, while a 100% success rate can produce 56 extra cases per year. Overall, this shows the extent of resources wasted by overtime costs, and the potential for their use in reducing wait times. Future work can explore optimal staffing procedures to account for these extra cases.

Acknowledgements

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I am grateful for my family and friends for their support, faith, and encouragement throughout my academic career. They have all contributed in unique ways to my development as a student and a researcher.

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Chapter 1

Introduction

1.1 Hip and Knee Arthroplasty

Arthroplasty is a surgical treatment employed for the restoration of proper joint function. It is the most common type of acute inpatient procedure, having over 44,000 operations performed in Ontario alone, between 2020 and the end of 2021 [1]. Though it can involve any joint, hip and knee replacements are the most common as they are among the 3 most performed inpatient surgeries in Canada [2]. In 2020-2021, 55,300 hip and 55,285 knee replacements were performed in Canada. Of these hip replacements, 69.4% were due to osteoarthritis, and 26.4% were a result of an acute hip fracture; knee replacements were more consistent however, as 99.3% were performed in response to osteoarthritis [3]. In total, $1.3 billion was spent on these surgeries; while this amount is $109.8 million less than the previous year due to 20.2% fewer replacements performed, the average estimated cost for a hip or knee replacement hospitalization increased by 15.9% from $10,547 to $12,223 [3].

In addition to being two of the most performed, hip and knee replacements are also among the most relieving elective procedures for the patients. Using the EuroQuol five-dimension (EQ-5D) questionnaire for quality-of-life assessment, a team from the UK determined that 35.0% and 22.3% of a 2020 cohort of patients waiting for a total hip arthroplasty or knee arthroplasty respectively had a score of less than zero, which is defined as a state "worse than death" (WTD) [4]. Further, there was a direct inverse correlation between waiting time and quality of life; each additional month spent on the waiting list further decreased quality of life (EQ-5D: -0.0135, p-0.004), while every six-month period was associated to a clinically significant deterioration in quality of life. These findings were subjectively reinforced by the patients, as over 80% stated a deterioration in their quality of life while waiting for their procedure [4]. When comparing pre- and post-operative EQ-5D scores, it was found that 88.6% and 80.8% of hip and knee replacement patients respectively reported an increase in general health after surgery. These mark the two highest recorded scores among tested elective inpatient surgeries, with the next highest value being 52.5% for varicose vein surgeries and are reinforced by two other metrics (EQ-VAS, and condition-specific questionnaires) [5]. Furthermore, benefits remain for years after the operation; one study followed total joint replacement patients for up to 5 years after their procedures and found that the beneficial effects on quality of life after 1 year were maintained up to the 5th [6]. Altogether, these studies show the effectiveness and the relief that hip and knee replacements offer to patients in need.

1.2 Overview of Canadian Healthcare

Healthcare in Canada is delivered on the foundation that medically necessary health care services are universally covered. Although Canada is generally considered to have a single-payer system, its healthcare system operates on a provincial level, as each province and territory is responsible for the administration of their health insurance plans, planning and funding of care, and for negotiation of fee schedules with health professionals [7]. To ensure that provinces operate under national principles, Parliament passed the *Canada Health Act* in 1984, which states that to receive federal funding, provinces and territories must provide universal coverage for all services and persons that qualify for insurance under the act [8]. Hospital services such as hip and knee replacement surgeries are examples of services covered for Canadian residents under this act, making it important to ensure that these services are delivered efficiently.

Under this system, it was estimated that Canada's total health spending reached approximately $331 billion in 2022, or $8,563 per Canadian, representing 12.2% of Canada's gross domestic product (GDP) in that same year [9]. Typically, 70% of total costs are funded through general tax revenues, with 78% being generated by provinces and territories themselves, and the rest being provided by the federal government through the Canada Health Transfer (CHT) [10].

The remainder of the total cost is funded via the private sector, whether by private insurance or out of pocket, and is generally spent on services that are not covered such as prescriptions drugs, eye care, and dentistry [10]. Shares of all spending are largely consistent year-to-year, as hospitals (24.34%), physicians (13.60%) and drugs (13.58%) continue to cost the most. A visualization of 2018's funding breakdown can be shown in *Figure 1*.

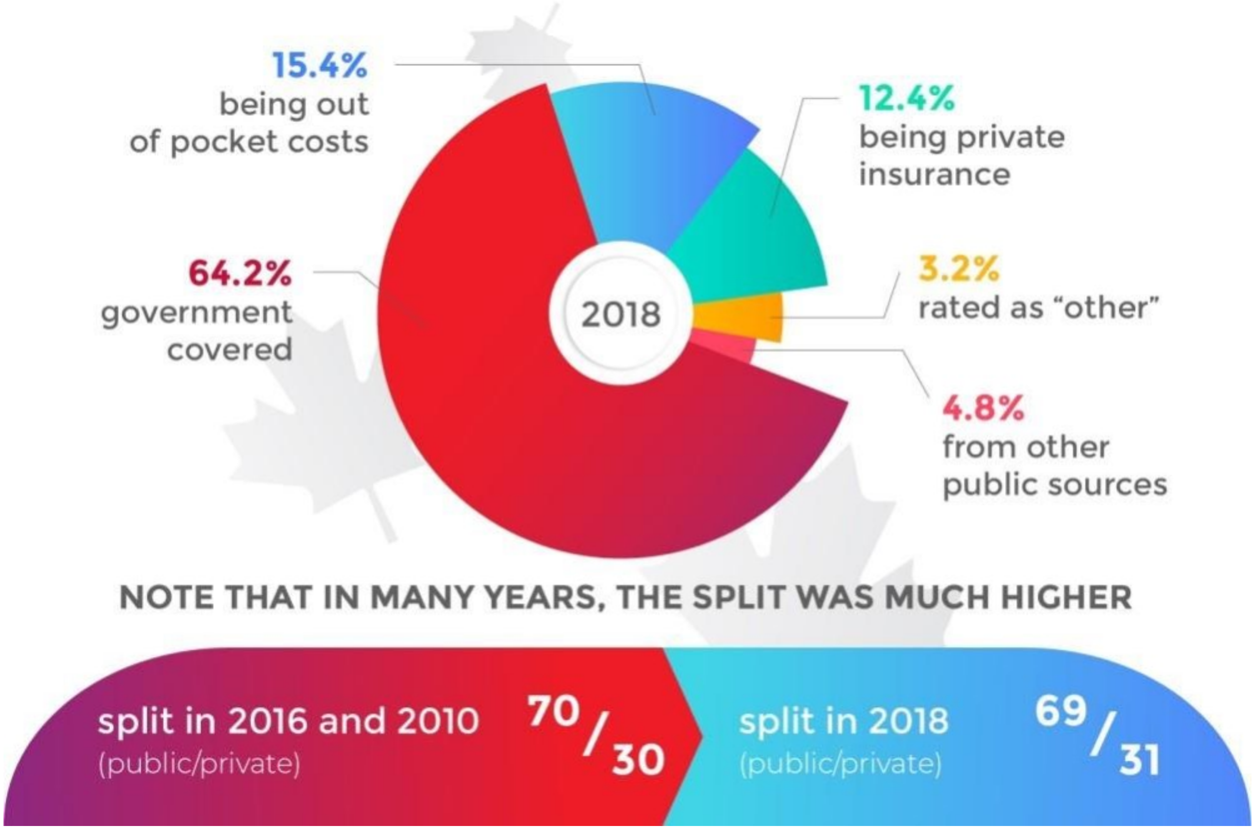

Figure 1: A breakdown of the Canadian Healthcare System's funding in 2018. Image was taken from [11].

1.3 Wait Times in Canada

The COVID-19 pandemic placed a large burden on the Canadian healthcare system and its patients, as surgeries and procedures were delayed in favor of more urgent COVID-19 patients. In the first 22 months of the pandemic (March 2020 to December 2021), there were almost 600,000 fewer surgeries performed than in 2019, with hip and knee replacements representing 48,000 of these surgeries [3]. The decrease in volume also led to large surgical backlogs, as procedures were postponed while throughput levels were never reclaimed [3]. Between April 2020 and September 2022, approximately 35,850 (20%) and 12,000 (11%) fewer knee replacements and hip replacements respectively were performed on adults over 18 compared to before the pandemic. The number of Canadians receiving knee replacements rounds nearer to pre-pandemic between April and September 2022, as shown in *Figure 2*, but data indicates that even nearing pre-pandemic levels of monthly surgery scheduling is insufficient to clear the backlog and improve wait times. This means that provinces will need to exceed pre-pandemic surgery numbers to do so, something that has only been done at the national level in 3 separate months since the pandemic began [12].

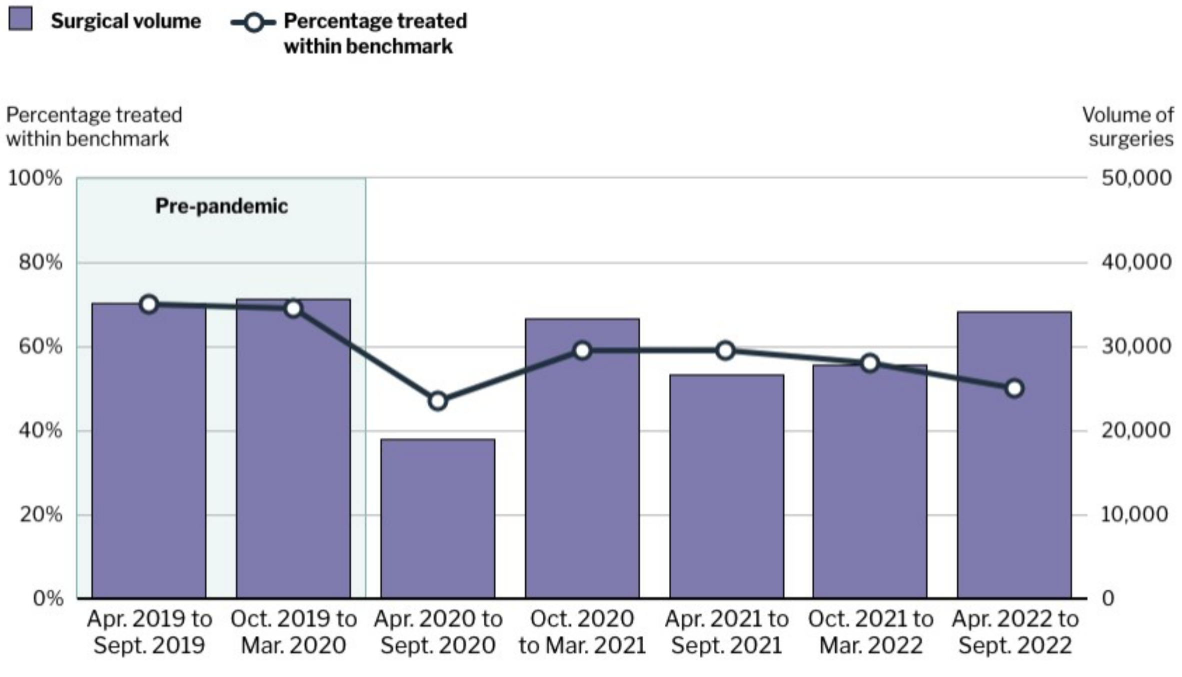

Figure 2: Percentage of adult patients in Canada receiving knee replacement surgery within the recommended waiting time (182 days) compared to the same time period's surgical volume. Image taken from [12].

Unlike most other operations that recovered their pre-pandemic wait times such as cataract surgeries, hip and knee replacements' longer wait times persisted [12], [13]. *Figure 3* shows the percentages of Canadians that received their knee replacement surgery within the recommended waiting time of 182 days. This recommended waiting time was established by the National Wait Times Initiative (NWTI), a program introduced by the federal government in 2005 to improve access to care and reduce wait times, with a large focus on hip and knee replacements [14]. Prior to the pandemic, 70% and 75% of hip and knee replacements were completed within this 6-month period respectively. In the latest published period of April to September 2022, these values have dropped to 50% and 57% despite the increase in volume [12], marking the lowest values of any procedures with established benchmarks (see *Figure 3*) [15]. These results reinforce the conclusion that establishment of pre-pandemic surgical volume is insufficient to improve wait times.

Data specific to hip replacements is also reported and is displayed in *Figure 4*, highlighting Canada's continuing issues with wait time. The 50th percentile of waiting times has increased to 164 days in 2022, only 1 day less than the year of COVID's peak (2020), while the 90th percentile wait time continues to increase, now hitting 411 days, as shown in Figures *4b* and *4d* [15]. These values arise despite the increase in surgical volume and number of patients included in the calculations (see *Figure 4c*).

Figure 3: Percentage of adult patients treated within each procedure's benchmark waiting time in Canada. Plot was taken from [15].

Similar, but even worse results were acquired for knee replacements, whose data can be found in *Figure 5*. Both their 50th and 90th percentile waiting times are higher in 2022 than in 2020 (198 vs 197 days and 479 vs 405 days respectively), once again despite the increase in patients accounted for (see *Figure 5*) [15]. Overall, these figures all reinforce the pressing need for volume-increasing interventions in order to overcome the current backlog and reduce waiting times.

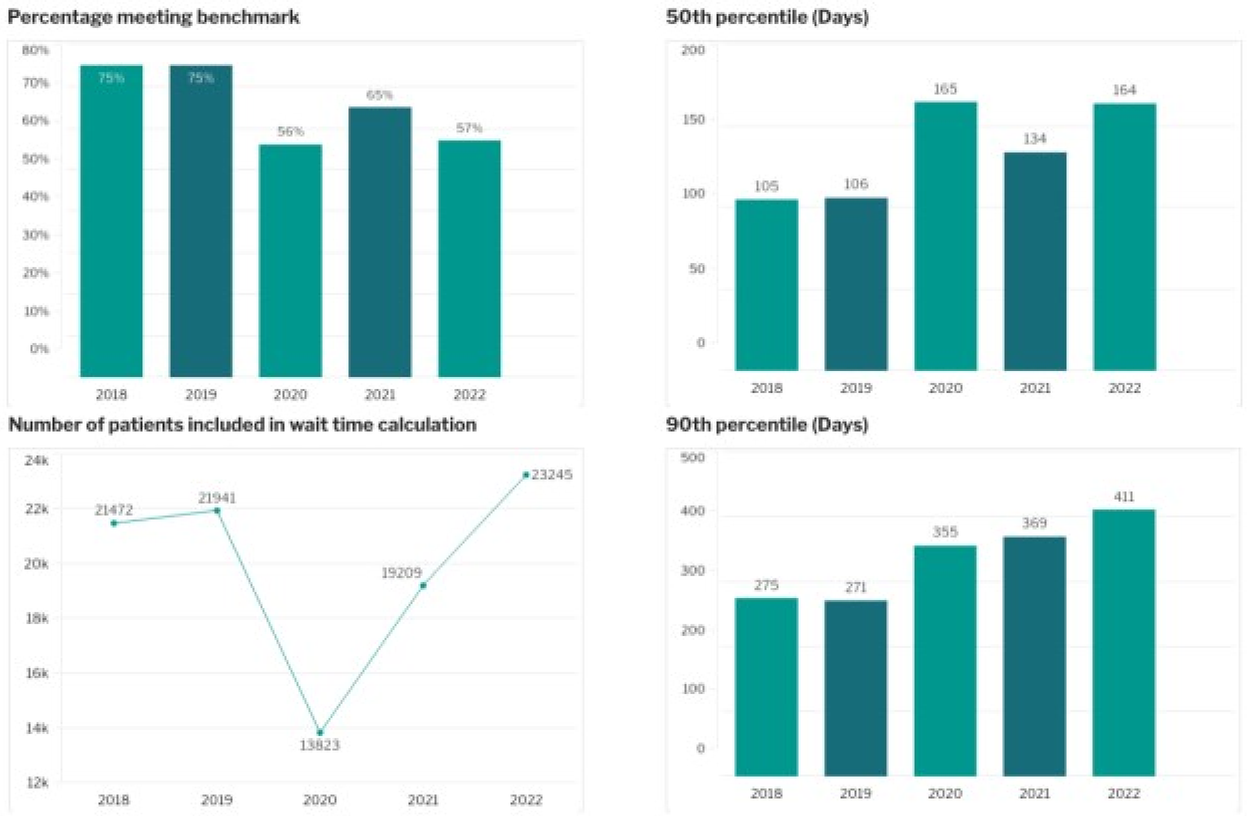

Figure 4: Hip replacement wait times in Canada for patients age 18 and older. Each year's timeframe is from April 1 to September 30. *a*) (top left) Percentage of hip replacements that were performed within the recommended waiting time (182 days) per year; *b*) (top right) 50th percentile waiting time in days for hip replacements per year; *c*) (bottom left) Number of hip replacement patients included in wait time calculation per year. *d*) (bottom right) 90th percentile waiting time in days for hip replacements per year. All plots were taken from [15].

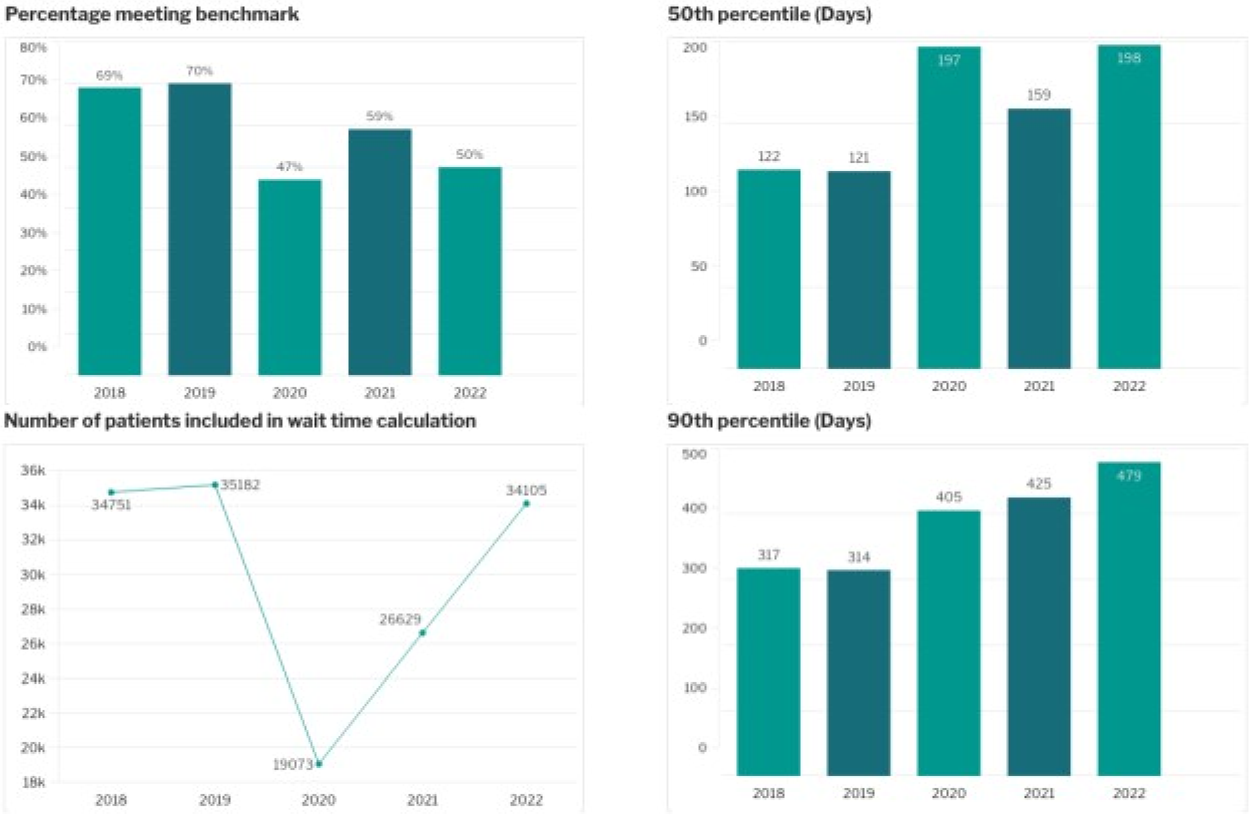

Figure 5: Knee replacement wait times in Canada for patients age 18 and older. Each year's timeframe is from April 1 to September 30. *a*) (top left) Percentage of knee replacements that were performed within the recommended waiting time (182 days) per year; *b*) (top right) 50th percentile waiting time in days for knee replacements per year; *c*) (bottom left) Number of knee replacement patients included in wait time calculation per year. *d*) (bottom right) 90th percentile waiting time in days for knee replacements per year. All plots were taken from [15]

1.4 Case-Scenario at The Ottawa Hospital

The Ottawa Hospital (TOH) is Ottawa's main teaching hospital and is composed of 3 sites: the Civic Campus, the Riverside Campus, and the General Campus, where joint replacement surgeries are performed. TOH's current goal is to rank among the top 10% of North American hospitals, something they intend to do by improving wait times, patients' rating of experience, and other key measures of hospital performance.

In 2004, TOH's General Campus introduced a 4-joint operating room (OR) initiative, which defines success as the completion of 4-joint OR cases within a standard 8-hour shift (as well as a 15-minute buffer window), with the goal of reducing wait times for joint replacements by increasing surgical throughput. Although this succeeded in increasing throughput, 2012 saw only 49% of days completed successfully [16], a value that has since gone down to 39% in the following period of 2012-2020 [17]. The inability to consistently complete the 4 cases within the standard 8-hour shift leads to wasted resources due to overtime salaries, with calculations estimating $312,051.60 in extra cost per year for the orthopedic surgery department [17].

Additionally, despite the increase in surgical volume, the General Campus still struggles greatly with reducing waiting times. Hip and knee replacement patients are triaged by surgeons, specialists, and other health care providers to 4 different priority levels based on urgency, each of which has a different target waiting time; priority 4 patients have a target waiting time of 182 days, priority 3 patients should be treated within 84 days, priority 2 patients have a target time of 42 days, while priority 1 patients are urgent and seen immediately, so are not included in wait time calculations. At TOH's General campus, priority 4 hip replacement patients waited an average of 375 days (106% greater than the benchmark), priority 3 patients were too small in number to report, while priority 2 patients waited an average of 135 days (221% greater than the benchmark) between the decision for surgery to the surgery itself. Overall, only 16% of hip replacement patients were treated within the target time, the lowest value of any hospital campus in Ottawa [18]. Knee replacements showed even worse results: priority 4 patients waited an average 398 days (119% greater), priority 3 patients waited an average 214 days (155% greater), and there were not enough priority 2 patients to report, for an overall 10% of all knee replacement patients treated within the target time [18]. Interestingly, this issue is not as drastic city-wide, as Hôpital Montfort and the Queensway Carleton Hospital treated 65% and 51% of their knee replacement patients within the target time respectively [18].

1.5 Proposed and Attempted Solutions

Recognizing the pressing issue of healthcare wait times, the Canadian and Ontario governments have initiated many plans to boost procedural capacity. In terms of funding, the Ontario government announced a new plan involving the investment of $300 million in 2021. In this plan, $216 million is allocated to hospitals to extend operating room hours into evenings and weekends, allowing for up to 67,000 surgeries (on top of the existing 650,000 scheduled surgeries) to be performed. However, only 4,300 of these new surgeries were to be in orthopedics [19]. March of the following year saw a funding initiative at the federal level, as Bill-C17 was introduced to provide a $2 billion top-up that is distributed among the provinces and territories equally per capita, which would result in $775,500,000 being sent to Ontario alone. This $2 billion was in addition to a previous $4.5 billion top-up that had been delivered at the start of the COVID-19 pandemic [20]. In February 2023, a long-term federal plan was delineated by Prime Minister Justin Trudeau which promised an increase in health care funding to the provinces by $196.1 billion over 10 years, including $46.2 billion in new funding [21]. Among this $196.1 billion is another immediate, unconditional $2 billion top-up, summing to $8.5 billion in pandemic top-ups, and $25 billion over the next 10 years as part of a bilateral agreement to address family health services, health workers and backlogs, mental health and substance abuse, and the modernization of the health system [21]. That same month, the province of Ontario agreed to this deal, which would grant it $73.97 billion of the grand total over 10 years, $8.413 billion of the bilateral agreement's sum, and $776 million of the top-up [22]. However, representatives of other provinces stated that this is only a step in the right direction, as they hope for more money, and that this plan contains no details on how the money should be spent or any checks on its potential use in private care [21]. Not including this recent change, *Figure 6* shows Canada's increasing trend in annual total health expenditures, while

Figure 7 displays their relatively high spending as a % of GDP. Despite all this, wait times continue to cause concern, begging questions of whether the system is fundamentally broken or whether funds are not being spent properly, prompting a revaluation of existing assets. These questions are further reinforced by overflooded ERs, waves of nurses quitting, and a shortage of medical personal protective equipment that occurred as a result of the COVID-19 pandemic [23], [24].

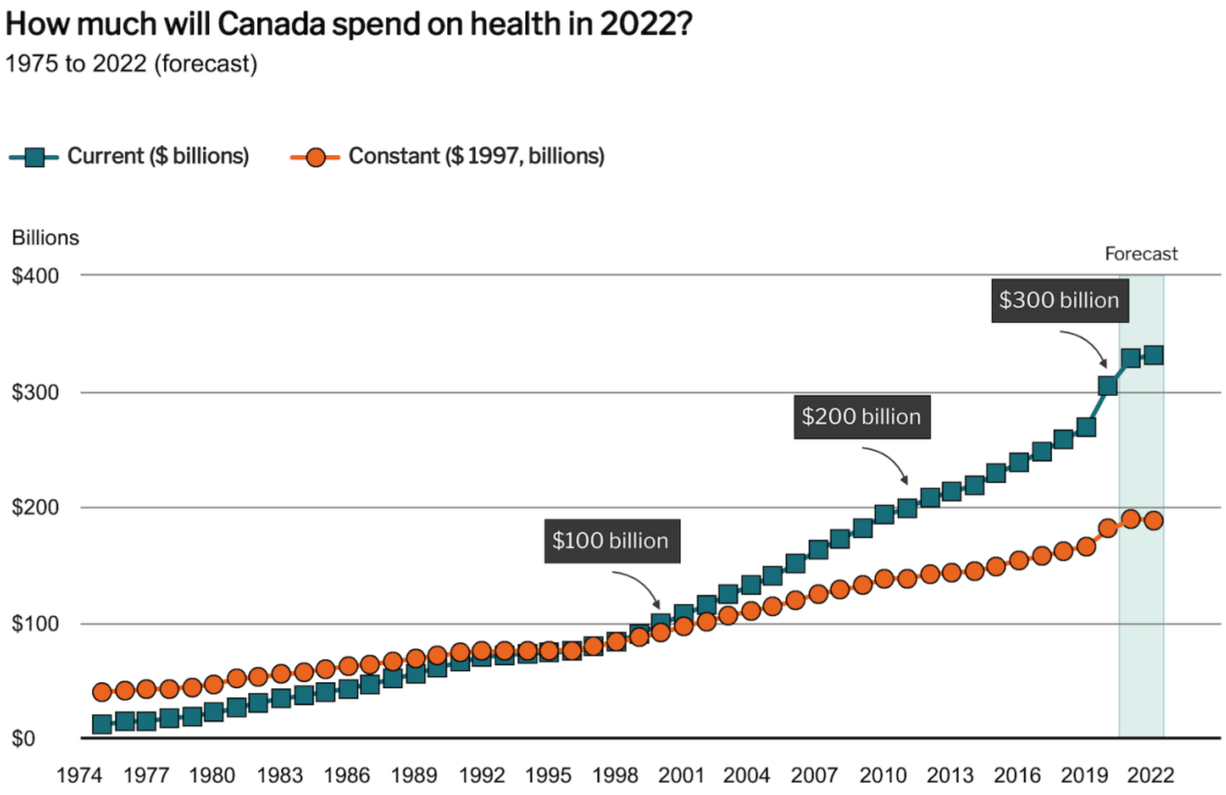

Figure 6: A line chart of total health expenditures in Canada in current and 1997 constant dollars from 1974 to 2022. Not shown in this plot is a coincidental increase in spending per capita as well. This plot was taken from [9].

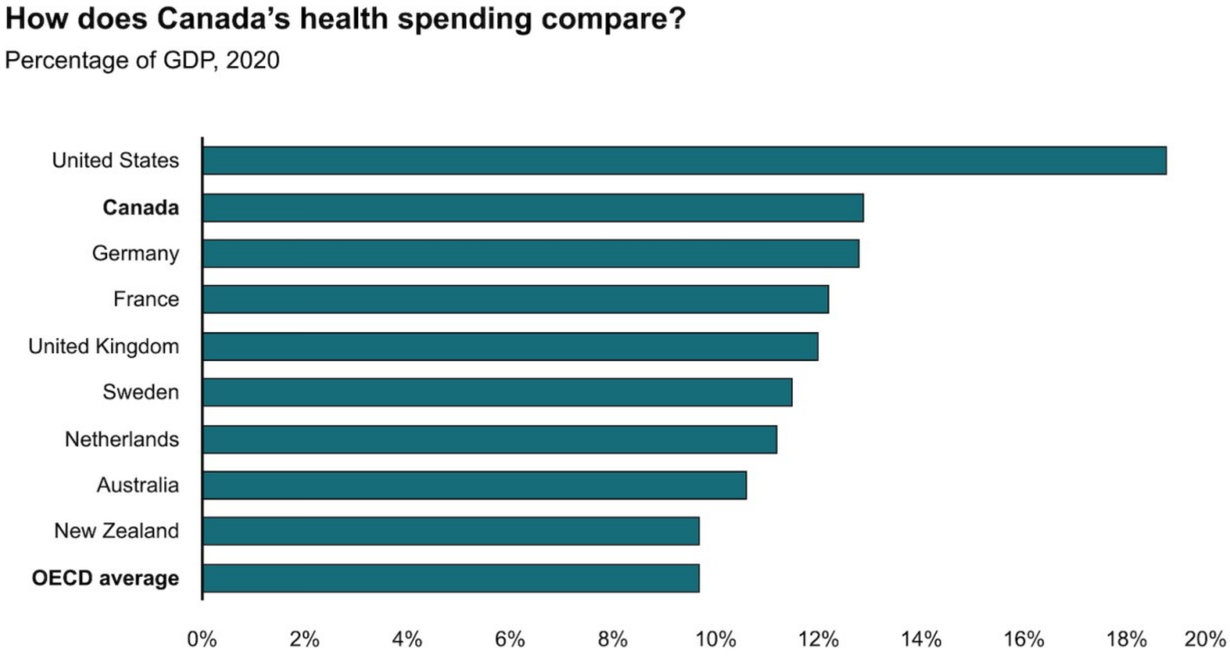

Figure 7: A bar chart comparing Canada's health spending in 2020 as a percentage of its Gross Domestic Product (GDP) to other Organization for Economic Co-operation and Development (OECD) countries. This chart was taken from [9].

To reduce wait times for certain diagnostics, cataract removals, and hip and knee replacements at the provincial level, Ontario Premier Doug Ford and his government introduced a plan in 2023 to increase procedures in for-profit clinics. According to the official, this change will reduce wait times by performing thousands more surgeries and diagnostic procedures each year [25]. However, this announcement came with many concerns. Under this system, Ontario residents still do not pay out of pocket, but the government will be charged more for each procedure due to the for-profit nature of the transactions. This money, direct from taxpayers, could reduce the available funds from the existing publicly funded system solely to improve the owners of the private sector. Additionally, resources such as staff are also likely to be drained, widening the gap between urban and rural access to healthcare, and further straining publicly funded hospitals. Finally, this change could lead to a slippery slope of healthcare privatization in the future, something that Canada has pridefully avoided for many years. Instead, research into proper funding and modification of the existing publicly funded system is not only safer, but a potentially more effective approach as well for reducing waiting times.

Other initiatives have been implemented at the institutional level, evaluating the effects of new or additional assets such as additional staff, dedicated rooms, Real-Time Locating Systems (RTLS), or single-use instruments [26]–[31]. These approaches generally lead to positive results, managing to decrease operation time by up to 15.4 minutes per case, nonoperative time by up to 36 minutes per case, and turnover time by 26 minutes per case [26]–[28]. However, these advantages can come at the cost of additional risk, whether financial, ethical (such as the RTLS monitoring of staff and patients [29], [30]) or environmental (single-use instruments have a greater environmental impact [31]). Other methods look instead to change, evaluate, or rearrange existing assets within a hospital based on data analysis, for example the surgical instrument tray or hospital policies, with some leading to decreases in delays per month (10.8), $30,000 to $93,000 in savings over 300 procedures, or a 6.8% increase in total patients [32]–[34]. While these methods remove the risk and expenses seen when adding assets while still retaining great benefits, they only greatly improve one aspect of efficiency at a time, whether time or cost, and are not individually useful in trying to improve all aspects of OR efficiency at once. To retain the benefits of both approaches, solutions based on artificial intelligence (AI) and machine learning (ML) have been growing in popularity. The majority of these solutions aim to predict a certain aspect of an operation, whether before surgery [35], after surgery [36], [37], or the duration of the surgery itself [38]–[40]. Doing so allows for optimal patient scheduling, leading to benefits such as an 80% decrease in admission delays, and theoretical savings of $469,000 over 3 years ($156,333 per year) [36], [37]. Less-explored ML solutions aim to establish attainable benchmarks that help maximize efficiency or achieve set goals. For example, one study found that when using their cancellation-predicting model, overbooking 65% of predicted cancellations yields the best results in terms of average overtime per day, while another was able to establish time benchmarks for each portion of a case to achieve a 60% success rate in doing 4 cases within a set 8-hour period [16], [41].

1.6 Contributions to thesis

This thesis is written in an article format in which an article that is to be submitted for publication is included in Chapter 2. Chapter 1 explains the greater context that caused motivation for this work, while Chapter 3 further synthesizes the work with previous articles from which it is based on, providing a more holistic summary.

My **thesis objective** is to implement a machine learning (ML)-based procedure to evaluate the potential for an additional arthroplasty surgery in a day using only costs saved from decreasing overtime hours. This will involve both the prediction of 5th cases, as well as the calculation and distribution of costs to accommodate these predictions without paying overtime.

My **research aims** include the development of a simple and interpretable case-predicting methodology, to offer an opportunity to further reduce wait times without additional financial burden, encourage the revaluation of existing hospital and OR assets in other institutions, and to identify new areas for data-driven research on hospital and health care efficiency.

For my **contributions** to this work, most of the sections describing our previous work (sections 2.3-2.5, and section 2.6 not including *Descriptive Analytics*) were written by Farid Al Zoubi, PhD candidate. Development, implementation, and evaluation of the work, as well as the writing of all other sections, were done by me.

Chapter 2

Journal Article

Leveraging Machine Learning and Prescriptive Analytics to Improve Operating Room Throughput

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2.1 Abstract

To reduce the increasing wait lists for hip and knee surgeries, we aim to verify whether it is possible to add a 5th surgery, to the typical 4 surgery per day schedule, without adding extra overtime hours and cost at our clinical institution. Time data for surgery (i.e., case) was recorded retrospectively using our institution's Surgical Information Management Systems (SIMS). In total, 3044 hip/knee patient cases over 761 total operation days from 2012 to 2019 were captured. Successful days are defined as days when four cases were completed before 3:45pm, and overtime hours are defined as time spent after 3:45pm. Based on these definitions and the 460 unsuccessful

days isolated from the dataset, 465 hours, 22 minutes, and 30 seconds total overtime hours were calculated. To predict 5th cases, 301 successful days were isolated and used to fit linear regression models for each individual day. After using the models' predictions, it was determined that increasing performance to a 77% success rate can lead to approximately 35 extra cases per year, while performing optimally at a 100% success rate can translate to 56 extra cases per year at no extra cost. Overall, this shows the extent of resources wasted by overtime costs, and the potential for their use in reducing long wait times. Future work can explore optimal staffing procedures to account for these extra cases.

2.2 Introduction

In Canada, the median wait time for treatment from referral by a general practitioner (GP) was 27.4 weeks (12.6 from GP to specialist, and 14.8 from specialist to treatment) in 2022. This value continues to trend upwards, even relative to pre-determined reasonable wait times [1]. When looking at individual specialties, orthopaedic surgery not only consistently demonstrates long median wait times over several years, but also has the longest median wait time from specialist to treatment in 2021 (30.2 weeks) and is second only to plastic surgery in 2022 (32.4 vs 34.3 weeks) [1]. Despite having an estimated median reasonable wait time of 15.4 weeks, hip and knee replacement surgeries were still given a Pan-Canadian benchmark wait time of 26 weeks as a maximum, yet it is still lower than the national median wait time of 38.0 weeks in 2022 [1]. In Ontario alone, there are currently an estimated 206,000 patients waiting for surgical procedures [42]. For orthopaedic surgery in Ontario, the median waiting time is 19.9 weeks, 75% greater than the province's reasonable median wait time of 11.4 weeks, leaving an estimated 38,275 patients waiting for orthopaedic treatment, 25,372 of which are for arthroplasty surgeries [1].

Before the COVID-19 pandemic, hip and knee replacements were increasing at a rate of 5% per year. During the COVID-19 pandemic, hip and knee replacements between April and December decreased by 16.1% and 29.8% respectively from 2019 to 2020 due to an abundance of cancellations, creating an excess of waiting patients. In fact, current trends in Canada have led to 138,500 surgeries and estimated inpatient costs of over $1.4 billion a year, imposing a huge burden on the economy, in addition to large backlogs in waiting lists [43]. Unfortunately, data indicates that in order to overcome these large backlogs, provinces will need to exceed pre-pandemic rates of surgery, something that has only been accomplished 3 times nationally since the beginning of the pandemic [12].

In Ontario, patients are triaged into different categories based on urgency: priority 4 patients have a target treatment time of 182 days, priority 3 have a target treatment time of 84 days, and priority 2 patients should be treated within 42 days. When evaluating the wait time from the decision for surgery to the surgery itself, only 16% of hip replacement patients and 10% of knee replacement patients are treated within the target time at our institution [18]. For the former treatment, the average wait time for priority 4 patients is 375 days, while that for priority 2 patients is 135 days (not enough data for priority 3), while knee replacement patients yield average wait times of 398 days for priority 4 patients, and 214 days for priority 3 patients (not enough data for priority 2) [18]. Efforts such as 4-joint operating rooms (OR) (i.e. dedicated to serving 4 operations within 8 hours) have been implemented to increase throughput and shrink existing waiting lists [16]. However, the issue persisted, as the 4-joint room was only able to report a 49% success rate in 2012, indicating a lack of consistent efficiency [16]. This is additionally concerning as inefficient use of resources and time contribute to 30% of total healthcare expenditures [36], further emphasizing the need to optimize time and cost. These numbers highlight the burden placed on this hospital, and the pressing need for solutions to reduce the waiting list.

2.3 Previous Work

Our institution has a dedicated orthopedic OR for 4-joint arthroplasty procedures. The OR is specially designed for high-volume arthroplasty surgeries, i.e., partial, and complete joint replacement, and facilitates four procedures each day (from Monday to Friday, excluding Wednesday). Each procedure is subdivided into six stages, including Anesthesia Preparation, surgical procedure, and turnover, the final stage (see *Figure 8*).

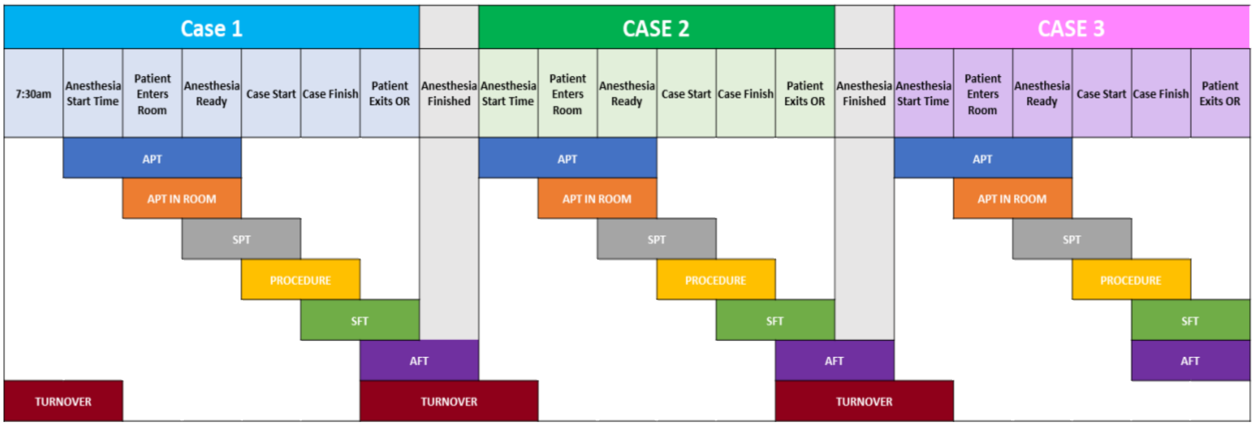

Figure 8: An overview of each stage of a procedure, as well as the transition between two (turnover). At the top are the stage markers of a case, while the black region shows the different duration variables used. Acronyms are fully explained in Table 3.

A successful day in this arthroplasty OR is defined as the completion of all four procedures within the allocated time; in this case, the eight hours assigned between 7:30 am and 3:30 pm; however, because there is a 15-minute buffer window for overtime pay at our institution, 3:45pm is used in the proposed methods of this article. The Surgical Success Rate or SSR was the metric designed to keep track of the percentage of successful days in a predetermined period (typically a year).

The original SSR was dismal - 39%, and the overtime cost for our institution was roughly $570,000 annually. Multiple initiatives were introduced to improve this SSR with varying degrees of success [16], [17], [44].

Recently, we suggested the most comprehensive solution to this problem - a data-driven, Machine Learning (ML)-based, prescriptive analytics system. It not only predicts the probability of whether a particular day would be successful based on time variables, but also monitors each stage of the procedure in real-time, modifying its prediction if needed, and offers suggestions through a proposed list of actions at a given stage to increase the probability of success [17], as demonstrated in *Figure 9*.

Figure 9: A visual demonstration of the artificial intelligence model's function. Colors are used to indicate timeliness at each stage of the procedure, while suggestions are provided for ways to maintain or catch up to the desired rate.

These suggested actions are updated stage-by-stage for each procedure. The multiplicity of suggestions ensures that the surgical team has multiple viable options to choose from, allowing them to leverage their experience and expertise to employ what they believe would be the most positively impactful suggestion in any given circumstance (see *Figure 9*). These real-time proposals allow the system to not just monitor but optimize the procedures and influence the SSR.

The suggestions offered by the ML-based prescriptive analytics system were developed and tested during a comprehensive and highly successful program designed to optimize OR procedures. The program focused on Positive Deviance seminars offered by the most successful surgical professionals in their respective domains. This included surgeons, registered nurses (RNs), and anesthesiologists with the highest SSR, with the idea of sharing their expertise and best practices with the team to improve overall SSR [44].

These professionals shared the processes and procedure optimization techniques that allowed them to complete all four surgeries on time (without compromising patient safety) with the rest of the team (see *Table 1*). These processes and techniques were made part of the ML system, which would suggest the right set of actions at various stages of the procedure to optimize the process.

Following the system's suggestions resulted in a significant improvement in individual procedure times and, as a result, an improvement in the overall SSR.

Table 1: Examples of suggestions offered by surgeons and nurses at Positive Deviance seminars to optimize OR procedures.

Surgeons:	**Nursing:**
1. Be there from positioning to patient transfer from the table. *2. Have a standardized/protocolized approach for each type of procedure.* *3. Anticipate next steps, calling for instruments/implants.* *4. Assist with turnover and putting away instruments, but in a way that is supported by nurses.* *5. Institute an incentivization for the entire team to be done by 3:30, and that would drive efficiency.* *6. Bring the patient into the room for spinal preparation such that instruments may be opened simultaneously (in parallel rather than in series)* *7. Anesthesia does the blocks and spinals in the procedure room.*	*1. Have an engaged, familiar team working together.* *2. Have equipment ready to go before patient enters the room.* *3. Whole team (nursing, surgery, anesthesia) is present during turnover.* *4. Begin putting away instrumentation during closing.* *5. Have experienced, knowledgeable scrub nurses who know the steps to the procedure and will know when certain instruments (implants) are needed.* *6. Have attendants available to help with turnover.* *7. Ensure nurses in the room have received total joint training.* *8. Minimize phone call interruptions from pre-op and PACU during the case.* *9. Ensure attending available for prep. Make use of free staff in room when prepping/positioning. Ensure no revision of surgical positioning.* *10. Need team lead (TL) to have adequate time for training and administration.* *11. Ensure improvements in efficiency don't come at cost to patient outcomes.*

2.4 The Benchmarks

The model establishes multiple sets of benchmarks to track success and failure by monitoring the six stages of individual procedure case. More specifically, both stage duration benchmarks and recommendations are produced for any desired SSR. Based on the sets produced, a 77% success rate was defined as the baseline, replacing the default SSR of 39% [17]. This SSR's benchmarks represent the 75th percentile values for each individual time interval see (*Table 2*), and was ultimately selected as the baseline because these benchmarks were deemed easily achievable by the clinicians. In doing so, it leads to improve nearly three out of five (61%) failed days on which the 4 surgeries were not completed on time. These failed days, on average, cost the hospital about 36 minutes of overtime (more than $2,000 a day).

Another benchmark is the best-case scenario - 100%. This is achievable when the prescriptive analytics system is fully leveraged, and the most potent actions/suggestions are followed to optimize the overall procedure time. This results not only in a successful day, but also with an adequate amount of time left within the eight-hour window. It is this scenario that encouraged us to suggest a follow-up model. Example benchmarks for this scenario as well as others are shown in *Table 2*.

Table 2: Examples of benchmarks established by the AI model for different success rates. The baseline and the optimal scenarios are used for evaluation in this paper.

Scenario	APT (mins)	Case (mins)	AFT (mins)	Turnover (mins)	Success Rate
Baseline (75th percentile)	<10.5	<71.5	<20.5	<21.5	77%
Fast Procedure	<10.5	53	<20.5	<21.5	93%
	<10.5	64	<20.5	<21.5	89%
Slow Procedure	<10.5	>71.5	<20.5	<21.5	59%
Slow Turnover	<10.5	<71.5	<20.5	>21.5	69%
Slow Anesthesia Preparation	10.5-18.5	<71.6	<20.5	<21.5	64%
Optimal Performance	<7	<62.5	≤7	≤20	100%

2.5 Relation to this work

With the development of our ML-based prescriptive analytics system, the ideal scenario would be zero overtime and all surgeries completed on time on any given day. However, even if we disregard the anomalies during procedure and preparation, there are several factors preventing this ideal scenario from becoming the norm, including a limited number of high performers and the inevitable concentration of more time-consuming patients on certain days (statistically significant).

This encouraged us to consider the above two benchmarks, 77% and 100% SSR outputs of our perspective system to predict the possibility of completing an additional surgery (i.e. a 5th case) during a successful day. To do this, savings from the decrease in overtime hours and its increased pay will be evaluated for its ability to fund the 5th cases, leading to an increase in throughput with no extra cost. This will ensure fair compensation to the surgical staff for a higher number of overall surgeries because additional surgeries would be covered under the saved overtime that the staff has already been paid for. A flowchart visualizing this process can be found in *Figure 10*.

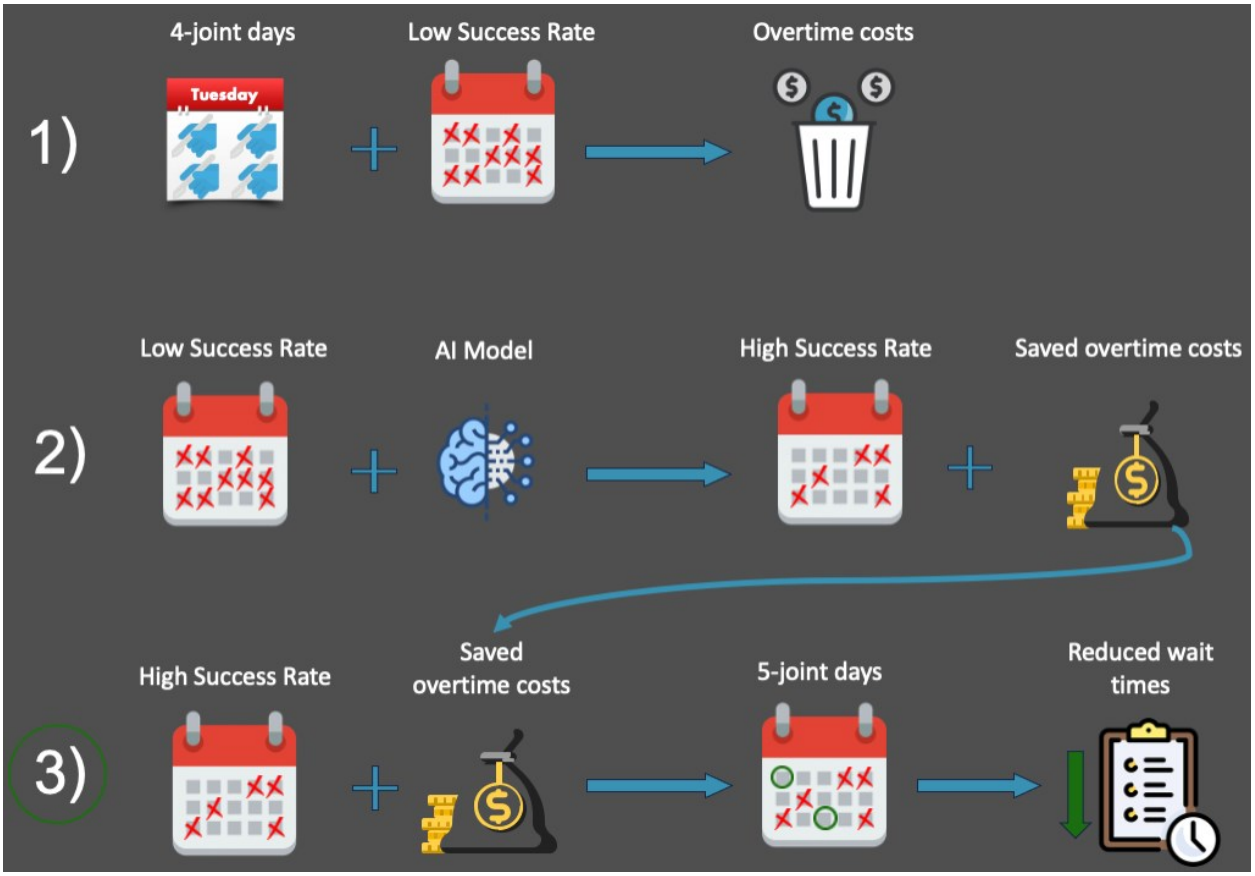

Figure 10: A flowchart showing an overview of our research plan. This article focuses on row 3.

Even with a rudimentary calculation, the average overtime for four unsuccessful days (36 minutes times four) will be roughly enough to justify fitting in a fifth surgery on a successful day. With the cost and time justified, the analytics systems will be applied to different time distribution scenarios to identify how many successful five-surgery days are feasible and justifiable. This may require us to consolidate recommendations like scheduling multiple low-risk/less-time-consuming patients on a single day or deferring monitoring in the Post-Anesthesia Care Unit (PACU).

Therefore, the contribution of this article is to implement a predictive method to estimate of likelihood of fitting a 5th surgery during a successful 4-joint operating room day, using only cost-savings accrued from use of our previous work - an Artificial Intelligence (AI)-based model that produces time-based benchmarks for different success rates. Cost savings from two success rates that will be evaluated: 77%, our realistic baseline, and 100%, optimal performance [17]. To do this, we will utilize linear regression by fitting a model to every successful day, generating a histogram of 5th case predictions that will be leveraged to explore different distribution strategies of saved costs.

2.6 Arthroplasty Data Set

In order to leverage the existing ML-based prescriptive analytics system for the proposed fifth case simulation, it's imperative to understand the foundational data used to build the model/system.

Time Period: The data collected for building use in this paper spans from 2012 to 2019. This is enough time to recognize almost all short-term and long-term patterns in data. The statistically significant amount of data naturally lowers variance estimation, leading to more accurate predictions and, consequently, drawing more relevant recommendations.

Nature of Procedures: To streamline the data and identify better optimization techniques, we adhered to non-complex cases and unilateral surgeries. Our early analyses found that bilateral surgeries take more time, and even if it is not twice as long as unilateral surgeries (such as the actual difference in the surgical procedure), it is statistically significant enough to prevent the on-time completion of four surgeries in a day. It is also important to consider that typically, there is an approximate 4:1 unilateral to bilateral surgery ratio, so the bulk of the procedures were considered.

Similarly, complex surgeries where health complications, which may prolong the procedure, are identified beforehand were also excluded from the data set since they are predictable rarities, not the norm.

Nature of Data: The data our machine-learning systems were trained on was both numerical and categorical in nature. The numerical data mostly consisted of timestamps for every stage of the procedure, which were converted to durations to generate a rich number of numerical variables and metrics. The categorical data came from the individuals and the type of surgeries performed. Collectively, the data pool consisting of 40 different variables covering almost all medically relevant details about the patient and procedure, the surgical team performing the procedure, and the necessary time variables; however, the final dataset was filtered down, resulting in 29 of the pool's 40 variables being used (see *Table 3*).

Table 3: The selected variables that were present in the dataset used for the development of the previous AI model. Of these variables, Case Number and Out of Room Time (the time at which the patient is escorted out of the operating room) are used in this article.

Time Metrics	**Staff (Team) Metrics**	**Patient Metrics**	**Safety metrics**
Anesthesia Preparation time (APT)	Surgeon	Campus	90-day Readmissions
Anesthesia Start time	Anesthesiologist	Type of Surgery	Reason for Readmission
Time in Room	Circulator Nurse 1	Type of Anesthesia	Length of Stay
Anesthesia Ready time	Circulator Nurse 2	Sex	
Anesthesia Stop Time		Age	
Anesthesia Finish Time (AFT)		BMI	
Surgical Preparation Time (SPT)		ASA	
Case Start			
Case Finish			
Surgery finish time (SFT)			
Turnover			
Surgery (Procedure) Time			
Out of Room Time			
Case Number			
Date			

Data Collection Source: The data for most of the identified metrics came from the Surgical Information Management System (SIMS), though some data points came from patient charts and daily notes. This consolidated sourcing of the relevant data prevented the need for integrating different information management systems and overcomplicating the process. This is also one of the factors making this system extrapolatable to different healthcare facilities.

Treatment of Data: Since we already removed anomalies like complicated cases and statistical outliers (bilateral surgeries) that would undermine the pattern recognition and generation of useful insights, the treatment was relatively minimal. The data was cleaned for missing information and incorrect values, both of which represented less than 1% of the observed data set, so the removal was not significant enough to impact the statistical outcome. Regardless of their dissent with median values, rare cases (categorized as non-complex before the procedure began) were kept in the data set. They had a modest impact on the extremes, but not enough to deviate from the trends enough to draw wrong conclusions.

Demographics of patients and Other Quantifiable:

Table 4: General patient demographics from the sample dataset.

Number of surgery days (total surgeries):	761 (3044)
Distribution of male and female patients:	1,560 (51.25%) M; 1,484 (48.75%) F
Average patient age:	63.2±11.9
Average patient BMI:	30±5

Descriptive analytics:

Of the 761 4-joint operation days, 301 were successful (4 operations before 15:45), marking a 39.55% success rate. In these successful days, there was a total 97 hours and 49 minutes of spare time (time between the end of the final case and 15:45), averaging to 19 minutes and 30 seconds per day. Overtime-cost hours were calculated using the remaining 460 unsuccessful days by multiplying the number of overtime hours (hours worked past 15:45) by 1.5 (the paid overtime rate). Doing so reveals a total 465 hours, 22 minutes, and 30 seconds overtime-cost hours, leading to an average of one hour per unsuccessful day.

Each case's out of room time, which is the time at which the patient is taken out of the operating room, is plotted on a histogram, showing distributions of successful cases and all cases (see *Figure 11*). Peaks on the graph belong to individual distributions of one of the four cases in a day. The distribution of all 4th cases shows a tail that extends past 8pm, marking over 4 hours of overtime on some days. In general, the skew of all cases appears to increase to the right with each subsequent case number, while that of successful cases appear to do so minimally to the left. In line with the trend of increasing skews, the spread of each distribution also increases with each subsequent case number, going from having a standard deviation of 00:17m:44s for first cases to 00:42m:05s for fourth cases, as shown in *Table 5*. *Table 5* also shows a stark difference between successful cases and all cases, as the former is much more consistent with their times, as demonstrated by their smaller standard deviations.

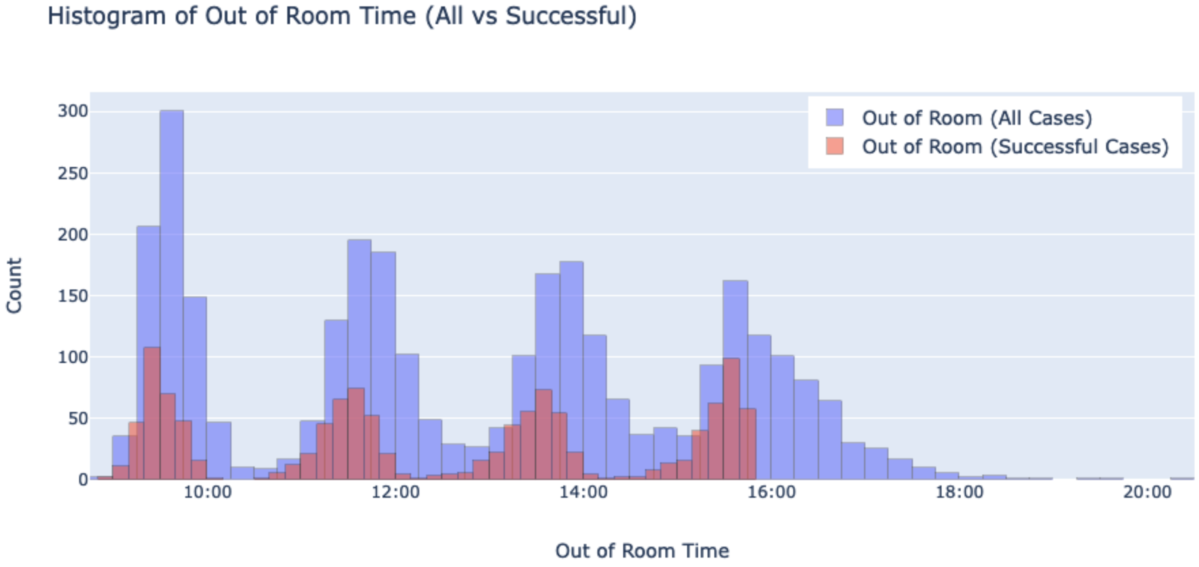

Figure 11: A histogram of out of room times showing all individual cases, and successful cases. The x-axis shows bins of times at which patients have been escorted out of the operation room, while the y-axis shows the number of cases that are in each bin.

Table 5: The standard deviations of successful cases and all cases.

	All Cases	Successful Cases
1st Case	00:17:44	00:12:07
2nd Case	00:26:14	00:17:01
3rd Case	00:31:26	00:18:56
4th Case	00:42:05	00:16:51*

*Reduced by a cut of the distribution due to the limit at 15:45

Individual successful days were isolated, and their out of room times were each graphed against their case number. *Figure 12* shows an example of 4 different days, all of which demonstrate the linear nature of out of room times for a specific day. This observed trend inspired our method of predicting 5th cases as described in the *Methodology*.

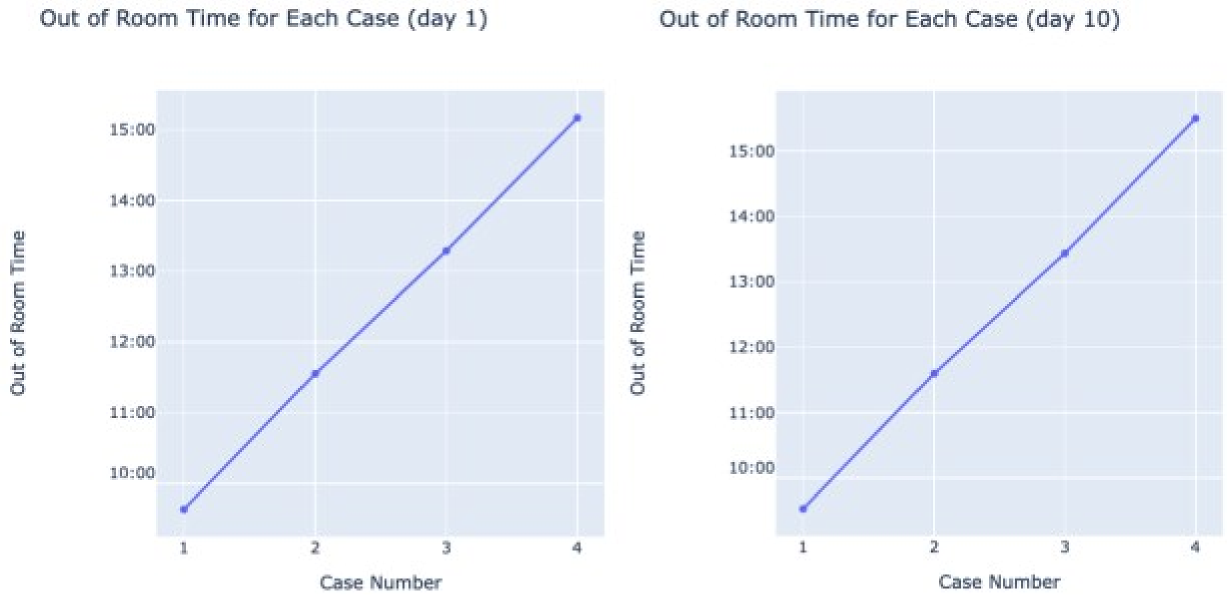

Figure 12: Random examples of successful days' out of room times with case numbers on *x* and out of room times on *y*.

2.7 Methodology

The data was first divided into successful and unsuccessful groups: the successful group contains all days where the fourth case was completed (as defined by its out of room time) at or before 15:45, while the unsuccessful group contained all days where the 4th case was completed after 15:45.

As previously mentioned, there is an average of 19 minutes and 30 seconds of spare time per successful day; to ensure that this spare time is used and that staff do not end their days later than needed, it was decided that 5th cases will only be added to successful days. This decision is further reinforced by the successful group's more consistent trends, which facilitates model training to yield more accurate results. Thus, the successful group is used for the prediction of 5th cases and their potential addition, while the unsuccessful group is used for the calculation of overtime-cost hours and the distribution of their hypothetical savings among all days.

To predict 5th case out of room times, the linear nature of each successful day's cases is leveraged (see *Figure 12*). All 301 successful days are isolated, along with their 4 cases. For each isolated day, a linear regression model is used to fit the out of room times with case number as the independent variable, and a 5th case prediction is generated from each one. Following the prediction for each day, a distribution of 5th case predictions is produced (shown in *Figure 13*). This distribution will be used to evaluate the potential of adding extra cases by using previous cost savings calculated from unsuccessful days. The use of linear regression is advantageous due to its interpretability, simplicity, and its ability to make predictions without ground truth data. Due to the nature of the problem, no 5th case ground truth data is available, limiting the scope of methods to choose from. Linear regression overcomes this problem by not requiring the desired input to be in the training set. Given the approach of isolating successful days, each day's model can be individually analyzed and adjusted, with its slope representing that day's average case duration. Further, linear regression accounts for the day's start time by accounting for the first case, and naturally produces variability in case durations without compromising overall accuracy by fitting to the existing variability within the dataset. Finally, this method allows for the prediction of further cases (ex. 6th, 7th, etc.) if needed by simply changing the input variable.

Other methods were also considered, but ultimately failed in comparison. For example, gradient boosted trees and random forest regressors could not directly predict 5th cases due to the lack of required 5th case ground truth labels. Instead, different approaches were attempted, such as using case step durations to predict success, which yielded an accuracy of 66.14% and an F-score of 0.65, but they were considered both unreliable and useless in the context of our work. Additionally, simply adding the average case duration to 4th case out of room times was also looked at for the prediction of 5th cases as this method is likely to give the most accurate estimation of the 5th case on any given day, but it fails in producing a representative distribution as it simply copies that of the 4th case (which is shown to change for each subsequent case), and yields no variation in case duration.

Calculations for overtime-cost hours saved (OCHS) were made using this equation:

$$(1) \qquad OCHS = 465.375 - 761x(1 - y)$$

Where x is the previously calculated average overtime-cost hours per unsuccessful day, y is the new success rate, 465.375 represents the current number of overtime-cost hours (based on the 39.55% success rate), and 761 is the total number of days in the dataset. Thus, a 100% success rate would lead to saving 465.375 overtime-cost hours. Given the lack of available information, this equation currently assumes that x does not change after the application of our previous AI model, as it is unclear how all unsuccessful cases would be affected. However, it is important to note the possibility that this assumption would result in an overestimation of time saved if use of the AI model increases x; thus, a recalculation of x on data post-AI model intervention would yield a more accurate value.

Once calculated, the OCHS are then divided in 3 ways: daily (761 days), bi-daily, and once a week (4-day work weeks), each producing a different 5th case success time benchmark. Once done, the predicted 5th cases are used to generate success rates for each success time and calculate the number of potential extra cases delivered at no extra cost.

2.8 Validation

Because there is no ground truth data, two methods of validation are employed. Both methods rely on Mean Absolute Error (MAE), which is described by the following equation:

$$(2) \quad MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Where n is the sample size, y is the actual value, and $\hat{y}$ is the predicted value. MAE is used because of its interpretability, as it provides the actual mean time difference between the generated values and the ground truth.

The first method is the prediction of 3rd and 4th case out of room times, so that MAEs can be generated from their existing ground truth data. To do this, the same procedure that is used to predict 5th cases is also used to predict 3rd and 4th, with the difference being that the lines are only fit to the first 2 and 3 cases of each successful day respectively. Once all the errors are calculated, histograms and 95% mean confidence intervals are produced for the MAEs to gain a deeper understanding of the model's performance. Through this method, we are leveraging existing ground truth within the data to produce MAEs that can be used to infer that of the prediction of 5th cases.

The second method is used to give an impression of how well the lines fit to the existing data. Each day's model has their MAE calculated using the points on the line and the actual 4 case out of room times. From there, another distribution and 95% mean confidence interval is generated for further insight into linear regression's performance on the dataset, as well as the 5th case predictions' errors themselves.

2.9 Results

All predictions were compiled and visualized as a distribution (*Figure 13*). The predictions have a mean time of 17:24:17 (95% CI = 17:21:46, 17:26:48) a median of 17:29:30, and a standard deviation of 22 minutes and 10 seconds. Of the 301 predictions, 256 of them (85.7%) fall below the 2-hour mark (17:45), while all 301 (100%) are predicted to end before 18:00, as the latest predicted time is 17:56:30.

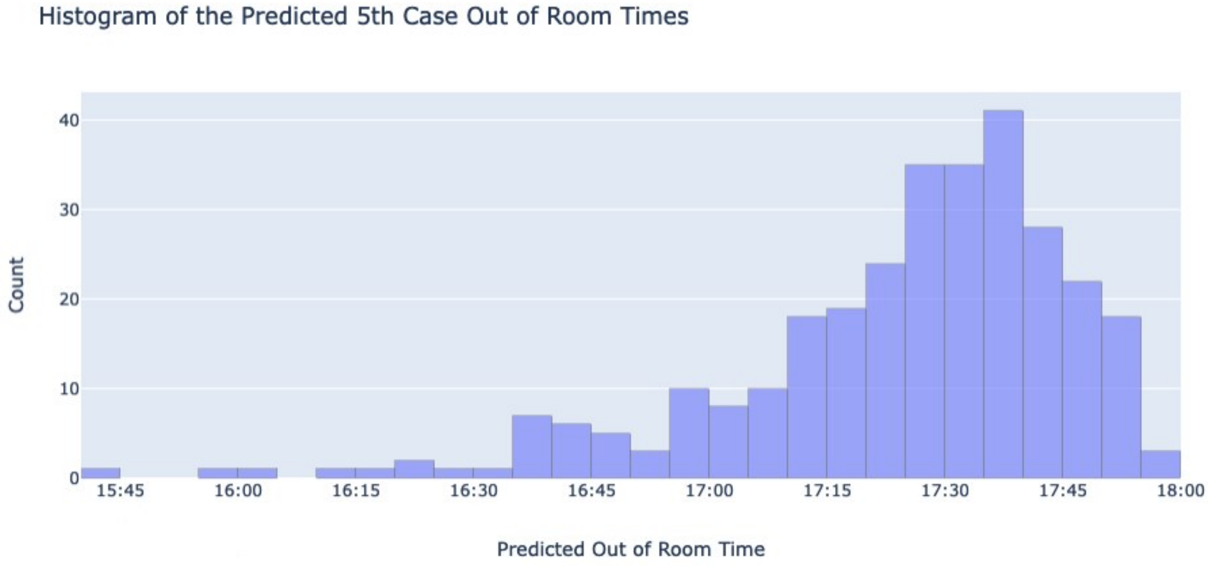

Figure 13: A histogram of all predicted 5th case out of room times. The x-axis represents different bins of predicted 5th case out of room times (time at which patients are escorted out of the operation room), while the y-axis shows the number of predicted cases that are in each bin.

After training 3rd and 4th case-predicting models, mean absolute error values of 13m:40s and 14m:13s minutes respectively were calculated. A distribution of every day's error for each model is shown in *Figure 14.* These distributions yield 95% mean confidence intervals of

00h:12m:28s, 00h:14m:50s and 00h:12m:53s, 00h:15m:31s for the 3rd and 4th case models respectively.

Similar outputs were produced for the second method; the mean of all daily MAEs was 4:45 minutes, with a 95% mean confidence interval of 00h:04m:25s, 00h:05m:05s and a standard deviation of 2:55 minutes. The histogram of all daily MAEs can be found at *Figure 15*.

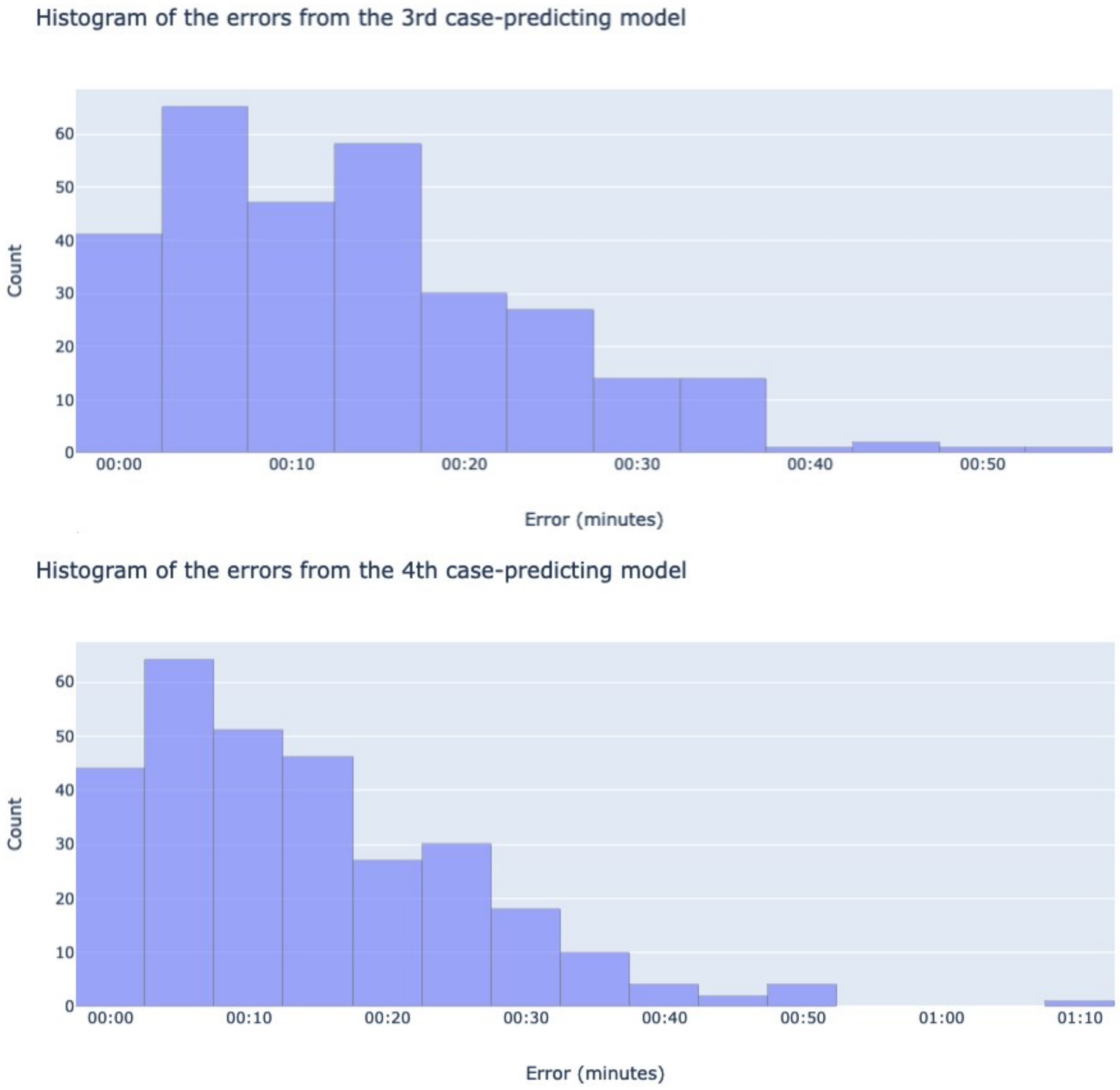

Figure 14: Histograms showing the distribution of the absolute values of each recorded error for the 3rd case-predicting model (top), and the 4th-case predicting model (bottom). The x-axes denote

bins of absolute error values in minutes, while the y-axes show the number of predictions in each bin.

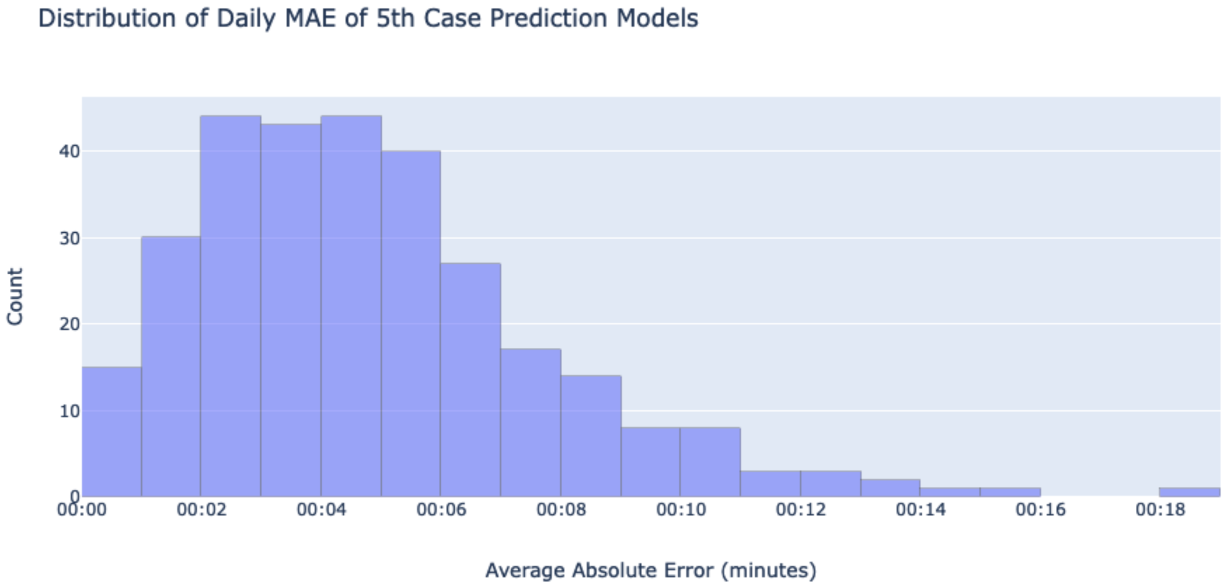

Figure 15: A histogram showing a distribution of the absolute values of each day's MAE. MAEs were calculated using the differences of each ground-truth case and their fitted lines. The x-axis shows bins of mean absolute errors for any given day's 5th case-predicting model, while the y-axis counts the number of days in each bin.

2.10 Predicting the Potential to Fit a 5th Case During Successful Surgery Days

The predictions were considered under two potential scenarios: 77% success rate, and 100% success rate. Using *Formula 1,* achieving a 77% success rate would yield hypothetical savings of 288h:17m:50s overtime-cost hours, which is approximately 38 hours and 26 minutes per year. Distributing these hours daily leads to 22m:44s extra minutes per 5th case day, which when added to the original end time of 15:45, would produce a new end time of 16h:07m:44s. Based on predictions, 5th cases would be completed at a 1.00% success rate for that time. This extra time is doubled when distributed bi-daily to 45:28 minutes per day, marking a surgery end time of 16:30:28 and more than doubling the 5th case success rate to 2.66%. Finally, given that 4-

joint days are only run 4 days a week, the extra time is once again doubled when pooling them for a weekly 5th case. Doing so yields 90:56 extra minutes per 5th case day, for a surgery end time of 17:15:56 and predicted success rate of 26.25%. However, because an end time of 18:00 (135 extra minute) has a predicted success rate of 100%, one week can be skipped to split its extra time among the following two weeks and lead to two days with a predicted 100% 5th case success rate every 3 weeks. Ultimately, this sums up to approximately 35 extra cases per year at no extra cost. A map of potential distributions at a 77% success rate is shown in *Figure 16*.

Under the situation where a 100% success rate is achieved, all 465h:22m:30s overtime-cost hours would be saved. With a daily split, this amounts to 36m:42s per 5th case day, an end time of 16h:21m:42s, and a predicted 5th case success rate of 1.99%. Distributed bi-daily, these values increase to 73m:21s, 16:58:24, and 12.6% respectively. When divided weekly, 146:48 extra minutes, adding to an end time of 18:11:48, are given per day, producing a predicted success rate of 100% with a minimum of 10 minutes to spare. These spared minutes can be pooled to contribute to another 4 cases per year, leading to a total of 56 potential cases per year (assuming the hospital runs all year long). A schematic showing these results is found at *Figure 17*.

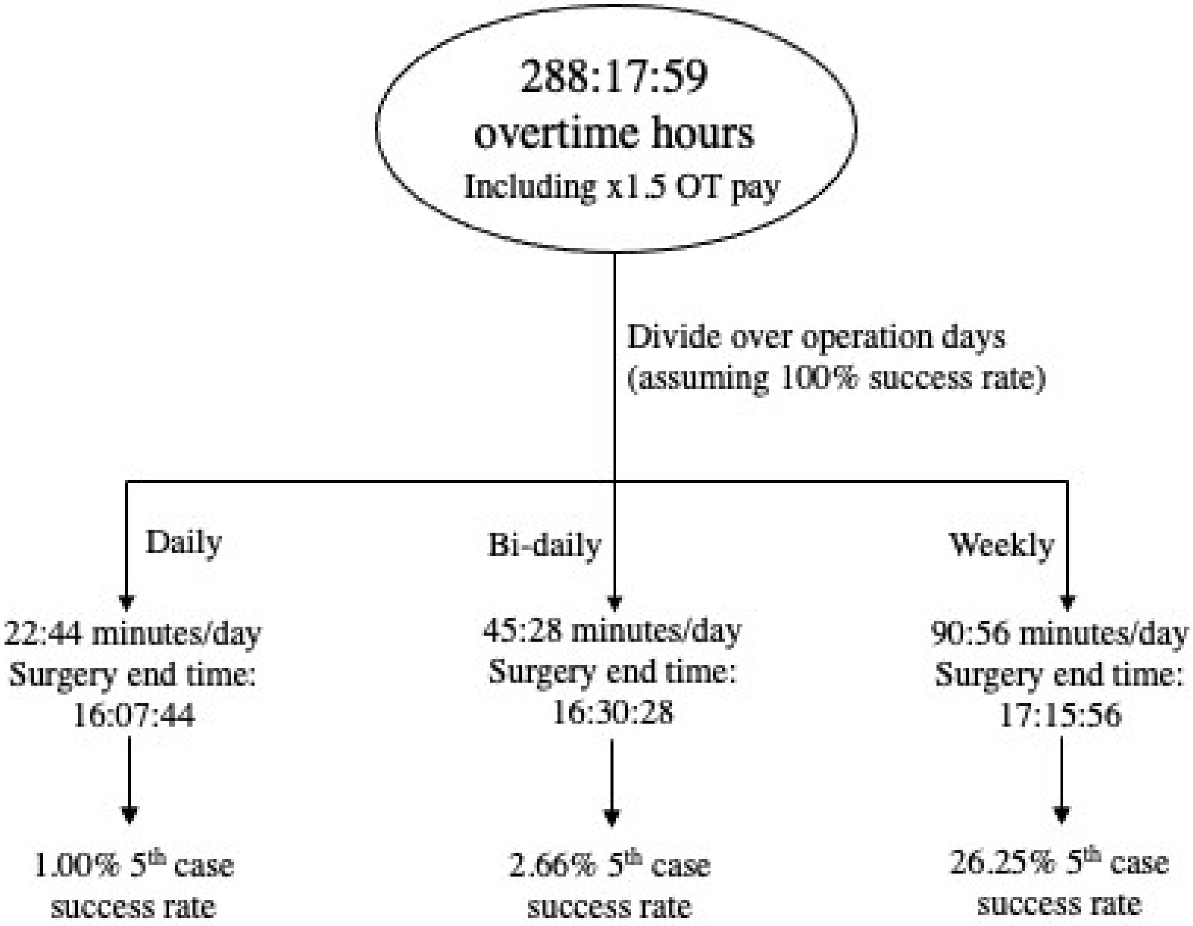

Figure 16: A schematic demonstrating the division of saved overtime-cost hours from performance at a 77% success rate. There is only a 1% chance of fitting a 5th case successfully each day, and up to 26.25% chance to add a 5th case per week.

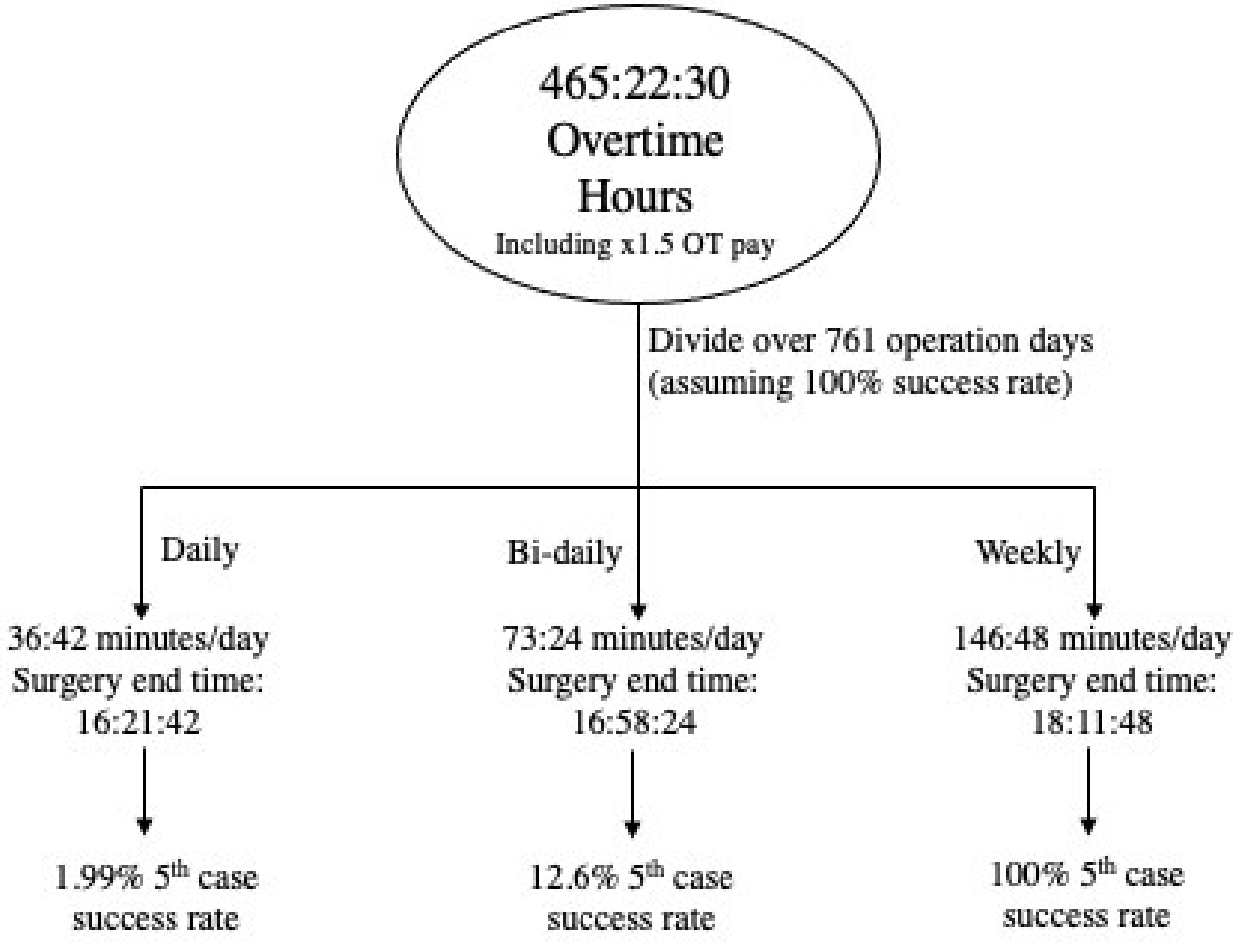

Figure 17: A schematic demonstrating the division of saved overtime-cost hours from performance at a 100% success rate.

2.11 Discussion

Considering poor 4-joint day success rates, our previous work sought the development of an AI model that provides benchmarks to achieve a certain success rate. Given our institutions' current wait list issues with hip and knee replacement surgeries, 5th cases were predicted to evaluate the potential of their addition using only overtime savings from an increase in success rate. This can lead not only to better staffing efficiency, but higher surgical throughput to help reduce the waiting list as well.

After completing 5th case out of room time predictions, a mean out of room time of 17:24:17 and a median of 17:29:30 were predicted. A negatively skewed distribution was expected due to the same trend with 4th case out of room times. The predictions' standard deviation of 22 minutes and 10 seconds also falls within expectation, as it increased relative to previous ground truth cases, as shown in *Table 5.* Despite the average successful case time of an hour and 59 minutes, not all predicted 5th cases (85.7%) fall below the 2-hour mark (17:45) while all 100% are predicted to end before 18:00, as the latest predicted time is 17:56:30. These findings highlight the presence of nuances in trying to find the optimal balance between time added and prevention of further overtime waste.

When applying the predictions to evaluate how cost-savings can be used to fund 5th cases, two contexts are considered: performance at a 77% success rate, our baseline rate that is deemed achievable and realistic by the clinicians (based on the model's benchmarks), and performance at a 100% success rate, which is the ideal, best-case scenario. In both cases, it seemed preferable to pool the hours at different intervals in order to maximize throughput while minimizing the risk of overtime costs.

At a 77% success rate, the time saved would lead to sub-3% success rates when divided daily or bi-daily. Although this would lead to much higher throughput, it would do so at the cost of many overtime hours, where salary is increased by a factor of 1.5. This case is also true when dividing the hours weekly, as 90 extra minutes leads to a 5th case success rate of only 26.25%. Intuitively, this gives the impression that extra time can be pooled further to guarantee one extra case per month with no extra cost; however, simply adding another 45 minutes is enough to guarantee success based on the predictions, something that can be done for two weeks by skipping one. In other words, when distributing hours to one day a week, skipping one week leads to a 100% 5th success rate in the following two. Overall, this means that approximately 35 extra cases per year at our institution can be funded solely from the savings accrued by increasing performance to a 77% success rate.

When performing optimally (100%), results were similar, as pooling the saved costs also drastically reduced 5th case overtime costs. Daily and bi-daily distribution of saved costs yielded

5th case success rates of 1.99% and 12.6% respectively, while weekly pooling of saved costs allowed for 100% success rate, with a minimum 10 minutes to spare. In total, savings can be optimized to project 56 extra cases per year, meaning that 56 cases worth of overtime-cost hours are currently being spent due to inefficient performance at our institution (39.55% success rate).

However, one limitation with our output is the inability to conclusively measure prediction accuracy due to the lack of ground truth 5th case data. Instead, existing data was leveraged to infer the models' accuracy. The first method of doing so, training models to predict 3rd and 4th cases, yielded mean absolute error values of 13m:40s and 14m:13s minutes respectively. Based on the histograms, most errors are smaller than the means (see *Figure 14*), with a few large outliers. This is deemed acceptable as these errors can represent variations in case durations that exist in the dataset, making a more representative distribution of predictions. The second method looked instead at how well linear regression fit to the existing data, yielding a mean absolute error value of 4m:45s. As with the previous method, the distribution of errors shows a positive skew, indicating that most of the errors are below the mean with a few large outliers. Overall, linear regression fit well to the trends of the dataset. However, as mentioned, the lack of any ground truth 5th case data makes this evaluation inferential, as a more direct evaluation cannot be made.

Another limitation is the uncertainty of how the data might change once the AI model [17] is implemented. Whether use of the model would work by improving the speed of all cases, reducing the number of slow cases, or simply streamline case durations so that they are more consistent is unknown, and could impact both the distribution of predictions as well as the calculation of saved cost-hours (see *Equation 1*). Fortunately, in terms of predictions, it is likely that the use of the model would shift the distribution to the left, potentially making the current evaluation a pessimistic one.

Despite these limitations, we propose a simple, effective, and reproducible method of calculating potential throughput gains with no extra cost as a result of improved performance efficiency. In our case, this improvement relies on the success of a benchmark-establishing AI model developed by members of our team. Furthermore, the gains are only attainable with the modification of staffing procedures so that longer days are had without spending overtime rates;

one example for this is to benefit from staff that show up late, and who can stay late, by having them stay longer for the fifth case. This work also opens many avenues of future research: reproduction of this work after implementation of the AI model may produce further refinements to cost-free throughput enhancement depending on how the model affects all cases, and whether it improves successful case durations as well. Research into how staffing can best be modified to account for extra cases could also offer another level of optimization, and a potential area of healthcare reform.

2.12 Conclusion

Due to the COVID-19 pandemic, the Canadian healthcare system was burdened with long hip and knee replacement wait lists and extra costs as a result of cancelled procedures. We aimed to leverage the savings that would be accrued from the use of our AI model to increase surgical throughput with no extra costs. To do this, linear regression models were used to predict 5th case out of room times that served as benchmarks to estimate success rates at different 5th case success times. Success times were determined by distributions of hypothetical overtime-cost savings that would be accrued using the AI model. Previously, our institution operated at a 39.55% success rate. Overall, it was found that increasing to a 77% rate can lead to approx. 35 extra cases per year funded solely by the savings acquired, while operating at a 100% success rate can lead to 56 additional cases per year. Future work can look at the optimization of staffing procedures to account for extra hours with no overtime pay, the effects of the AI model on all case durations, as well as optimal decision points for the addition of a 5th case on any given day.

Chapter 3

Conclusions

3.1 Summary

Hip and knee replacements are among Canada's most common inpatient procedures. Typically, they are performed to treat arthritis, and are very relieving to the patient in terms of pain and quality of life [3]. Because of the COVID-19 pandemic, cancellations of surgeries have created a backlog of patients on top of an already existing long wait list, and a financial burden on the healthcare system. This led to continuously growing wait times, something that is especially concerning due to a corresponding decrease in patient quality of life [4]. At The Ottawa Hospital General Campus, a 4-joint room system whereby 4 operations are performed within the 7:30-3:30 work period is in place to increase surgical throughput. However, this system working inefficiently, as they hold an average success rate of 39%, surpass priority 4 patient recommended wait times by 106% and 119% for hip and knee replacements respectively, and lose the hospital thousands in overtime costs per year [17], [18]. Furthermore, research shows that to overcome current waiting lists, surgeries must be performed at rates greater than those of before the pandemic. Thus, strategies to increase surgery throughput are needed to reduce waiting lists.

Aware of these issues, the federal government has contributed additional billions to the healthcare system since the pandemic. Despite this and the continuous annual increase in government spending, the issues remain at large. Overall, this indicates a potentially broken system itself, and the need for the reevaluation of existing assets. In accordance with this, the permission of for-profit clinics to perform hip and knee replacement surgeries (among other procedures) was introduced in Ontario as a potential solution, but this suggestion could do more harm than good through much higher costs, the draining of resources from the public to the private system, and the opening of a slippery slope towards further privatization. Instead, improvements to the current public system could provide a safer approach.

To address the issue of inefficiency, our team previously developed an AI model that proposes benchmark durations for each stage of the procedure for any given success rate (4 cases performed within the 8-hour work window). This allows clinicians to stay on pace within certain benchmarks and have smaller goals that could translate to greater success. Additionally, using strategies discussed and acquired from positive deviance seminars, the model can propose suggestions based on the current stage of the procedure if the team is behind relative to the benchmarks. Through the benchmarks established by this model, a 77% success rate was defined as the baseline due to the clinicians' agreement that its benchmarks are easily realistic and achievable.

With the use of this model, we aimed to evaluate the potential of increasing throughput using only cost savings accrued from an increase in the hospital's success rate. First, linear regression was used to predict 5th cases for every successful day, creating a distribution of predicted 5th cases. Then, saved overtime-cost hours were calculated for two scenarios: a 77% success rate (our baseline, and a 100% success rate (the optimum). After analyzing the distribution, it was found that at a 77% success rate, the overtime hours saved can be pooled to fund 2 extra procedures every 3 weeks, totaling to approx. 35 extra cases per year, while a 100% success rate can lead to an extra case every year, each with at least 10 minutes to spare, leading to a potential 56 extra cases per year with no extra charge.

Ultimately, this work completes a 4-part plan to improving hospital efficiency and throughout. The first part involved the selection of the best approach by comparing different types of models, leading to the selection of a time-monitoring model. The second part saw the development of this model through data analytics, leading to the establishment of benchmarks for achieving success. Following this, the third part sought ways to achieve these benchmarks through

Positive Deviance seminars, where industry professionals discussed what works for them, eventually incorporating their suggestions into the model. Finally, this work looked to apply this culmination of work to try to leverage its optimization towards more cases with no extra cost. A flowchart providing a general overview of this 4-part plan is shown in *Figure 18*.

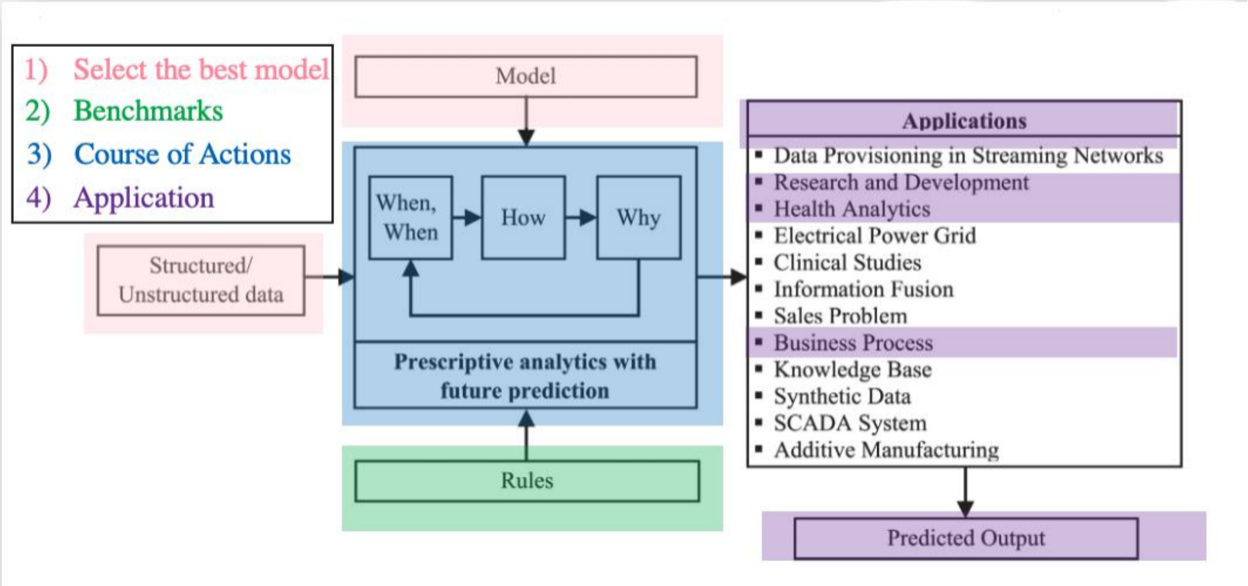

Figure 18: A flowchart providing an overview of the entire research process which involves 4 parts: 1) The comparison and selection of approaches; 2) The establishment of benchmarks for success; 3) Research into the means for achieving these benchmarks via Positive Deviance seminars; 4) Optimal application of the model to add extra cases with no extra cost (this paper). This chart was taken and adapted from [45].

3.2 Future Work

Our work provides insight into the addition of new cases and whether they can be funded by savings alone. However, optimal integration of these new cases is still uncertain, prompting future research to delve into this topic. For example, insight into incidence of late staff and whether they can be leveraged to adopt later cases can improve both cost efficiency and throughput. Furthermore, research into staffing strategies may provide another avenue of optimization that can benefit the entire healthcare system.

Future work can also look to revaluate the distribution of overtime-cost hours based on the impact of the AI model on cases. Whether the model reduces the duration of all cases, or simply reduces the number of longer cases could impact the number of cases that could be added. Finally, the application of the AI model will also help identify ways that the decision to add a 5th case on any given day can be made, as currently, the answer of when to decide to go ahead with a 5th case is still undecided. Research into the case by which this decision can be reliably made (for example after the second or third case), the benchmarks needed to help inform this decision, as well as proper staffing accommodations to reward extra work will maximize this work's success in its implementation. In general, the implementation of fifth cases opens new pathways to explore in terms of operating room efficiency and throughput.

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