Telemedicine Scheduling Optimization in Surgical Outpatient Clinics

Amy Lorincz, Experimental Surgery,
McGill University, Montreal

March 2022

A thesis submitted to McGill University in partial fulfillment of the requirements of the degree of Master of Science – Experimental Surgery

1 ABSTRACT

Background: The COVID-19 pandemic has imposed restrictions on in-person interactions creating a need for exploring alternative methods of healthcare delivery while maintaining high-quality treatment. In an initial study with Orthopaedic (Ortho) and Ear, Nose, and Throat (ENT) surgeons, it was found that 66% of consultations could be completed virtually. This presents the opportunity to reduce unnecessary hospital visits for patients. The objectives of this study were to develop a predictive model that will classify the suitability of patients for in-person versus telemedicine (TM) consultations and to develop an optimal scheduling template for TM consultations. Associated outcomes to be measured were the patient perception of the quality of TM consultations.

Methods: Data was collected from patients requiring surgical outpatient consultations in Ortho, ENT, and plastic surgery in Quebec. A machine learning model was developed where four machine learning classifiers were implemented to compare the accuracy of the classification. A discrete-event simulation model was developed and used to test the various template scenarios that were generated using lean engineering analysis to find the optimal template that minimizes wait time.

Results: A logistic regression model was found to predict a patient's suitability for TM with 91% accuracy. It was found that 41% of all patients and 57% of follow up patients were suitable for TM consultations. Lean engineering techniques were used to estimate the optimal number of patients that should be seen in TM clinics for each surgeon where patients would wait a maximum of 10 minutes for their appointment. Patient perception of TM being the same or better quality as an in-person appointment increased by 23% after completing a TM consultation.

Conclusion: Statistical modelling techniques and lean engineering have high potential to eliminate non-value-added activities in the healthcare system. Using this model, patients can avoid unnecessary visits to hospitals and surgeons can increase the amount of suitable TM visits offering an alternative to in person appointments.

2 LIST OF ABBREVIATIONS

C19	COVID-19
CRC	Clinical Research Coordinator
DB	Double Booking
ED	Education
ENT	Ear, Nose and Throat
Ortho	Orthopaedic
PHYS	Physical Limitations
SDC	Socio-Demographic Characteristics
SVM	Support Vector Machine
TM	Telemedicine

3 ACKNOWLEDGEMENTS

I cannot begin to express my gratitude to my supervisor, Dr. Gregory Berry, for the stellar research support, trust in taking me on as a master's student, the constant encouragement in applying to grants and opportunities to continue research activities, all while being a joy to work with.

I am grateful to my co-supervisor Dr. Suzanne Morin for her guidance, Dr. Elie Girsowicz for being my Research Advisory Committee Chair and to Dr. Adam Hart and Dr. Rolando Del Maestro for being committee members and providing valuable feedback. Thanks to the NeuroSim Lab for the opportunity to present my research and providing expert AI insight. Thanks to Dr. José Ramirez Garcia Luna for providing a technical review of the research and Nicole Pal for providing a review of the thesis.

Thank you to TD Bank for awarding me a $350,000 grant to conduct this research and contribute to a higher goal of connecting vulnerable populations with telehealth care. Thank you to the McGill University Health Centre Foundation for helping me apply and secure this grant.

I am grateful to the Department of Experimental Surgery, notably Dr. Fackson Mwale and Dr. Jake Barralet who provided an opportunity for me to participate in a prestigious program while furthering my educational and professional development. Thanks to Mary Amedeo who helped with reviewing the ethics application, Elias Jabbour for his dedication and expertise in conducting research activities, and preliminary analysis of results. Thank you to the admin team Angie Vernie and Maude Carbonneau who called many patients and adjusted their normal work routine to make this research happen.

Finally, this research would not have been possible without the participation of the patients and surgeons from Orthopaedic, Ear, Nose, and Throat, and Plastic surgery who graciously volunteered their time to collect and label data from their patients.

4 TABLE OF CONTENTS

5 INTRODUCTION

The Canadian healthcare system faces challenges of providing timely and convenient access to healthcare, which directly relate to patient satisfaction (Bleustein et al., 2014). In recent years, the COVID-19 (C19) pandemic has limited in-person interactions and presented an additional challenge: safety for patients and physicians. Despite the challenges it brings, the C19 crisis has provided an opportunity to increase the use of telemedicine (TM) and provide a new model of clinical work in the process. Leveraging TM technology and developing personalized scheduling templates in clinics can provide timely, safe, and convenient access to healthcare (Sinsky et al., 2021). There is currently no published work on creating a systematic model leveraging machine learning to classify patients based on their suitability for in-person versus TM consultations. Patients who are suitable to receive care virtually have the potential to save unnecessary hospital visits and thus reduce their risk of contracting the C19 virus. Going beyond the context of the pandemic, TM has the potential to be a long-term viable option for surgical outpatient clinic scheduling. Healthcare resources and improved workflow are associated benefits in adopting a hybrid telemedicine and in-person clinical visit model (Lupton & Maslen, 2017).

5.1 TELEMEDICINE APPLICATIONS IN SURGICAL OUTPATIENT CLINICS

There is a need for convenient and safe access to healthcare; the pandemic has triggered a change in how surgical outpatient clinics operate. Clinics must adapt from having a high number of patients in close proximity, which poses a risk of spreading the virus. Additionally, the C19 pandemic has imposed substantial pressure on hospital resources (Boehm et al., 2020), giving surgical clinics an opportunity to better leverage TM technology. TM uses telecommunication technology such as a phone or video conference platform (e.g., Skype, Zoom, Teams) where remote diagnosis and treatment of patients can be performed without an in-person physical exam. This is compared to telehealth, which refers to broader scope of remote health care services outside of clinical expertise.

TM is predicted to be a viable solution in healthcare delivery where 96% of patients consider TM as good or better than in-person consultations (Buvik et al., 2016). Additionally, delivering care to patients with foot wounds via telehealth has been proven to statistically decrease the risk of amputation compared to conventional care (Chen et al., 2020). In a Urology study, approximately 60% of patients were identified as suitable for TM care based on the judgment of a panel of physicians considering their risk from C19 and willingness to participate in a TM consultation (Boehm et al., 2020).

There are limitations to providing virtual care. TM cannot completely replace in-person consultations. Patients must be classified by their suitability in benefiting from an in-person versus TM consultation. Criteria that influence the need for in-person consultations such as language barriers, availability of technology, post-surgical procedures, highly complex problems, and the expectancy of advanced physical examinations (Hammersley et al., 2019) can be used as variables in classification. Expected diagnoses can aid in predicting a patient's clinical trajectory (e.g., surgery needed, tests required, pharmaceuticals prescribed) and can provide insights into their suitability for TM. The surgical specialties that were focused on were Orthopaedic (Ortho), Ear, Nose, and Throat (ENT), and plastic surgery based on their need for improved telemedicine processes within their clinics.

Based on an initial study conducted in May-August 2020, it was found that 67% of patients were suitable for TM consultations where the breakdown can be seen in Table 1. The results were acquired through surveying Ortho and ENT surgeons on what the next steps were for the patient (e.g., in person follow-up, problem solved, TM follow-up, book surgery). If a patient required a TM follow-up or their problem was solved, this meant they were suitable for a TM consultation.

Appointment next steps	Number of patients
In person follow up	**51**
PRN/Problem solved	**28**
TM follow up	**67**
Surgery waitlist	**9**

Table 1: Appointment next steps for 155 Ortho and ENT patients (Lorincz et al, 2020)

Additionally, the outcome of the TM consultation (e.g., test required, prescription required, consult another physician) was recorded as seen in Figure 1 to gain further insight into why patients would not be suitable for a TM consultation.

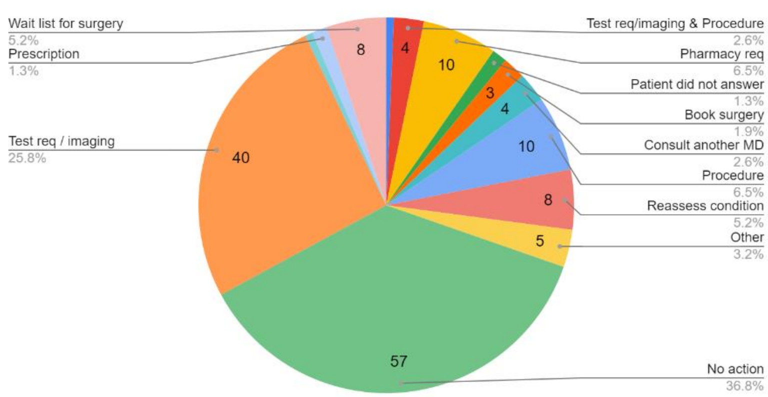


Figure 1: TM outcomes for 155 Ortho and ENT patients (Lorincz et al, 2020)

5.2 Machine learning applications in healthcare for classification problems

Statistical techniques such as machine learning algorithms in healthcare can be used to identify significant features that influence the outcome of a process from data. These insights can be useful for improving clinical processes. In the context of determining the suitability of a patient for TM or in-person consultations, the models can predict this outcome by classifying the patient as suitable or not suitable for TM. Machine learning algorithms use patient variables such as age, gender, comorbidities, etc. as inputs to an algorithm which can predict outputs such as clinical activities, diagnoses, or treatment plans (Shameer et al., 2016). Machine learning classifiers such as Support Vector Machine (SVM), Naïve Bays, and Decision Tree are popular in healthcare for their high accuracy and ability to identify significant features in the data. These machine learning classifiers can be used to build a classification model which will classify patients as being suitable for TM or in-person consultations based on variables that are used as inputs in the model.

In similar healthcare classification research, Sisodia et al., developed a machine learning model for early prediction of diabetes. The model was able to predict with 76% accuracy if patients were at risk for developing diabetes using a Naïve Bayes algorithm classifier (Sisodia et al., 2018). Additionally, a study conducted by Deepika et al., revealed that the accuracy in predicting the risk of patients developing heart disease was 96% when using a SVM classifier and the accuracy in predicting the risk of patients developing diabetes was 74% using a Naïve Bayes classifier (Deepika et al., 2016). Using machine learning models to classify patients as suitable or not suitable for TM consultations can reduce the need for a resource to review patient data to make the classification and thus contribute to alleviating the burden on limited healthcare resources.

5.3 Lean engineering and discrete-event simulation applications in reducing wait times

The premise of lean engineering is to eliminate waste in a system while providing more value to the customer (Sundar et al., 2014). Lean in healthcare is focused around improving the performance of quality in systems. Lean applications in healthcare include improving operating room efficiency, decreasing wait times, increasing patient satisfaction, and improving hospitalization capacity (D'Andreamatteo et al., 2015). Despite Lean Engineering having roots in manufacturing that arose at an automotive plant to improve efficiency of production, there are parallels between manufacturing and the operations of a surgical outpatient clinic. In lean manufacturing, Takt time is a term used to describe the required product assembly duration that is needed to match the demand of a manufacturing plant. Compared to a clinic, the demand is dictated by the surgeon's availability to see patients during the duration of a clinic, and the time it takes to treat the patient would be compared to the assembly duration. The metric of Takt time is helpful in determining the optimal number of patients that can be seen at a clinic based on a specific surgeon's treatment time.

Discrete-event simulation (DES) modeling is used to model real world systems where the process can be decomposed into a set of logically separate processes that progress through time autonomously (Barrett et al., 2008). The statistical paradigm upon which these models are based, is queuing theory which models a Poisson process. DES is a low-cost way to compare and test various solutions without disrupting the flow of in-person processes and reduce the downtime associated with testing these solutions. DES applications are largely related to scheduling and time-specific variables such as decreasing the time to delivering antibiotics to children with cancer presenting fevers in emergency departments (Barrett et al., 2008).

Long wait times in the Orthopaedic Outpatient Clinic at the Montreal General Hospital prompted an initial study supervised by Dr. Gregory Berry leading the development of a scheduling model by a team of Concordia University Engineering students. Personalized templates were optimized for surgeons based on their average consultation time and consultation time for each appointment type (i.e., follow-up, new patient, post operative). A DES model was developed to represent the current state of the clinic where process distributions were modelled. Alternate scheduling templates were developed using lean engineering techniques to balance the idle time of surgeons and waiting time of patients. Scheduling templates were tested in the model and the optimal template was implemented where average wait time (time spent waiting in the waiting room and exam room to receive care) was reduced by 65% from 55 minutes to 19 minutes and average time spent at the hospital (total time including treatment, waiting and x-ray time) was reduced by 46% from 105 minutes to 57 minutes (Lorincz et al., 2019).

Long wait times are common in surgical outpatient clinics and can pose a risk to patient safety. In a study conducted by Hashemi-Sadraei et. al, it was found that the delays in patients receiving chemotherapy infusion are linked to patients receiving suboptimal care, which eventually leads to increased costs and decreased patient satisfaction (Hashemi-Sadraei et al., 2021). DES can be an effective solution to reducing wait time in the hospital system.

5.4 Research Questions, Objectives, and Hypotheses

5.4.1 Research Questions

This research explores if the combination of utilizing predictive and simulation modelling techniques improve planning of schedules in surgical outpatient clinics. Specific questions that will be explored throughout this research include:

1. Can a machine learning model accurately predict if a patient should be seen via TM or in-person so that unnecessary hospital visits can be reduced?
2. Will the development of optimized scheduling templates have the potential to improve clinical workflow?

Associated qualitative outcomes assessed include patient perception of TM care in addition to the specific research questions.

5.4.2 Objectives

The objective of this research is to assess the benefits of leveraging predictive and simulation modelling techniques to provide greater insight into surgical outpatient capacity planning. To address the objective and research questions, two experimental aims are of focus:

1. Classify the suitability of patients for TM or in-person
2. Develop optimized scheduling models based on surgical speciality

5.4.3 Hypotheses

As seen in predictive machine learning research literature with similar data sets and binary output classifications, it is hypothesized that the model can predict if a patient should be seen in person or via TM with at least 85% accuracy.

Based on past research conducted, lean engineering and DES modelling techniques were employed to develop scheduling templates. Optimal scheduling templates reduced idle time for clinicians and decreased wait time for patients. It is hypothesized that by optimizing scheduling templates, the simulation model will project that patient will wait no longer than 15 minutes for their appointment.

Associated outcomes assessed include patient and clinician satisfaction where it was posited that satisfaction will be increased in both groups. By adapting a questionnaire developed by Buvik et al., results from patient's experience with a TM consultation before and after the consultation can be compared with results that have been published in this study.

The knowledge generated from this research is a deeper understanding of how TM technology can be leveraged, and which factors influence the suitability of patients for TM consultations to improve the scheduling workflow and satisfaction among patients and clinicians. Clinic scheduling can be optimized and scheduled in a way that reduces wait time and increases satisfaction among stakeholders. Classification of patients based on their suitability for in-person versus TM consultations using statistical models have not been fully investigated and presents the opportunity to develop a framework for classification that can be adopted across surgical specialties and healthcare practices. This study aims to be inclusive of patients in all socio-economic backgrounds to ensure a fair investigation of the needs of the Montreal, Quebec population.

6 MATERIAL AND METHODS

6.1 STUDY PROCEDURES

The study involved the participation of surgeons and their patients to create the data set that was used to build the statistical models. An ethics application was completed and submitted in December 2020 where it was reviewed and approved by the McGill University Health Centre Research Ethics Board in January 2021. Informed consent was obtained through a waiver of consent that was provided to patients and surgeons before they completed questionnaires outlining how their data will be used and how long it will be stored.

Questionnaires were developed for both patients and surgeons. Pre-consultation questionnaires were completed by patients to learn more about their attitude towards TM, their medical history, and tech savviness to assess their suitability for TM. The post-consultation questionnaire assessed the patient's attitude toward TM and their satisfaction level with receiving virtual care. The questionnaires have been adapted from relevant questions from the Canadian Longitudinal Study on Aging (National Coordinating Centre, 2011). A breakdown of the rationale behind asking each question can be found in Appendix 2 where three sections were covered in capturing information from patients including: background information, TM insight, and medical history. Patients had the option to choose between an online or phone questionnaire in English or French facilitated by a clinical research coordinator to ensure the study was inclusive of patients from different socioeconomic backgrounds. REDCap was the questionnaire instrument used to model the questionnaire and collect and store the data from patients. The complete questionnaire can be found in Appendix 3.

For surgeons, a TM questionnaire was developed where they completed a record for each patient. The questionnaire captured a pre-assessment of complexity (low, medium, high) estimated by the surgeon, the outcome of the TM consultation, and the next steps for the patient. The surgeon was asked to rate the quality of the consultation and validate if the consultation was sufficient via TM. The complete questionnaire can be found in Appendix 5. The durations of the consultation as well as pre- and post-consultation notes were automatically recorded by a HIPAA and PIPEDA compliant Google Meet Enterprise platform.

6.1.1 Sample size of data

Patient data was collected from four surgeons within Ortho, Plastic, and ENT specialties. Based on previous work, approximately 30 records of patient-encounter data were collected which was adequate to develop an initial simulation model to model distributions of treatment service times, appointment types, external process times (e.g., x-ray process, hospital card renewal,), tardiness of patients, and no-show rates (Lorincz et al., 2019).

The sample size that was used in this data set was approximately 250 data points. From sample size calculation research for classification models conducted with a balanced design and a low odds ratio, the equation n = 100 + 30i where “i” is the number of independent variables and “n” is the number of data points was used to estimate a data set (Hsieh et al., 1998). Using five independent variables in the model and by combining the data from four surgeons, approximately 250 data points provide an adequate data set to train a classification model. The data was structured since it was recorded through questionnaires with closed-answer questions.

6.1.2 Study Participants and study setting

The study required approximately 50 patients from each surgeon in Orthopaedic, Plastic, and ENT surgical specialties. All surgeons were part of the McGill University Health Centre, and their clinics were located at the Royal Victoria or the Montreal General Hospitals. Inclusion and exclusion criteria of patients were defined based on the advisement of clinicians and research conducted in a similar study (Buvik et al, 2016).

Inclusion criteria: all patients should be above the age of 18 years old and under the age of 65 years old and must be able to provide informed consent.

Exclusion criteria: in-hospital patients, patients who do not speak French or English, patients who are unable to give informed consent (e.g., Dementia, intellectual disabilities, etc.), patients who are above the age of 65 years old and under the age of 18 years old, patients with no fixed address, prisoners, and patients who are critically ill.

6.1.3 Recruitment strategy

To recruit patients for the study, there was a six-step process that was followed to acquire each patient record as seen in Figure 2. First, participating surgeons identified patients for the study based on the inclusion criteria. Either a phone call or letter was sent to the patient to introduce the study and gauge the patient's interest as required by the Research Ethics Board. If a patient expressed interest, a clinical research coordinator contacted the patient where they explained the study in detail and obtained consent where a recruitment script can be found in Appendix 1.

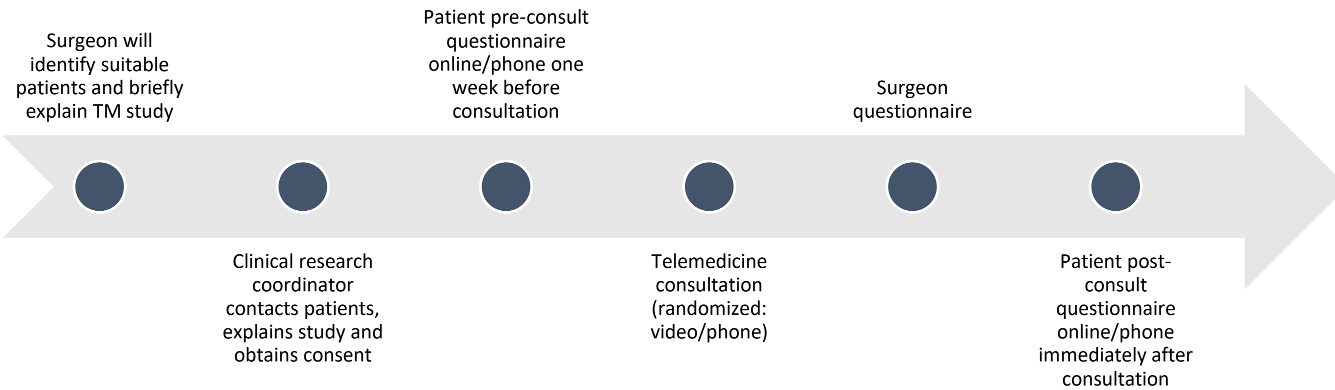


Figure 2: Data collection flow to obtain each data record

Next, a pre-consultation questionnaire was conducted by phone or online one week before the consultation to capture the relevent data. Before the consultation, the patient would be sent detailed instructions on how to join the call and get set up for the TM consultation. Instructions that can be found in Appendix 6 were developed and adapted from the Ministry of Health Quebec to ensure a seamless log-on process (Télésanté Quebec, 2021). The consultation would occur where a patient was randomly assigned to a video or a phone consultation with their surgeon. After the consultation was complete, the surgeon completed a questionnaire online for each patient. Finally, a post-consultation questionnaire was sent to the patient to evaluate their satisfaction with the TM consultation format.

6.2 Classifying suitability of patients for TM

To optimize scheduling processes, there is a need for a binary classification model to predict if a patient is suitable or not for TM. To determine the significant variables that influence the prediction of if a patient is suitable for TM or not, a machine learning model was used. The machine learning model was developed using Python and utilized the Scikit-learn library. Patients who possess medical conditions such as Type 2 diabetes, cancer, heart disease, compromised immune systems, etc. are at a higher risk of developing a severe reaction to the C19 illness (National Center for Immunization and Respiratory Diseases, 2020). These patients would benefit from TM consultations to reduce their risk of contracting the C19 virus from a hospital visit. Based on a preliminary study of TM outcomes, it is hypothesized that complex cases require advanced in-person physical examinations and tests such as x-rays or ear exams that must be completed in-person.

Surgeons recorded what the next steps were for the consultation, therefore patients who participated in the study were labelled as suitable or not suitable for a TM appointment. Since the data was labelled by surgeons, a supervised learning model was used. Supervised learning models use algorithms that are trained through learning from examples of various observations that are related to a class. The model will be trained using labels that classify the patients as being suitable or not suitable for TM appointments. If a TM appointment is completed without needing an immediate in-person follow-up consultation, then the patient was deemed as suitable for the TM appointment. Based on past research, it was expected that approximately 60% of surgical patients will be suitable for TM based on outcomes.

Machine learning algorithms were used to assign optimal weights depending on the significance of variables in the model. Variables that will be assessed can be seen in Table 2. The detailed description of each measured variable can be found in Appendix 3.

Variable	Description of measurement	Variable type
Consultation preference	English/French/other	Categorical
Patient type	Follow-up, new patient	Categorical
Level of education	Elementary school, high school, university	Categorical
Occupation	Full-time, part-time, retired, etc.	Categorical
Hearing or seeing impairments	Yes/No	Categorical
High risk patient for COVID-19	Yes/No	Categorical
Comorbidities	High blood pressure, diabetes, lung disease, etc.	Categorical
Access to internet	Yes/no	Categorical
Age	Numerical value	Nominal
Surgical specialty	ENT, Ortho, Plastic	Categorical
Appointment outcome	Referral, prescription, problem solved, etc.	Categorical

Table 2: Variable attributes of patients used in classifying the suitability for TM consults

Four machine learning classifiers were chosen based on their success in healthcare classification applications. The accuracy of the classifiers was compared where the output is based on comparing the test set to the results that have been obtained through the surgeon's labelled outcomes and next steps.

A logistic regression classifier was used since its dependent variable is a binary output classification which answers the questions of if a patient is suitable for a TM consultation or not. The inputs will be used as a set of independent variables to determine how they affect the dependent variable. The Naïve Bayes classifier was used as it is widely used in healthcare classification applications, and it requires a small amount of training data which was beneficial to this study. An SVM classifier was used for its applications in healthcare classification models and potential for high accuracy. The decision tree classifier was used since it allows for simplicity in its explanations and as well for its applications in healthcare classification models. These models are all directly interpretable as the weights that are assigned to each variable through the optimization process depict the influence they have on the classification (Vapnik, 1998).

Bias may result when training a machine learning model. This is due to certain demographic aspects such as activity level, age, and gender, producing the biases. To avoid these biases, the aspects will be included as features in the model which will account for them (Vapnik, 1998).

6.2.1 Preprocessing of data

All continuous variables listed in Table 2 were normalized using z-score normalization using Python. The normalization transformed the mean of continuous variables to a value of zero and mapped the rest of the values to be centered about the mean. It assigned positive and negative z-scores for variable values above and below the mean, respectively (Vapnik, 1998).

6.2.2 Data analysis and validation of the model

The performance of all algorithm classifiers is compared by evaluating their accuracy and precision-recall scores to determine which model performs best in classifying patients as suitable or not for a TM consult compared to the classification made by the surgeon. The classifications made by the surgeon form the ground truth labels for the data set. To train the model, a random sample of 80% of the total data was used and the remaining 20% was used to validate the algorithm. This randomization is a function of the Scikit-learn library in Python.

When the number of variables used as inputs increases, the risk of the model overfitting the data increases. To ensure that the model does not infer a relationship that does not exist through excessive optimization, an F1 score was used to evaluate the performance of the classifiers (Vapnik, 1998). The F1 score provides an accurate estimate of performance considering the risk of overfitting and can be used with smaller data sets (Brownlee, 2019). Additionally, since the data set procured is imbalanced, meaning that the target class (suitable for TM) has an uneven distribution of observations, an F1 score can be an effective way to ensure that the classifier was not biased towards the prediction (Vapnik, 1998).

The following formulas were used to model the performance of the classifiers. Precision is the ratio of correctly predicted positive observations compared to the total predicted positive observations (Vapnik, 1998).

$$Precision = \frac{True\ positives}{True\ positives + False\ positives}$$

Recall, also known as the sensitivity, is the ratio of correctly predicted positive observations compared to all observations within the class (Vapnik, 1998).

$$Recall = \frac{True\ positives}{True\ positives + False\ negatives}$$

The F1 score is a weighted average of precision and recall. This score helps in predicting the levels of false negative and false positives in the output. A higher F1 score is favourable meaning that the risk of getting a false negative and positive as an output is minimized (Vapnik, 1998).

$$F1\ Score = \left(\frac{recall^{-1} + precision^{-1}}{2}\right)^{-1}$$

6.3 Developing an optimized scheduling model

Building on previous work, TM scheduling templates will be designed using a lean strategy. To design the templates, the optimal number of patients will be determined based on the surgeon's average service time duration. The templates will be tested in a discrete-event simulation (DES) model to determine the optimal scheduling template that minimizes patient wait time and idle time of clinician. Wait times will be tracked to ensure that patients do not wait more than 15 minutes for their scheduled consultation. To build the model that represents the current state of the clinic, the data that was collected will be modelled in the best fit distribution. The model was validated to ensure that it was an accurate representation of the system. Various templates were then tested in the model so that changes in certain variables such as wait time can be observed. The optimal template was then validated statistically using a 95% confidence interval test. After the data collection and pre-processing activities were completed, the process of developing an optimized scheduling model was used and can be seen below in Figure 3.

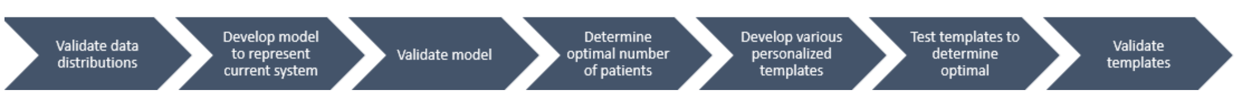


Figure 3: Flow of developing optimal scheduling templates

6.3.1 Data collection and pre-processing

Consultation time data was recorded for three steps of a TM consultation: medical history review (pre-consult notes), the consultation itself, and concluding notes and actions (post-consult notes). These durations were recorded by the Google Meet platform used to facilitate TM consultations and were used to build the structure of the scheduling template.

6.3.2 Validating data distributions

To create a model that accurately represents the current model of a clinic, it is imperative that accurate distributions are chosen. For each service time distribution, Input Analyzer software, which is an add-on feature of Arena software, was used to find the best fit distribution. In circumstances where data was limited, a Triangular distribution was used because it is the best representation of the sample in healthcare problems (Law, 2016).

A Goodness of Fit test was used to validate if a distribution accurately represents a data set. A Chi Square test is used to validate the fit of a distribution for discrete distributions such as Normal, Triangular, Binomial, or Poisson (Vapnik, 1998). For continuous distributions such as Exponential or Weibull, a Kolmogorov-Smirnov Goodness of Fit test was adequate in testing if a sample of data came from a population with a specific distribution (Vapnik, 1998).

6.3.3 Developing a model to represent current system

Arena, a DES software, was used to create the model of the current system. A model was developed for each surgeon to capture the uniqueness of the specialties and scheduling templates. The models were developed based on the understanding of the flow of surgical outpatient clinics. DES has the ability to create entities that arrive to the system, which would represent patients. Entities move throughout the system from the time they are waiting for their appointment to begin until the time their consultation ends. The system modeled the average lateness of the surgeon and the average number of patients who do not show up to their appointments. Throughout this process, the system recorded the average time the patient is waiting for their appointment and how long they spent in the system, which is the waiting time plus the consultation time.

6.3.4 Validating the model to ensure it represents the current system

To validate the simulated model, the performance of the simulated model with 10 replications was compared to the actual system, which is represented by the data collected. The metrics used to evaluate the system were:

1. The average total time spent in the system (from the time the patient's appointment is scheduled to begin until their consultation with the surgeon is completed)
2. The average time spent waiting to meet with the surgeon

These two metrics were compared against the actual system values using a 95% confidence interval t- test to verify if the actual values of the two metrics recorded were the similar to the simulated results. If the average of the time spent in the system and the waiting time fall within the confidence intervals, it can be validated that the model developed is an accurate representation of the actual system.

6.3.5 Determining the optimal number of patients

To develop the various templates, the optimal number of patients to schedule at a clinic were determined using the principal of Takt Time, which was used to determine the flow of patients through a TM clinic. It was used to determine the demand, which would be the optimal number of patients that should be seen during that clinic day to minimize the waiting time of patients and idle time of surgeons.

The first step to finding the optimal number of patients to schedule is to determine the Average Weighted Cycle Time (AWCT) which is the average time it takes for a surgeon to complete an appointment including the pre and post consultation notes. This is because the surgeon is utilized during all the three steps of the TM encounter.

$$AWCT = (Average\ Cycle\ Time\ of\ RTFU) + (Average\ Cycle\ Time\ of\ NPC)$$

Next, the Takt Time is calculated where it is the AWCT divided by the value of Takt. The Takt Value is the ratio between the consultation time and the total time the surgeon is utilized which includes the time it takes the surgeon to complete notes.

$$Takt\ Time = \frac{AWCT}{Takt\ Value}$$

The total demand of the clinic is then calculated based on the time that the surgeon has available on a given clinic day.

$$Total\ demand = \frac{Total\ time\ available}{Takt\ Time}$$

Finally, the total demand with no shows is the number of patients that can be scheduled during the clinic. It includes the assumption that some patients will not show up for their scheduled appointment. The percentage of no-shows is obtained from the data collected.

$$Total\ demand\ with\ no\ shows = (Total\ demand\ \times \%\ of\ no\ shows) + Total\ demand$$

6.3.6 Developing various personalized templates to determine the optimal

The validated DES model developed can test various template scenarios with generated results to compare the output of the metrics used to evaluate the best template. To create alternative template scenarios, three sequence strategies were taken into consideration based on their success in past research conducted by Lorincz et al, 2019:

1. **The random strategy**: sequence alternates randomly between patient types where the sequence is randomly assigned using Excel
2. **The variance strategy**: patient types that are known to have a low variance in consultation time are scheduled at the beginning of the clinic and the patient type with the higher variance is scheduled at the end
3. **The hybrid (ratio) strategy**: the ratio of follow-up to new patient types, e.g., if the clinic is comprised of 75% follow-up and 25% new patients, the schedule would alternate between three follow-up patients and one new patient successively

The different scenarios tested in the simulation model combine one of the three strategies (random, variance, hybrid) if there are at least two types of patients being scheduled. If the patient types scheduled were homogenous (only new patients or only follow up patients) the strategies above would not apply. In this case, variations with changing the duration of appointments based on the cycle time or double-booking strategies could be used. Double-booking (DB) is when two patients are scheduled at the same time. DB is effective in scheduling when appointment durations are low in variability. DB can also be helpful to account for patients that do not show up to their appointment.

6.3.7 Testing and Validation of the templates

After various templates have been analyzed, a statistical validity comparison of various templates for each surgeon was carried out to select the best template. This validity comparison was based on a 95% confidence interval. Additionally, a higher order replication of 20 replications was carried out to further narrow down the alternative choices. To enable the selection of the best scenario, a scenario that provided the lowest reduction in patient wait time and total time in the system was identified and chosen.

7 RESULTS

The following results were obtained through the data collection process from patients and surgeons as well as application of statistical modelling analysis. First, TM scheduling insights were analyzed. Second, the output of the machine learning classifiers was compared for best performance of classifiers. Finally, scenarios generated from various template alternatives were input in the simulation model and were compared.

7.1 TELEMEDICINE SCHEDULING INSIGHTS

The data collected from the patient and surgeon questionnaires provided insight on patient's suitability for TM, the outcome of the consultation, and patient's perception of TM consultations.

7.1.1 General patient profile

There were 319 patients enrolled in the study from March-July 2021 with a 58% participation rate for full completion of both questionnaires. Table 3 below outlines the number of patients enrolled per surgeon and their participation rates.

	Surgeon 1	**Surgeon 2**	**Surgeon 3**	**Surgeon 4**	**Total**
Enrolled	98	90	38	92	319
Completed study	56	44	13	41	186 (58%)

Table 3: Participation rate of patients enrolled in the study

The average age of patients who participated in the study was 48 years old ranging from 18 to 65 years of age. Most patients work full time as seen in Figure 4.

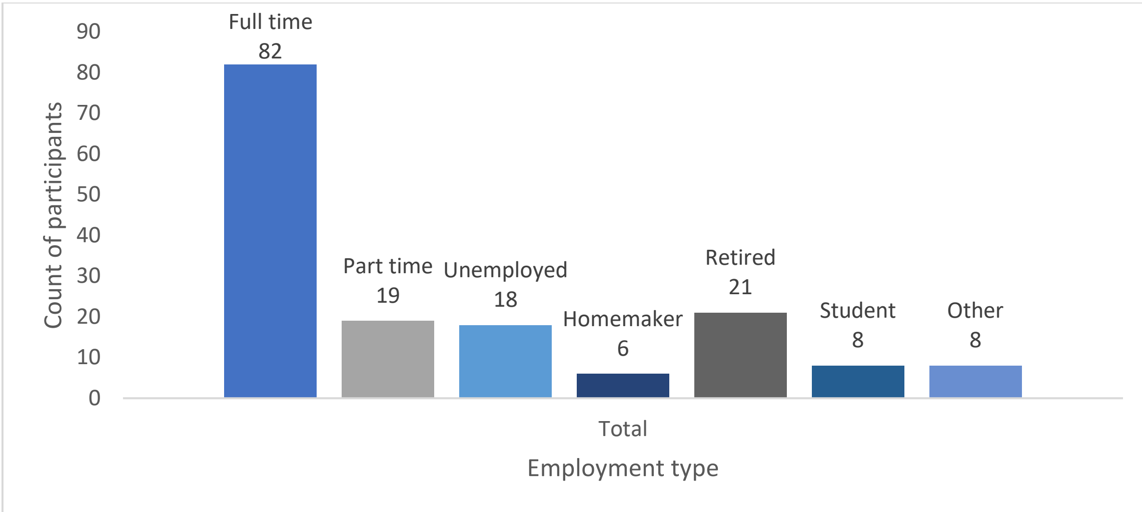


Figure 4: Employment level of patients (n = 162 patient records)

63% of patients who participated in the study had a degree at the level of college (CEGEP) or above as seen below in Figure 5.

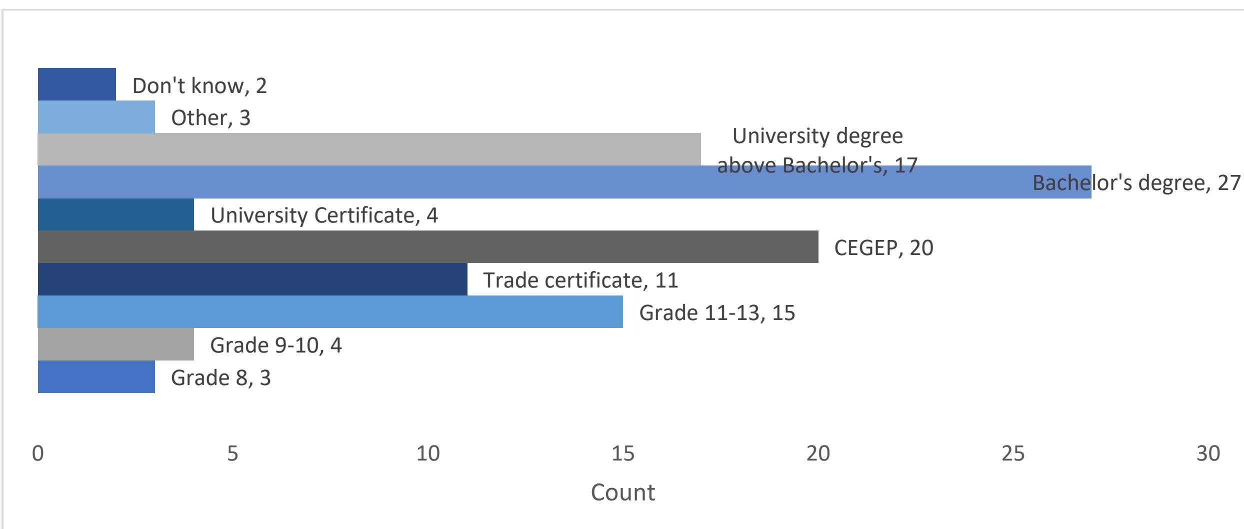


Figure 5: Patient education levels (n = 106 patient records)

Table 4 below displays the number of patients with hearing and seeing impairments and risk of developing severe C19 disease.

Classification	Hearing impairments	Seeing impairments	Risk of developing severe C19
Yes	30 (19%)	21 (13%)	31 (19%)
No	124 (77%)	137 (85%)	107 (66%)
Don't know	8 (5%)	4 (2%)	24 (15%)
Total count	162	162	162

Table 4: Factors that influence suitability of TM classification

Figure 6 below shows the frequency of comorbidities in patients. It was found that 78% of all patients had at least one comorbidity. The most common comorbidity was "other" where the comorbidity was not listed. High cholesterol, diabetes, cancer, and hypertension were among common comorbidities. These four comorbidities put patients at risk for developing a severe C19 disease.

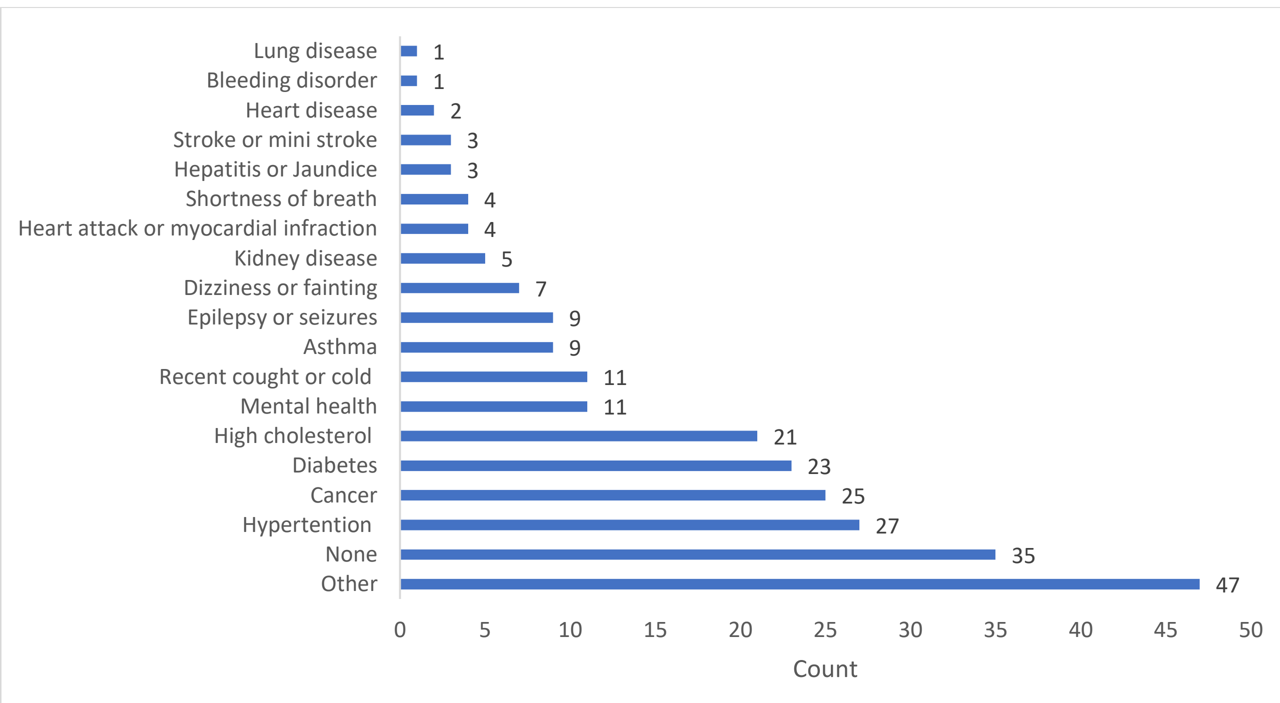


Figure 6: Comorbidity frequency in all patients

7.1.2 Suitability for telemedicine

Surgeons recorded the next step for the patient after completing a consultation. If an in-person follow-up was required, patients were not suitable for TM. However, if the problem was solved or if a TM follow-up was required, then the patient was considered suitable for TM. On average, TM consultations are suitable for 40% of patients, which means there is potential to reduce 40% of unnecessary hospital visits for patients. For the second ENT surgeon, 25 labelled entries were not recorded in the surgeon questionnaire.

Surgeon	Total # patients	In-person follow-up	Problem Solved	TM follow-up	TM Success Rate
Ortho	75	53 (70.67%)	9 (12%)	13 (17.33%)	22 (29.33%)
ENT	66	32 (48.48%)	9 (13.64%)	25 (37.88%)	34 (51.52%)
ENT	40	24 (60%)	8 (20%)	8 (20%)	16 (40%)
Plastic	15	9 (60%)	5 (33.33%)	1 (6.67%)	6 (40%)

Table 5: Next steps after a TM consultation

In the table below, the types of consultations were analyzed to determine how suitable they are on average for TM consultations. The results below show that approximately 57% of follow-up patients are suitable for TM consultation. Only 17% of new patients are suitable for TM consultation. It can be concluded that follow-up patients are best fit for TM clinics.

Patient type	Emergency Room	New patient consult	Return to follow-up
In-person follow-up	1 (100%)	82 (72.57%)	35 (42.68%)
Problem solved	0 (0%)	17 (15.04%)	14 (17.07%)

Patient type	Emergency Room	New patient consult	Return to follow-up
TM follow-up	0 (0%)	14 (12.39%)	33 (40.24%)

Table 6: Suitability of patients for TM by appointment type

In addition to next steps for the patients, outcomes of the TM consultation were analyzed. Figure 7 below shows the outcomes of the consultation. Outcomes include prescriptions, in-person exam required, testing or imaging, procedure required, or consult another specialist. Most patients required testing or imaging as well as an in-person follow up exam.

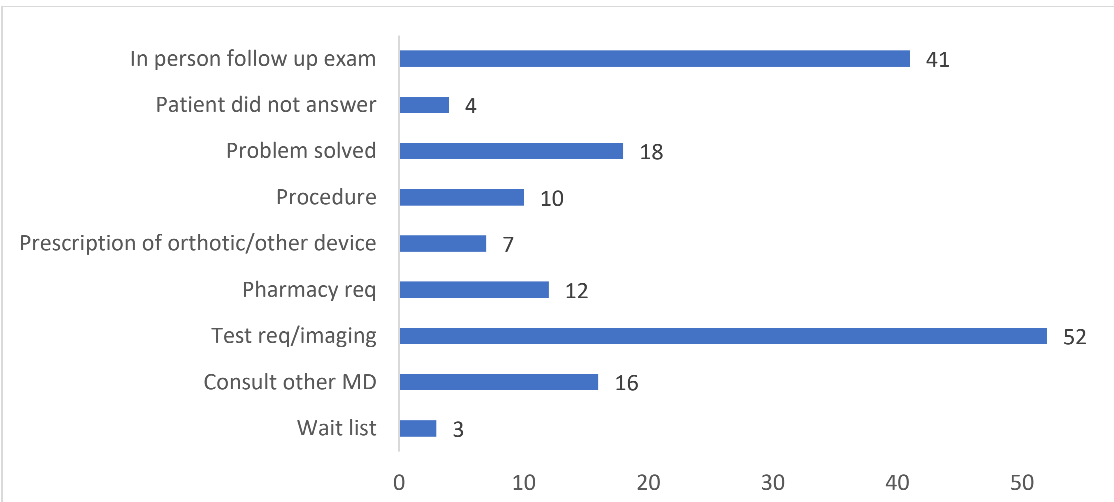


Figure 7: Outcome of the TM consultation

7.1.3 Qualitative results

The perceived quality of a TM consultation was analyzed before and after the consultation took place. As seen in Figure 8, 44% of patients perceived TM consultations to be worse compared to in-person consultations, however this perception was reduced by 29% after patients experienced a TM consultation. Before the consultation, 56% of patients perceived TM to be the same or better as an in-person consultation. After the consultation, 69% of patients perceived TM to be the same or better than an in-person consultation.

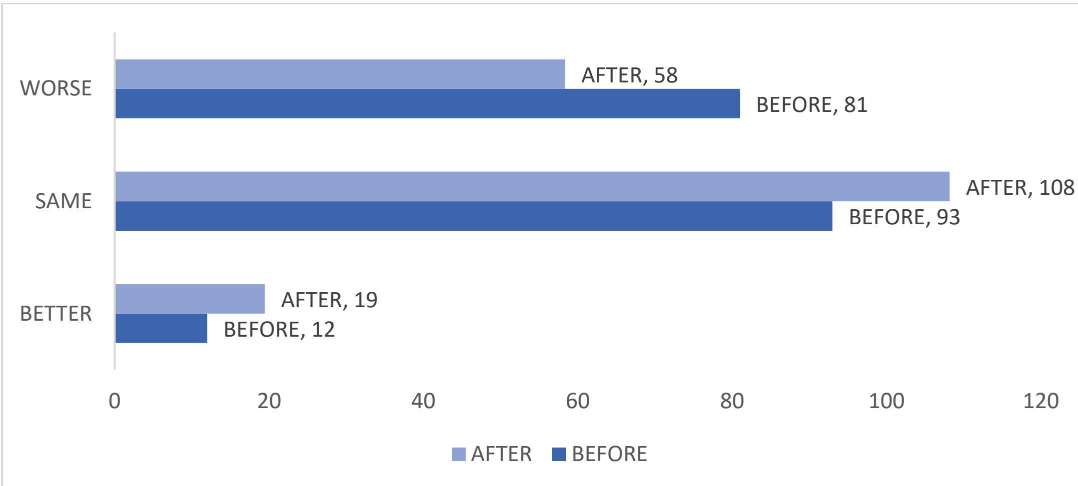


Figure 8: Perceived quality of a TM consultation before and after (n = 186 patient records)

Patients were overall satisfied with their TM consultations where the average level of satisfaction for all patients was 81% satisfied. The Histogram of satisfaction levels can be seen below in Figure 9.

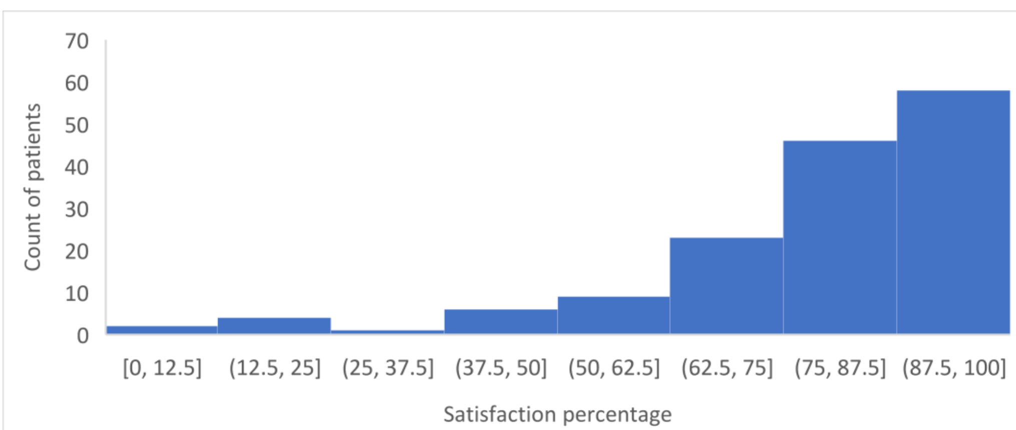


Figure 9: Overall satisfaction levels with TM consultations

TM benefits were also explored in the study where it was found that patients value TM consultations because it saves time, travelling, it is more convenient, and patients do not have to take time off work to receive care. In the context of the pandemic, patients also perceived TM to be a safer option than travelling to a hospital. A breakdown of the benefits can be seen below in Figure 10.

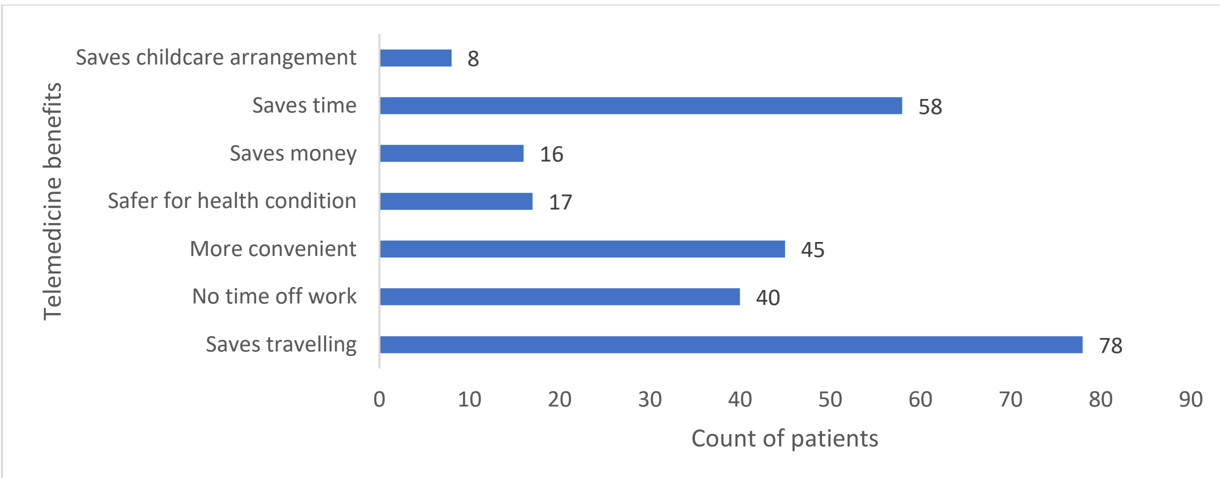


Figure 10: Patient perceived TM benefits

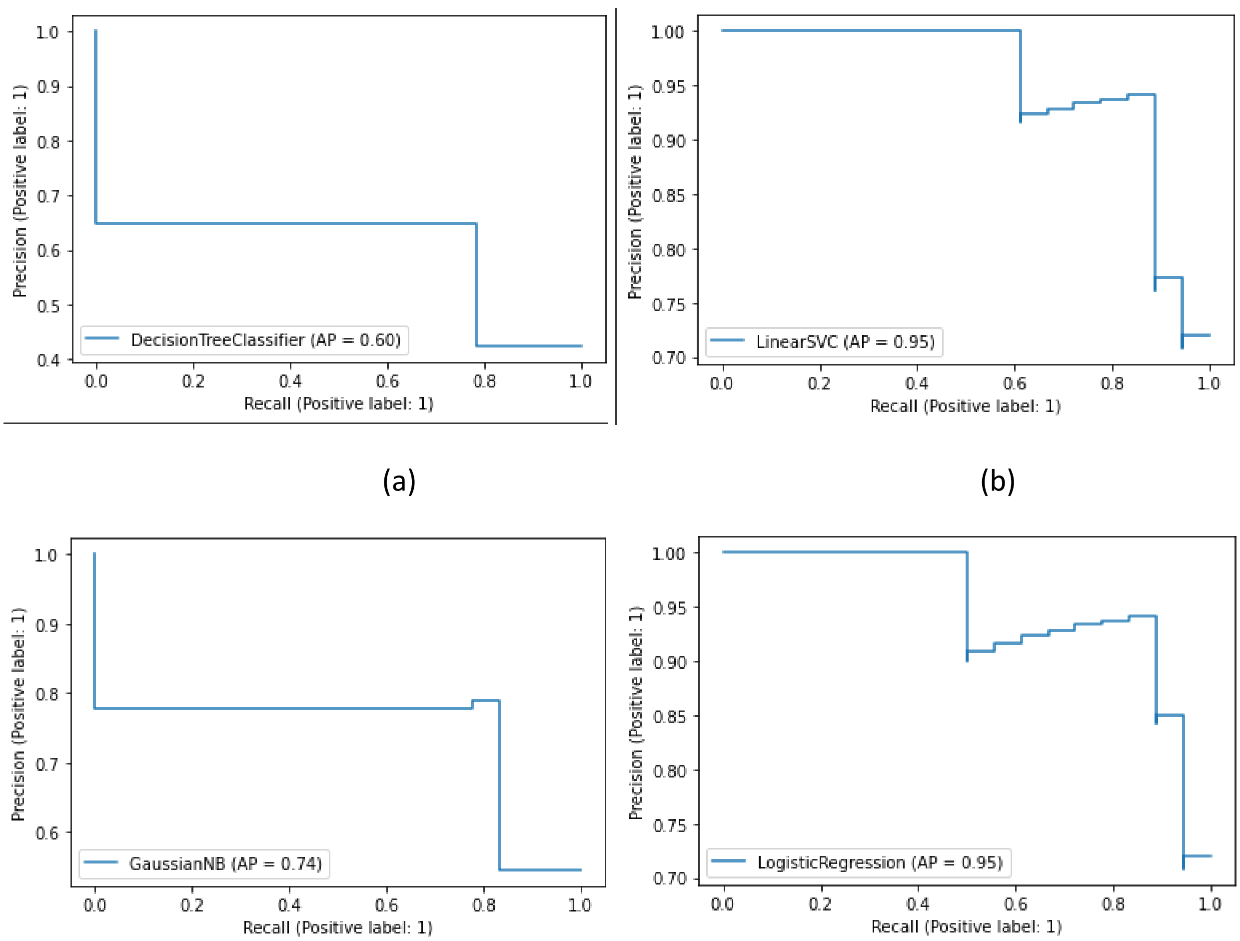
7.2 Machine Learning

Four machine learning classifiers were used to compare accuracy so that the best performing classifier can be chosen to predict if a patient should be seen in person or via TM with the highest probability of making the correct decision. Table 7 shows a summary of the accuracy and precision-recall scores. The best performing classifier was Logistic Regression with 91% accuracy and a precision recall score of 93%. This means that the algorithm can predict if a patient is suitable for a TM consultation with 91% accuracy.

Classifier	Accuracy	Precision	F1 score
Decision tree	73%	60%	68%
SVM	91%	95%	92%
Naïve bayes	79%	74%	76%
Logistic Regression	91%	95%	93%

Table 7: Performance comparison of four machine learning classifiers

The output from the Python model for the 2-class prediction curve can be seen below for all four classifiers.



(a) (b)

(c) (d)

Figure 11: 2-class Precision-Recall curves for each machine learning classifier: (a) Decision Tree, (b) Support Vector Machine, (c) Naïve Bayes, (d) Logistic Regression

7.3 Simulation

The results acquired for the simulation model regarding consultation time were used as metrics to evaluate the system and model. Two surgeons were considered in the analysis from ENT and Ortho where there was a high number of data points acquired. The comparison between the two specialties demonstrates that consultation durations vary between surgical specialties. In the histograms below, the mean consultation time for an Ortho consultation was 12 minutes compared to the average ENT consultation duration of 8.5 minutes.

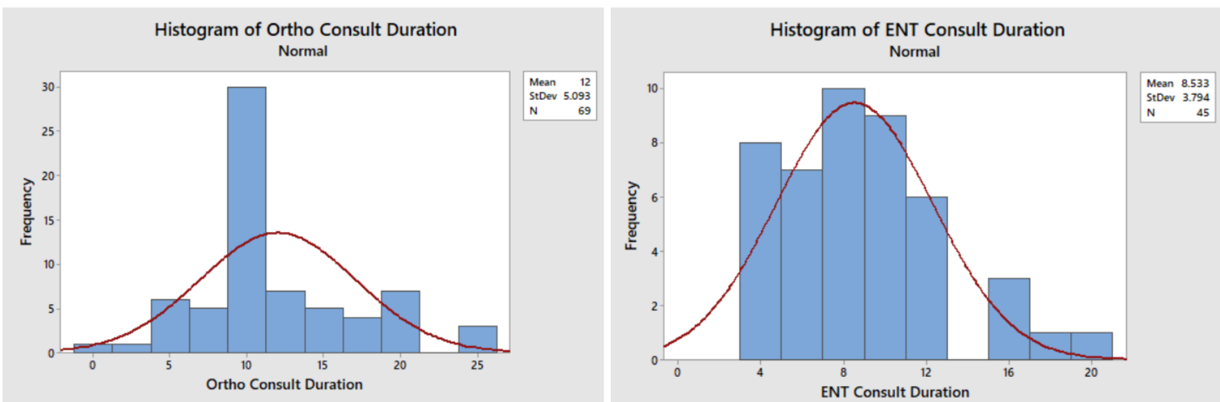


Figure 12: Histogram of Ortho and ENT Consultation Durations

The Empirical CDF below shows that the average consultation duration is normally distributed for both Ortho and ENT specialties.

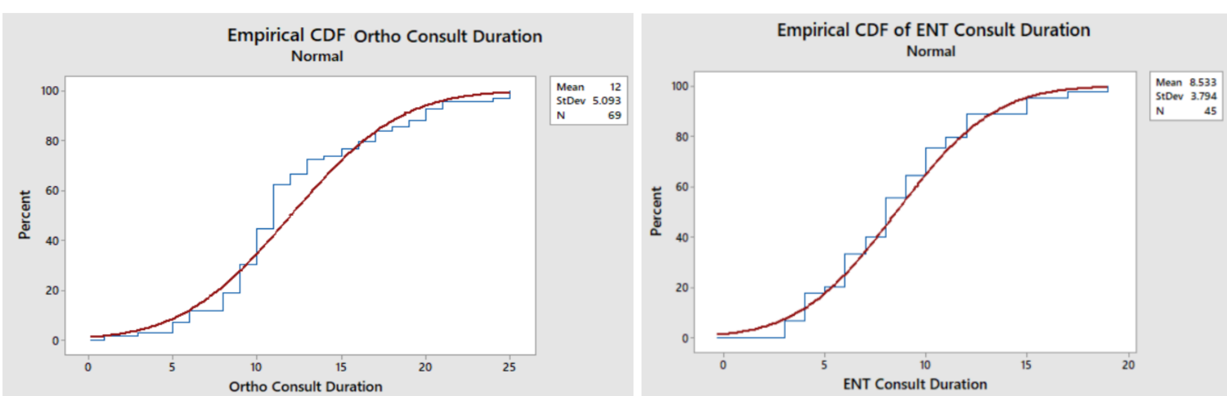


Figure 13: Empirical CDF of Ortho and ENT Consultation Durations

Pre-consultation reviews on average took the least amount of time where note taking after the consultation and filling out requisitions took more time which was accounted for in scheduling template development.

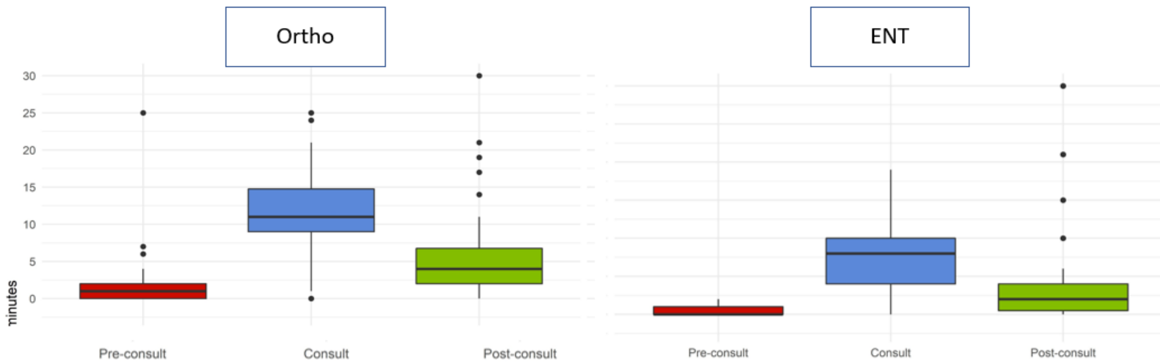


Figure 14: Box and Whisker Plot for pre-consultation, consultation, and post-consultation duration

7.3.1 Data distribution analysis

To build the base scenario for the simulation model which can be found in Appendix 10, data distributions were collected and modelled. Using Input Analyzer, metrics such as the time it took for a new patient or follow up appointment as well as the time to complete pre and post consultation notes were modelled which can be seen in Table 8. Input Analyzer chooses the best fit for the data; however, the distribution must be validated using a Goodness of Fit test to ensure it the appropriate distribution. When data is limited in health care applications and service time must be modelled, the Triangular distribution is the best distribution to use to model the data irrespective of square error or p-values (Law, 2016). Figure 15 shows a sample output from Input Analyzer that models the new patient service time for ENT.

Metric	Data points	Distribution	Expression	Square Error
New patient service time	9	Triangular	TRIA(6.5, 7, 19.5)	0.096529
Follow up patient service time	34	Erlang	-0.5 + ERLA(2.01, 4)	0.017799
Pre consult notes duration	53	Erlang	-0.5 + ERLA(0.336, 3)	0.002926
Post consult notes duration	53	Exponential	-0.5 + EXPO(4.2)	0.012007

Table 8: Base case representing real ENT

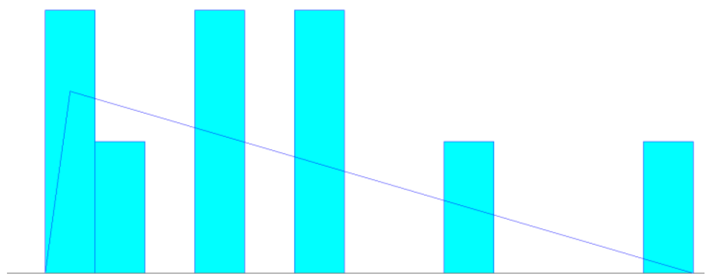


Figure 15: Triangular distribution of new patient service time output from Input Analyzer

The table below shows the results from the Goodness of Fit tests for the ENT distributions. It was concluded that all distributions appropriately model the metric measured. The p-values are below 0.05 meaning that at a 95% significance level, there is sufficient evidence to conclude the distributions are an accurate representation of the data.

Metric	Distribution	Statistical Test	Test stat	P-value
New patient service time duration	Triangular	Chi Square	2.23	0.005
Follow up service time duration	Erlang	Chi Square	1.61	0.059
Pre consult notes duration	Erlang	Chi Square	0.136	<0.005
Post consult notes duration	Exponential	Kolmogorov-Smirnov	6.73	0.016

Table 9: Goodness of Fit Test for ENT distributions

Table 10 shows the distributions that were recommended by the Input Analyzer for Ortho service time and note taking durations.

Metric	Data points	Distribution	Expression	Square Error
New patient service time duration	69	Gamma	0.5 + GAMM(2.66, 4.33)	0.028211
Pre consult notes duration	69	Lognormal	-0.5 + LOGN(2.18, 2.23)	0.025072
Post consult notes duration	69	Weibull	-0.5 + WEIB(5.96, 1.18)	0.021436

Table 10: Base case representing real Ortho

Table 11 shows the Goodness of Fit test results for the Ortho distributions where all the distributions are adequate because the p-values are below 0.05 meaning that at a 95% significance level, there is sufficient evidence to conclude the distributions are an accurate representation of the data.

Metric	Distribution	Statistical Test	Test stat	P-value
New patient service time duration	Gamma	Chi Square	14.6	0.00575
Pre consult notes duration	Lognormal	Chi Square	12.4	<0.005
Post consult notes duration	Weibull	Chi Square	15.5	0.0088

Table 11: Goodness of Fit Test for Ortho distributions

7.3.2 Sample base case templates

The following templates are samples from a typical clinic that was scheduled during the data collection period. The ENT template often included double-bookings, which resulted in the surgeon being late for the consultation. This is due to the high demand for consultations and limited clinic scheduling time. Patients were scheduled 10 minutes apart where there were two occurrences of DB. New patients and follow-up patients were included in this schedule with most patients being follow-up. A sample template can be seen below in Table 12.

Patient type	Appointment Time
Follow-up	9:00am
Follow-up	9:00am

Follow-up	9:10am
Follow-up	9:20am
New patient	9:30am
Follow-up	9:40am
Follow-up	9:50am
Follow-up	10:00am
Follow-up	10:00am
Follow-up	10:10am
Follow-up	10:20am
Follow-up	10:30am
New patient	10:40am
Follow-up	10:50am
Follow-up	11:00am

Table 12: Current ENT scheduling template

For the Ortho templates, the surgeon sequenced patients 30 minutes apart and this surgeon conducted new patient consultations exclusively. A template can be seen below in Table 13.

Patient type	Appointment time
New patient	9:00am
New patient	9:30am
New patient	10:00am
New patient	10:30am
New patient	11:00am
New patient	11:30am
New patient	12:00pm

Table 13: Current Ortho scheduling template

7.3.3 Determining the optimal number of patients

Since only 11% of new patients were suitable for ENT TM consultations, new patients were not considered in calculating the cycle time and optimal number of patients. Table 14 below shows the lean analysis conducted to determine the optimal number of patients. 20-21 patients are the optimal number compared to the original estimate of 14 patients with the same time available.

Metric	Value
Average weighted cycle time	8.65 minutes
Value used to find takt	0.72
Takt time	12.01 minutes
Time available	240 minutes
Demand	19.98 patients
No shows	3%
Demand with no shows	20.58 patients

Table 14: Lean analysis for ENT scheduling template

Table 15 below shows the lean analysis conducted for the Ortho templates. Only new patients were considered since this surgeon conducted new patient consultations exclusively. The optimal number of patients to be seen is 13 compared to the original number of 7 patients seen per clinic.

Metric	Value
Average weighted cycle time	12 minutes
Value used to find takt	0.67
Takt time	18 minutes
Time available	240 minutes
Demand	13.33 patients
Add no shows	0%
Demand with no shows	13.33 patients

Table 15: Lean analysis for Ortho scheduling template

7.3.4 Validating the base simulation

To validate that the base simulation is an accurate representation of the system, a 95% confidence interval t-test was carried out. Below in Table 16 are results from the base simulation after 10 replications compared to the actual average time in system and waiting time. The data from each replication can be found in Appendix 9.

Metrics	ENT		Ortho	
	Actual	Simulated	Actual	Simulated

Average time in system (minutes)	18.82	21.71	16.76	16.65
Average waiting time (minutes)	10.59	12.79	4.76	4.01

Table 16: Actual and simulated results based on 10 simulated replications

To conduct the t-test, the hypothesis tested for the total time in system and the total waiting time is seen below.

$$H_0: the\ simulated\ results\ are\ an\ accurate\ representation\ of\ the\ system$$

$$H_1: the\ simulated\ results\ are\ not\ an\ accurate\ representation\ of\ the\ system$$

If $t_{\alpha/2,\, n-1} > |t_0|$ the null hypothesis is accepted where $t_{\alpha/2,\, n-1} = t_{0.025,\, 9} = 2.262$ and

$$|t_0| = \left| \frac{\overline{x_1} - \mu_0}{\frac{s}{\sqrt{n}}} \right|$$

As seen in Table 17 it was concluded that the system has been validated based on 95% confidence interval t-test since the null hypothesis was accepted.

Metrics	**ENT**		**Ortho**	
	t_0	$t_{\alpha/2,\, n-1}$	t_0	$t_{\alpha/2,\, n-1}$
Average time in system (minutes)	1.364	2.262	-0.06045	2.262
Average waiting time (minutes)	0.682	2.262	-0.64042	2.262
Acceptance of H_0	Accept		Accept	

Table 17: t-test validity results

Additionally, to determine if the actual performance values fall within a 95% confidence interval, the test below was used.

$$\bar{X} - t_{\alpha/2,n-1}\frac{s}{\sqrt{n}} \leq \mu \leq \bar{X} - t_{\alpha/2,n-1}\frac{s}{\sqrt{n}}$$

Table 18 below shows the simulated confidence intervals where it was found that the actual system performance values fall within the simulated confidence intervals at 95% concluding that the simulated model adequately represents the actual system.

Metrics	**ENT**		**Ortho**	
	Actual	95% C.I. (low, high)	Actual	95% C.I. (low, high)
Average time in system (minutes)	18.82	(15.56, 27.86)	16.76	(12.65, 20.65)
Average waiting time (minutes)	10.59	(6.85, 18.73)	4.76	(1.35,6.66)
Acceptance of H_0	Accept		Accept	

Table 18: 95% confidence interval validity results

7.3.5 Template scenario comparison

Various templates were generated to compare scenarios in the simulation model to determine the optimal scenario that minimizes waiting time and fits within the bounds of the surgeon's availability. In Table 19, ENT scenarios were compared. Templates were generated using 10-minute and 15-minute appointment durations with and without double booking (DB) which is when two patients are scheduled at the same time. Scenarios were compared with different start and end times. Given hospital booking constraints for ENT surgeons, patients cannot be scheduled after 1pm. The surgeon typically calls patients earlier or later than their scheduled time which is why the average wait time was ~13 minutes. Scheduling patients with more time between appointments can lead to a reduction in wait time. Scenario 5 is the optimal however patients are scheduled until 1pm. Scenario 2 and 3 both end the clinic at 12pm and use double booking where patients will wait no longer than 5 minutes for the scheduled appointment. For all new templates generated, only follow-up patients were scheduled since they are most suitable for TM consultations. Templates generated can be found in Appendix 7.

Scenario	Replications	Avg wait time (min)	Total time in system (min)	No. of patients	Description
Base	10	12.78	21.72	15	Current template - one pt. every 10 mins, DB
Scenario 1	10	6.66	14.64	21	One pt. every 10 mins, 8:30am-12pm clinic
Scenario 2	10	4.92	12.84	20	One pt. every 15 mins, DB first appt and every hour
Scenario 3	10	4.92	13.2	20	One pt. every 15 mins, DB every 30 min and at 12pm
Scenario 4	10	6.84	14.88	20	One pt. every 15 mins, DB every 30 min and hour
Scenario 5	10	0.6	8.88	20	One pt. every 15 mins, 8am-12:45pm
Scenario 6	10	2.46	10.68	20	One pt. every 15 mins, DB each hour, 8am-12pm
Scenario 7	10	21.96	30.6	18	One pt. every 10 mins, DB at 30 and 60 min, 9am-11am

Table 19: ENT scenarios and template descriptions

To further validate the best scenario, the number of replications were increased to 20 and the output can be seen below in the Box and Whisker Plot. Scenario 2 and 3 both have low variability and wait times where the clinic ends at 12pm. Compared to the base scenario, the surgeon can see more patients with less wait time.

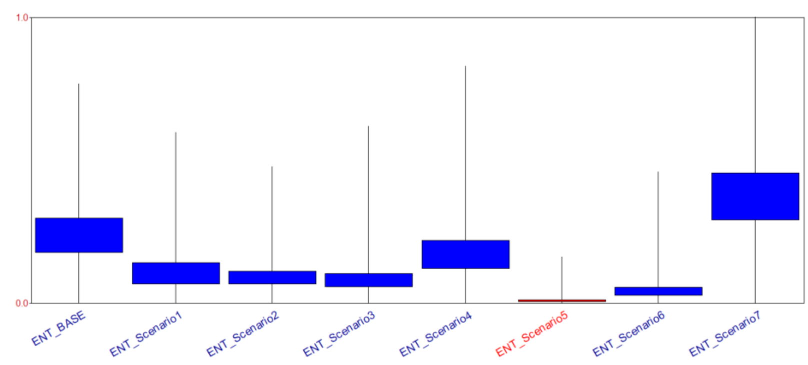


Figure 16: Box and Whisker Plot for ENT average wait time comparison of scenarios with 20 replications

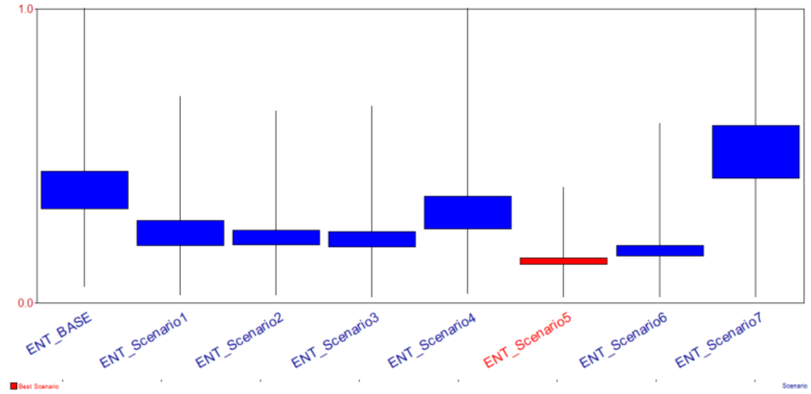


Figure 17: Box and Whisker Plot for ENT average time in system comparison of scenarios with 20 replications

A sample of the optimal template for Scenario 2 can be seen below.

Patient type	Appointment time	Appointment duration (min)
Follow-up	8:30am	15
Follow-up	8:30am	15
Follow-up	8:45am	15
Follow-up	9:00am	15
Follow-up	9:00am	15
Follow-up	9:15am	15
Follow-up	9:30am	15
Follow-up	9:45am	15
Follow-up	10:00am	15
Follow-up	10:00am	15
Follow-up	10:15am	15
Follow-up	10:30am	15
Follow-up	10:45am	15
Follow-up	11:00am	15
Follow-up	11:00am	15
Follow-up	11:15am	15
Follow-up	11:30am	15
Follow-up	11:45am	15
Follow-up	12:00pm	15
Follow-up	12:00pm	15

Table 20: Optimal template option for ENT clinic – Scenario 2

In Table 21, scenarios for Ortho templates were compared. The Base scenario has the lowest average wait time where 7 patients can be seen in the clinic. If the surgeon wanted to increase the number of patients seen during the clinic, Scenario 5 and 10 could be suitable options where patients would wait approximately 10 minutes on average. All patients scheduled in this clinic are new patient consultations which have a higher variability in appointment durations compared to follow-up. For this reason, double booking strategies are not as effective as it increases the average wait time significantly. Templates generated can be found in Appendix 8.

Scenario	Replications	Avg wait time (min)	Total time in system (min)	No. of patients	Description
Base	10	4.02	16.68	7	Current template - one pt. every 30 mins, 9am-12pm
Scenario 1	10	32.88	44.7	13	Pt every 15 mins
Scenario 2	10	42.6	54.42	13	Pt every 15 mins, first appt double booked
Scenario 3	10	47.82	60.42	13	Pt every 15 mins, one appt double booked
Scenario 4	10	30.9	42.96	13	Pt every 15 mins, first appt double booked, break
Scenario 5	10	11.1	23.04	13	Pt every 20 mins, clinic finishes at 1pm
Scenario 6	10	33.72	44.82	13	Pt every 20 mins, double booking every hour
Scenario 7	10	33.72	44.82	13	Pt every 20 mins, double booked at every 20 min mark
Scenario 8	10	27.6	38.76	13	Pt every 20 mins, double booking at 9am, 11am, 12pm
Scenario 9	10	11.04	22.92	12	Pt every 20 mins, clinic finishes at 12:45pm
Scenario 10	10	10.68	22.92	10	Pt every 20 mins, clinic finishes at 12pm

Table 21: ortho scenario comparison

To determine the optimal template, replications were increased to 20 and the output can be seen below in the Box and Whisker Plots. Scenario 5 and 10 both have low variability and wait times where the clinic ends at 12pm. Compared to the base scenario, the surgeon can see more patients with less wait time, however patients will wait 5 minutes longer on average.

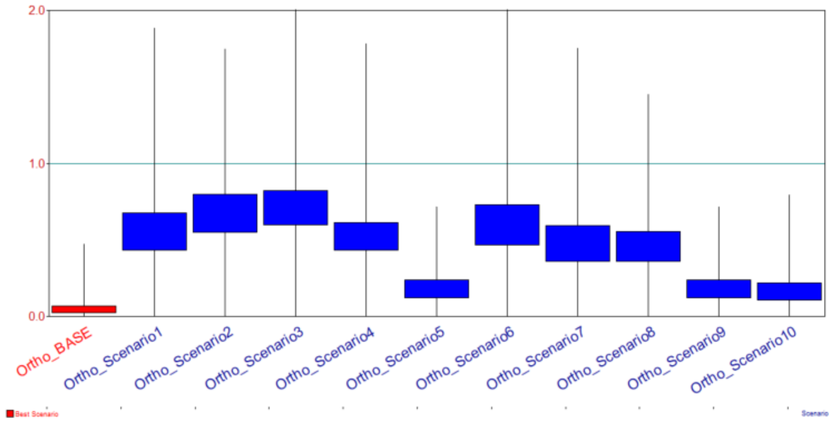


Figure 18: Box and Whisker Plot for Ortho average wait time comparison of scenarios with 20 replications

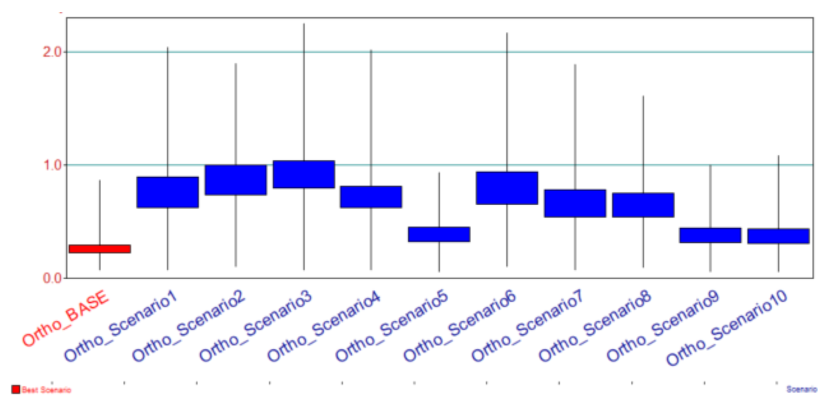


Figure 19: Box and Whisker Plot for Ortho average time in system comparison of scenarios with 20 replications

A sample of the Scenario 5 optimal template can be seen below.

Patient type	Appointment time	Appointment duration (min)
New patient	9:00am	20
New patient	9:20am	20
New patient	9:40am	20
New patient	10:00am	20
New patient	10:20am	20
New patient	10:40am	20

Patient type	Appointment time	Appointment duration (min)
New patient	11:00am	20
New patient	11:20am	20
New patient	11:40am	20
New patient	12:00pm	20
New patient	12:20pm	20
New patient	12:40pm	20
New patient	13:00pm	20

Table 22: Optimal template option for Ortho clinic – Scenario 5

8 Discussion

This research explored if the combination of utilizing predictive and simulation modelling techniques could improve the planning of schedules in surgical outpatient clinics. A machine learning model was developed to determine if various classifiers could accurately predict if a patient should be seen via TM or in-person so that unnecessary hospital visits can be reduced. Optimized scheduling templates were developed and analyzed using a discrete-event simulation (DES) model to determine if clinical workflow could be improved. Finally, as an associated outcome, analysis was conducted to assess if a patient's perception of TM care improved if the patient was suitable for a TM consultation.

8.1 Performance of the machine learning classifiers

The first objective of this study was to leverage a machine learning algorithm to determine if an accurate classification could be made for a patient to be seen in person or via TM. Due to the limited data size used in this study, the number of variables input into the model was minimized where only the ones with the highest weighted values were considered.

The variables with the highest weights used on the model were: Employment, Education, Comorbidities, Age, and Patient Type.

Four machine learning classifiers were compared: Naive Bayes, SVM, Logistic Regression, and Decision Tree where the Logistic Regression had the highest accuracy of 91% in predicting the suitability as well as the highest F1 score of 93% meaning the chance of predicting false negatives was minimized.

Based on past research, it was hypothesized that 60% of patients would be suitable for TM. This study included a higher percentage of new patients where it was found that follow-up appointments are more likely to be suitable for TM consultations. This was found through the surgeon's labelling of the data. Only 27% of new patients were suitable for TM appointments compared to 57% of follow-up patients being suitable for TM appointments meaning that these patients can save an unnecessary trip to the hospital.

The null hypothesis of predicting if a patient should be seen via TM with at least 85% accuracy is thus accepted since the logistic regression and support vector machine classifiers can predict if a patient should be seen via TM with 91% accuracy while minimizing the level of false positives and false negatives.

The variables that were used in this model to predict the output, is information that can be collected from the patient before their appointment takes place. This provides the opportunity to predict if a patient should travel to the hospital or if a virtual encounter is suitable before the appointment occurs. The implementation of the model has the potential to reduce unnecessary trips to the hospital or unnecessary TM consultations, which are an extra cost to the healthcare system. Additionally, derived benefits from avoiding unnecessary TM consultations include eliminating the time delay for a proper diagnosis due to the need to reschedule an in-person consultation.

8.2 Insights on Scheduling

The second objective of the study was to develop optimized scheduling models based on surgical speciality. The models were developed based on the specific surgeon's time used to treat patients and review notes. Models were developed and validated on a 95% confidence interval to ensure that it was an accurate representation of the real system. Two metrics were used to compare the success of scenarios explored that were generated using various templates. The metrics were waiting time and the total time spent in the system (waiting time plus treatment time for patients). Additionally, a lean strategy was used to determine the optimal number of patients based on the time the surgeon had available and the time they take to treat their patients.

For the ENT surgeon, their original clinic used double booking with an appointment duration of 10 minutes. This resulted in the real waiting time of approximately 11 minutes. Using lean analysis, it was found that the surgeon could increase the number of patients they could see from 14 to 20 patients while keeping wait time low. An optimal scenario with 20 patients resulted in a wait time of less than 5 minutes. Instead of booking patients every 10 minutes, patients were booked every 15 minutes because the surgeon's Takt time, which is the time to complete the consultation and notes, was 12 minutes. Since it was found that follow-up patients have the highest likelihood of being suitable for TM consultations, the ENT clinic was scheduled with only follow up appointments. Double booking was also effective in reducing the wait time because some appointments are completed faster than others and follow-up appointments are less variable in their durations.

For the Ortho surgeon's original scheduling template, appointments were scheduled 30 minutes apart since the surgeon wanted extra time between patients. Various scenarios were compared that tested double booking, different appointment durations, and an option of having a one-hour break during the clinic for other work. The surgeon's Takt time was 18 minutes meaning there was plenty of time between appointments and patient waited less than 5 minutes on average in the real system. This scenario was the best in terms of minimizing wait time for the patient. However, if the surgeon wanted to see the optimal number of patients for the clinic, which was 13 patients after conducting lean analysis, the wait time would increase. This surgeon scheduled only new patients in their clinic. New patient treatment durations are highly variable so scheduling can be more difficult. Double booking did not work well with new patients, in one scenario tested with double booking; wait time increased to over 30 minutes. The optimal scenario for the Ortho surgeon was a scenario with no double booking and patients scheduled 20 minutes apart where the wait time was 10 minutes, and 3 more patients were seen compared to the original clinic.

8.3 Patient perception of telemedicine

The ability to accurately predict if a patient should visit the hospital creates an opportunity to improve satisfaction of patients. The majority of patients work full time where a trip to the hospital can incur costs and become a time intensive experience. Patients were 81% satisfied on average with their consultations. Perception of a TM appointment was improved after a TM appointment took place. Before the consultation, 56% of patients perceived TM to be as good as or better than an in-person appointment. This statistic increased to 69% after patients experienced a TM encounter with their surgeon meaning that they found the opportunity to receive care virtually to be positive.

Most patients valued the opportunity to participate in a TM encounter because it saved them time, they did not have to take off work, and it saved the commute to the hospital. Given that most patients were working full time, this could help patients with busy lives receive the care they need without a trip to the hospital. Additionally, there were patients that felt safer to receive care virtually. With 19% of patients being at risk for developing a severe C19 disease, a virtual appointment could minimize the risk of contracting the virus at the hospital.

Lastly, socioeconomic factors must be considered to ensure healthcare is delivered fairly to all Canadians. Of the entire Canadian population, 83% of people own a smartphone (O'Dea & 20, 2020) making it likely they would be able to receive virtual care, however 9.3% of the population which is approximately 3.4 million people are living in poverty and may not have access to technology to facilitate virtual care (Government of Canada, 2019). Although TM has great potential, access to technology that is needed to facilitate a virtual consultation can be limited for a minority of people experiencing adverse socioeconomic factors (Crawford & Serhal, 2020).

8.4 LIMITATIONS

The data set that was acquired was limited and unbalanced. Approximately 9% of patients enrolled did not complete the study because they did not complete the post-consultation questionnaire. This could be due to the questionnaire design and the instrument used to record the data, REDCap. The REDCap system automatically emails the post-questionnaire to the patient; however, they often went straight to a patient's junk mail folder. This led to a loss of engagement from patients and a higher frequency of follow-ups and tech support from the clinical research coordinator.

Initially, the study was exploring a randomization of patients to video or phone calls. The randomization was applied for three surgeons; however, one surgeon did not want to participate in video calls. Additionally, if patients were randomly assigned a video call and did not have the technology or the technical expertise, they were switched to a phone call. Due to these constraints, the study was not randomized to a video or phone.

The platform that was used to facilitate TM consultations was not optimal if patients were waiting more than 10 minutes for their video consultation. Once connected to the link, the call would time out after 10 minutes and patients would have to reconnect. This caused some delays in the care provided and confusion among patients.

Finally, the study required manual labelling from surgeons. This interrupts their workflow to add extra notes amidst a busy clinic. The platform was set up to automatically record the time it took for pre-consultation, consultation, and post-consultation duration however there was no automation for labelling next steps of the patients or the outcomes of the consultation with current electronic medical record systems.

8.5 Future directions

To implement the model in practice, the first step would be to determine if a patient is suitable for a TM consultation. This could be accomplished by using a short, closed-answer questionnaire which can be sent to patients prior to the consultation, recording the variables effective in predicting the machine learning classification. The model can then predict if the patient is suitable or not suitable for TM. Suitable patients can be scheduled in the proposed optimal templates that reduce wait time. This presents the opportunity to minimize wait time for patients, allows the surgeon see more patients, and reduces unnecessary TM or in-person appointments.

The prediction classification of in-person or TM appointments can be valuable in reducing the spread of the C19 virus. In addition to that, providing access to telemedicine for patients living in remote communities is also beneficial (McDonnell, 2018). For example, patients living in communities in northern Quebec must travel to Montreal to receive care which can be disruptive to their lives. This research has the potential to minimize these visits which can be expensive and disruptive if they are not truly required.

Future work could explore which patients are more suitable for phone versus video calls. In some surgical specialities such as ENT where the surgeon is a throat specialist, a phone call is adequate since the surgeon needs to hear the patient's voice. In other specialties such as plastic surgery, it is valuable for the surgeon to see their patient via video call. For a patient-centric care approach, analyzing the impact on patient satisfaction in the case of the patient choosing if they would like a video or phone consultation could provide insight into improving patient satisfaction. Additionally, there are symptoms that can be collected from patients that could be used as a variable in a predictive model. The model could capture a data record regarding the experience of a significant weight loss in a short amount of time for a patient which could lead to the surgeon wanting to see the patient in person for a physical exam. Finally, since many consultations resulted in the need for prescriptions or imaging, it could be explored if TM encounters lead to additional testing or prescriptions.

9 CONCLUSION

This research explored the optimization of TM scheduling in surgical outpatient clinics. Data was acquired by patients and surgeons via questionnaire. There was an enrolment rate of 58% in the study where limitations included the availability of surgeon resources to manually label data and the instrument used to collect data. After completing a TM encounter, patient perception of TM improved where 69% of patients found TM consultations to be as good or better than in-person consultations. Patients valued the time and flexibility that the TM consultation offered in receiving their care. It was found that 57% of follow up appointments can be completed via TM saving patients the need to travel to the hospital unnecessarily.

The first objective of the study was to leverage a machine learning model to accurately predict if a patient should be seen in person or via TM. A Logistic Regression classifier had the highest accuracy of 91% in predicting the suitability of a patient for TM consultations.

The second objective of the study was to develop optimal scheduling templates that reduced wait time for patients. Lean analysis was conducted which determined the optimal number of patients to be scheduled during the surgeon's available time. In both cases for ENT and Ortho surgeons, the surgeons could schedule more patients in their clinic while minimizing patient wait time to less than 10 minutes on average. This is due to personalizing template appointment durations to reflect the surgeon's average treatment time. Additionally, double booking appointments worked well for less variable appointments such as follow up appointments and single bookings worked well with higher variable appointments such as new patient consultations.

There are many exciting advancements to be made leveraging predictive modelling in healthcare applications to improve hospital workflow and patient satisfaction. Future work includes further analysis in determining the suitability for phone versus video calls, exploring a patient-centric approach where the patient chooses a phone call or video call, and exploring other applications such as telehealth care provided to remote communities or other medical specialties.

10 REFERENCES

Barrett, J. S., Jayaraman, B., Patel, D., & Skolnik, J. M. (2008). A SAS-based solution to evaluate study design efficiency of Phase I Pediatric Oncology Trials via discrete event simulation. *Computer Methods and Programs in Biomedicine*, *90*(3), 240–250. https://doi.org/10.1016/j.cmpb.2007.12.008

Bleustein, C., Rothschild, D. B., Valen, A., Valatis, E., Schweitzer, L., & Jones, R. (2014). Wait times, patient satisfaction scores, and the perception of care. *The American journal of managed care*, *20*(5), 393–400.

Boehm, K., Ziewers, S., Brandt, M. P., Sparwasser, P., Haack, M., Willems, F., Thomas, A., Dotzauer, R., Höfner, T., Tsaur, I., Haferkamp, A., & Borgmann, H. (2020). TM online visits in urology during the covid-19 pandemic—potential, risk factors, and patients' perspective. *European Urology*, *78*(1), 16–20. https://doi.org/10.1016/j.eururo.2020.04.055

Brownlee, J. (2019, August 22). How To Estimate The Performance of Machine Learning Algorithms in Weka. Retrieved October 15, 2020, from https://machinelearningmastery.com/estimate-performance-machine-learning-algorithms-weka/

Bujang, M. A., Sa'At, N., Tg Mohd Ikhwan Tg Abu Bakar Sidik, & Joo, L. C. (2018). Sample Size Guidelines for Logistic Regression from Observational Studies with Large Population: Emphasis on the Accuracy Between Statistics and Parameters Based on Real Life Clinical Data. *Malaysian Journal of Medical Sciences, 25*(4), 122-130. doi:10.21315/mjms2018.25.4.12

Buvik, A., Bugge, E., Knutsen, G., Småbrekke, A., & Wilsgaard, T. (2016). Quality of care for remote orthopaedic consultations using TM: A randomised controlled trial. *BMC Health Services Research, 16*(1). doi:10.1186/s12913-016-1717-7

Chen L, Cheng L, Gao W, Chen D, Wang C, Ran X. TM in chronic wound management: Systematic review and meta-analysis. JMIR mHealth and uHealth. 2020;8(6). doi:10.2196/15574

Crawford, A., & Serhal, E. (2020). Digital Health Equity and COVID-19: The Innovation Curve Cannot Reinforce the Social Gradient of Health. *Journal of Medical Internet Research, 22*(6). doi:10.2196/19361

D'Andreamatteo, A., Ianni, L., Lega, F., & Sargiacomo, M. (2015). Lean in healthcare: A comprehensive review. *Health Policy*, *119*(9), 1197–1209. https://doi.org/10.1016/j.healthpol.2015.02.002

Deepika, K., and Seema, S. (2016). Predictive analytics to prevent and control chronic diseases. *2nd International Conference on Applied and Theoretical Computing and Communication Technology* (iCATccT), Bangalore, 2016, pp. 381-386, doi: 10.1109/ICATCCT.2016.7912028.

Government of Canada, S. (2019, February 26). Canadian Income Survey, 2017. Retrieved October 14, 2020, from https://www150.statcan.gc.ca/n1/daily-quotidien/190226/dq190226b-eng.htm

Hammersley, V., Donaghy, E., Parker, R., Mcneilly, H., Atherton, H., Bikker, A., . . . Mckinstry, B. (2019). Comparing the content and quality of video, telephone, and face-to-face consultations: A non-randomised, quasi-experimental, exploratory study in UK primary care. *British Journal of General Practice, 69*(686). doi:10.3399/bjgp19x704573

Hashemi-Sadraei, N., Sasankan, S., Crozier, N., Tawfik, B., Kittson, R., Abernathy, J., Lauer, R., & Dayao, Z. (2021). Improving outpatient infusion clinic wait times at a comprehensive cancer center. *JCO Oncology Practice*, *17*(12). https://doi.org/10.1200/op.21.00118

Hsieh, F. Y., Bloch, D. A., & Larsen, M. D. (1998). A simple method of sample size calculation for linear and logistic regression. *Statistics in Medicine*, *17*(14), 1623–1634. https://doi.org/10.1002/(sici)1097-0258(19980730)17:14<1623::aid-sim871>3.0.co;2-s

Law, A. M. (2016). A tutorial on how to select simulation input probability distributions. *2016 Winter Simulation Conference (WSC)*. https://doi.org/10.1109/wsc.2016.7822083

Lorincz, A., Nague, N., Sahyoun, A., Al Assaad, T., Thavarajah, S., Akgunduz, A., Ben David, L., Berry, G. (2019).
Patient Flow Optimization at an Orthopaedic Outpatient Clinic Using Lean Engineering and Discrete Event Simulation. *Capstone Industrial Engineering Design Project - INDU 490, Concordia University, student paper*

Lorincz, A., Berry, G., Mijovic, T., & Denault-Bois, M. (2020). *TM Outcome Survey*. McGill University Health Centre, Montreal.

Lupton, D., & Maslen, S. (2017). Telemedicine and the senses: A Review. *Sociology of Health & Illness*, *39*(8), 1557–1571. https://doi.org/10.1111/1467-9566.12617

O'Dea, P., & 20, A. (2020, April 20). Smartphone penetration in Canada 2018-2024. Retrieved October 14, 2020, from https://www.statista.com/statistics/472054/smartphone-user-penetration-in-canada/

McDonnell, M. E. (2018). Telemedicine in complex diabetes management. *Current Diabetes Reports*, *18*(7). https://doi.org/10.1007/s11892-018-1015-3

National Center for Immunization and Respiratory Diseases. (2020). Certain Medical Conditions and Risk for Severe COVID-19 Illness. Retrieved October 14, 2020, from https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/people-with-medical-conditions.html

National Coordinating Centre. (2011). Canadian Longitudinal Study on Aging. Retrieved 2020, from https://www.clsa-elcv.ca/researchers/data-collection

Participer à une rencontre virtuelle planifiée. Réseau québécois de la télésanté Accueil. (n.d.). Retrieved March 1, 2022, from https://telesantequebec.ca/patient/patient-rencontres-virtuelles/

Sinsky, C. A., Jerzak, J. T., & Hopkins, K. D. (2021). Telemedicine and team-based care. *Mayo Clinic Proceedings*, *96*(2), 429–437. https://doi.org/10.1016/j.mayocp.2020.11.020

Sisodia, D., & Singh Sisodia, D. (2018). Prediction of Diabetes using Classification Algorithms. *Procedia Computer Science, 132*, 1578-1585. doi:https://doi.org/10.1016/j.procs.2018.05.122

Shameer, K., Johnson, K. W., Yahi, A., Miotto, R., Li, L., Ricks, D., . . . Dudley, J. T. (2016). Predictive Modeling Of Hospital Readmission Rates Using Electronic Medical Record-Wide Machine Learning: A Case-Study Using Mount Sinai Heart Failure Cohort. *Biocomputing 2017*. doi:10.1142/9789813207813_0027

Sundar, R., Balaji, A. N., & Kumar, R. M. S. (2014). A review on lean manufacturing implementation techniques. *Procedia Engineering*, *97*, 1875–1885. https://doi.org/10.1016/j.proeng.2014.12.341

University of Waterloo. (2018). Research with Human Participants - Recruitment Samples. Retrieved 2020, from https://uwaterloo.ca/research/office-research-ethics/research-human-participants/application-process/samples-and-other-supporting-materials/recruitment-samples

Vapnik, V. N. (1998). *Statistical learning theory*. J. Wiley.

11 APPENDIX

APPENDIX 1: PATIENT RECRUITMENT SCRIPT

Hello,

My name is ***(CRC's name)*** and I am a Clinical Research Coordinator working with Amy Lorincz, a master's student who is working under the supervision of Dr. Gregory Berry and Dr. Suzanne Morin in the Faculty of Medicine and Life Sciences at McGill University. I am contacting you because you recently booked an appointment with ***(Dr. insert name)***. The reason that I am contacting you is that we are conducting a study to improve the accessibility and delivery of TM consultations to patients who are suitable to receive care through a phone or video call. We are currently seeking volunteers from ***(Dr. insert name)***'s patients as participants in this study.

Participation in this study involves two questionnaires: a pre-consultation and post-consultation questionnaires and would take a total of 7 minutes of your time. Depending on your preference, the surveys can be completed online through a form or on the phone where I will ask you questions. The pre-consultation survey will take 5 minutes. It will focus on questions about your demographics, level of technology use, opinion of TM and a few medical history questions. The post-consultation survey will take 3 minutes and take place after the appointment with ***(Dr. insert name)***. This survey will ask questions about your experience with your TM consultation and give you with an opportunity to provide feedback on how satisfied you were with your experience. These questions will help us learn more about the telehealth needs of Canadians.

I would like to assure you that the study has been reviewed and received ethics clearance through the Research Ethics Board of Canada and all data will be store in a secure HIPAA and PIPEDA compliant platform where only approved members of the study have access.

However, the final decision about participation is yours.

The pre-consultation survey will take place 1-2 weeks before your scheduled appointment.

If you are interested in participating, I will record your confirmation and if you would like to complete the online questionnaire, I will collect your email. Completing the online questionnaire or answering the questions on the phone means that you have consented to the survey. However, you may withdraw from participating at any time and your data will be deleted.

If you would like more information or have any questions before the survey, please contact me at ***(email or phone number)***.

Thank you very much for your time and your contribution to improving the delivery and accessibility of healthcare to Canadians.

APPENDIX 2: PRE-CONSULTATION QUESTIONNAIRE BREAKDOWN

The following breakdown of questions is based on the phone script. The online survey includes the same questions but is not split up by subsections for simplicity for the patient.

11.1.1 Section 1: Background information

11.1.1.1 AGE

These questions ask for the patients age and date of birth. They are necessary to cross reference pre/post surveys to ensure correlations between patients are linked and validated. Below 18 years and over 65 years of age are considered as exclusion criteria so therefore the age must be validated.

11.1.1.2 GENDER

Gender related questions will help us better understand the patient and if there are correlations between gender and specific drivers of needing an in-person consultation.

11.1.1.3 SOCIO-DEMOGRAPHIC CHARACTERISTICS (SDC)

Asking questions about language will help us understand the patient’s accessibility to TM. If a patient is not a native English or French speaker, they may have difficulty with a phone consultation. If they do not speak French or English at all, they are excluded from this study and must be seen in person.

11.1.1.4 EDUCATION (ED)

These questions aim to explore the level of education of patients and determine if education influences their level of tech-savviness to carry out a TM consultation or if they have the means to own devices that would facilitate a TM consultation.

11.1.1.5 EMPLOYMENT STATUS

Knowledge of the patient’s employment status and occupation will give us an idea of if TM is accessible to them or if having a TM consultation will enhance the delivery of care to them by saving time and money that would be used in attending an appointment in-person.

11.1.2 Section 2: TM

11.1.2.1 TECHNOLOGY KNOWLEDGE (TECH)

Understanding the patient’s technology literacy and devices owned will help us schedule the best type of consultation for the patient whether it is phone, video or in-person. Additionally, if a patient does not have access to an internet connection during their work hours, we would conclude that they would be better served with a phone consultation or an in-person consultation. This knowledge will also be cross-referenced with education and employment to explore correlations, if any.

11.1.2.2 TM (TM)

For these questions we want to get a sense of how patients view TM consultations – understanding what they like or don't like will help improve the shortcomings which can be addressed to increase satisfaction for patients. These questions will be compared with the post-consultation question for how they view TM to determine if their view of TM has changed after they have experienced a consultation.

11.1.3 Section 3: Medical History

11.1.3.1 MEDICAL HISTORY (MED)

The rating of general health allows us to explore correlations with the quality of health and if there is a link to needing an in-person consultation. It is hypothesized that a person with a higher number of comorbidities would need an in-person consultation. Asking about general comorbidities that are typically asked in a patient intake survey by the surgeon will allow us to explore correlations between the number of comorbidities and the need for in-patient appointments to determine if it is a driver in the classification of in-person consultations.

11.1.3.2 PHYSICAL LIMITATIONS (PHYS)

The physical limitations questions will help us determine which means of consultation the patient is best suited for. For example, if a patient experiences difficulty hearing, they will not be suitable for a phone call, but they may be suitable for a live transcription video consultation or an in-person consultation.

11.1.3.3 COVID RISK (C19)

These questions will help us determine if a patient is at risk for developing a severe C19 disease. If they are at a high risk, the risk of them contracting the virus increases if they were to visit a hospital. To minimize risk of contracting the C19 virus, the consultation could be conducted through TM if it makes a patient feel more comfortable while still maintaining the highest quality of care delivery.

APPENDIX 3: PRE-CONSULTATION QUESTIONNAIRE FOR PATIENT

Section 1: Background Information

1. Patient ID Code
2. What is your birth date?
3. What is your gender?
    a. Male
    b. Female
    c. Not specified
4. In what languages can you conduct a conversation? (Select all that apply)
    a. English
    b. French
    c. Other
5. What is the first language you learned that you currently speak?
    a. Short answer
6. In what country were you born?
    a. Canada
    b. Other (please specify)
7. People living in Canada come from many different ethnic and racial backgrounds. Are you…(select all that apply)
    a. White
    b. Black
    c. Chinese
    d. Filipino
    e. Latin American
    f. Arab
    g. West Asian (e.g. Afghan, Iranian)
    h. Southwest Asian (e.g. Cambodian, Indonesian, Laotian, Vietnamese)
    i. Korean
    j. Japanese
    k. North American Indian
    l. Inuit
    m. Metis
    n. Other (please specify)
8. What is the highest level of education you have ever completed?
    a. Grade 8 or lower (Québec: Secondary II or lower)
    b. Grade 9 - 10 (Québec: Secondary III or IV; Newfoundland and Labrador; 1st year of Secondary)

c. Grade 11 - 13 (Québec: Secondary V; Newfoundland and Labrador: 2nd to 4th year of Secondary)
d. Trade certificate or diploma from a vocational school or apprenticeship training
e. Non-university certificate or diploma from a community college, CEGEP, school of nursing, etc.
f. University certificate below bachelor's level
g. Bachelor's degree
h. University degree or certificate above bachelor's degree
i. Other (please specify: __________)
j. Don't know

9. What is your employment status?
    a. Full-time
    b. Part-time
    c. Unemployed
    d. Homemaker
    e. Retired
    f. Student

Section 2: TM

The following are some general questions related to technology and TM which will help us compare how people in Canada interact with technology and view TM.

TM is a form of healthcare that is used to diagnose patients and provide treatment from a distance using communication technology such as a phone call or a video call through applications such as Skype or Zoom.

1. Do you own any of the technological devices listed below? Select all that apply
    a. Cell phone
    b. Smartphone (device used for making calls and using applications, e.g. iPhone, Samsung Galaxy, etc.)
    c. Tablet/iPad
    d. Desktop computer
    e. Laptop
    f. None
2. Do you use any of the social media platforms listed below? Select all that apply)
    a. Facebook
    b. Twitter
    c. Instagram
    d. Pinterest
    e. YouTube
    f. Snapchat

    g. None of the above
    h. Other
3. Are you comfortable downloading a new application from the app store on your phone or tablet?
    a. Yes
    b. No
    c. Don't know
4. Do you have access to a stable internet connection during business hours (Monday-Friday, 9am-5pm) where you can take a 30-minute video call if it is scheduled in advance?
    a. Yes
    b. No
    c. Don't know
5. Do you have access to a location where you can feel comfortable having a private conversation with your doctor during business hours (Monday-Friday, 9am-5pm) where you can take a 30-minute video call if it is scheduled in advance?
    a. Yes
    b. No
    c. Don't know
6. Which statement do you agree with most about the quality of a TM consultation?
    a. The quality of a TM consultation is BETTER than a regular in-person consultation
    b. The quality of a TM consultation is THE SAME as a regular in-person consultation
    c. The quality of a TM consultation is WORSE than a regular in-person consultation
7. What worries you about having a video or phone consultation with your surgeon? Select all that apply
    a. Surgeon able to see living space
    b. Connection issues
    c. Lower quality care
    d. Stress related to setting up the call
    e. Other (please list)
8. What do you like about having a video or phone consultation with your surgeon? Select all that apply
    a. Saves travelling
    b. Do not have to take time off work
    c. More convenient
    d. Because of my health condition, it is safer/easier
    e. Saves money
    f. Takes less time
    g. Saves arranging childcare
    h. Other (please list)

9. What type of consultation would you be most satisfied with when meeting with your surgeon?
    a. Phone consultation
    b. Video consultation
    c. No preference
    d. In person
    e. Don't know
10. If you expressed a preference, what was the reason for your choice? (long form answer)

Section 3: Medical History

The following are general questions about your health so we can learn more about the type of care you would need which could influence whether you should be seen in-person or be seen by your doctor via TM

1. Has your doctor ever told you that you have any of the following health diagnoses?
    a. Hypertension (or high blood pressure)
    b. High cholesterol
    c. Lung disease
    d. Kidney disease
    e. Hepatitis or Jaundice
    f. Diabetes, borderline diabetes, or high blood sugar
    g. Asthma
    h. Stroke or mini-stroke
    i. Epilepsy or seizures
    j. Dizziness or fainting
    k. Bleeding disorders
    l. Heart disease
    m. Heart attack or myocardial infraction
    n. Shortness of breath
    o. Recent cough or cold
    p. Cancer
    q. Mental health illness
    r. Other (short form answer)
2. In general, would you say your health is excellent, very good, good, fair, or poor?
    a. Excellent
    b. Very good
    c. Good
    d. Fair
    e. Poor
    f. Don't know

3. On a scale from 0 to 5 how active are you? 0 being inactive (exercise 0-1 times per week and spend majority of day sitting) and 5 being highly active (exercise daily and spend majority of day moving)
4. Do you have difficulty hearing?
   a. Yes
   b. No
   c. Don't know
5. Do you have difficulty seeing?
   a. Yes
   b. No
   c. Don't know
6. Do you believe that you would be at a high risk of developing a severe COVID-19 disease because of your health status?
   a. Yes
   b. No
   c. Don't know
7. Do you live with someone who would be at a high risk of developing a severe COVID-19 disease?
   a. Yes
   b. No
   c. Don't know

Appendix 4: Post-consultation questionnaire for patient

Section 1: Background Information

This information is collected a second time to compare results with your first perspective of TM.

1. Survey Code
2. Birth date

Section 2: TM

For these questions, we would like to know about your experience with your TM consultation and if you were satisfied with the care hat you received.

1. Was your TM consultation on video or phone?
   a. Video
   b. Phone
2. On a scale from 0-10 how satisfied are you with your experience with TM?

3. How could your experience be improved? (long form answer)
4. Which statement do you agree with most about the quality of a TM consultation?
   a. The quality of a TM consultation is BETTER than a regular in-person consultation
   b. The quality of a TM consultation is THE SAME as a regular in-person consultation
   c. The quality of a TM consultation is WORSE than a regular in-person consultation

Appendix 5: Surgeon questionnaire

1. Select your initials (first name, last name)
2. What type of consult was the appointment?
    a. Video
    b. Phone
3. What type of patient was seen?
    a. NPC (New Patient Consult)
    b. RTFU (Return to Follow Up)
    c. ER (Emergency Room)
    d. POSTOP (Post Operative)
4. Pre- encounter assessment of complexity (based on consult info and any imaging/other info)
    a. Low
    b. Moderate
    c. Severe/significant
5. What is the next step for the patient?
    a. TM follow up
    b. In person follow up
    c. PRN/Problem Solved
6. What is the outcome of the consultation?
    a. Book surgery
    b. Wait list for surgery
    c. Consult another MD
    d. Test req / imaging
    e. Pharmacy req
    f. Procedure
    g. PRN
    h. Patient did not answer
    i. Other
7. Duration in minutes: Open chart until call
8. Duration in minutes: Call beginning to end
9. Duration in minutes: Notes & test reqs
10. Duration: Comment
11. Post- encounter assessment of complexity
    a. Low
    b. Moderate
    c. Severe/significant
12. What was inefficient during this encounter if anything?
    a. Patient did not answer

b. Video consult did not work
c. Could not see patient
d. Had to see patient in person
e. Other

APPENDIX 6: INSTRUCTIONS FOR GETTING PREPARED FOR THE TELEHEALTH APPOINTMENT

GOOGLE MEET
VIRTUAL MEETING PATIENT GUIDE

Centre universitaire de santé McGill

McGill University Health Centre

You are invited to a Google Meet virtual meeting by a healthcare professional. Here are some steps to follow to ensure the smooth running of the meeting.

You do not have to create an account or subscribe to use the Meet application on your internet browser.

STEP 1 – Before the virtual meeting

To participate in the meeting:

It is recommended to use headphones or earphones with a microphone

To prepare for the meeting:

Access via computer

It is not necessary to download an application before the meeting

Compatible Web Browsers

We recommend using the current version of one of the browsers listed below:

- Chrome Browser. Download the latest version
- Mozilla Firefox. Download the latest version
- Microsoft Edge. Download the latest version
- Apple Safari.

Access via mobile device

Make sure you download the application before the meeting

Sign in with a Gmail account

You will need a Gmail account to join the meeting on the Meet application.

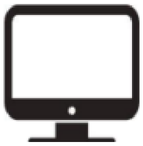
Sign in to your Gmail account or create one here:
https://accounts.google.com/signup

Open your invitation email, then click on the Google Meet meeting link to test the functionality

Check your audio and video

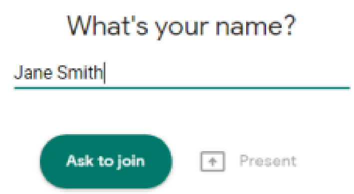
STEP 2 – Connecting to the virtual meeting

10 minutes before the virtual meeting, open your email invitation, then click on the Google Meet meeting link that is in the invitation

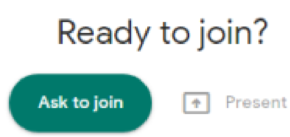


Access via computer

1. Open the link on the email invitation
   meet.google.com/rgd-xviz-ksc
2. If prompted, enter your **first** and **last name**



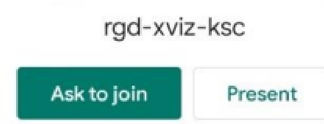
3. Click "Ask to join" when ready



4. Surgeon will accept you into the meeting when ready

Access via mobile device

1. Log in to the Meet app with Gmail
2. Click on the link in the email invitation and you will be redirected to Meet
   meet.google.com/rgd-xviz-ksc
3. Click "Ask to join" when ready



4. Surgeon will accept you into the meeting when ready

STEP 3 – Participating in the meeting

Here are the main options available to you:

Microphone To end call Camera

APPENDIX 7: TEMPLATES GENERATED FOR ENT

E_T1_10 min			E_T2_15 min_DB			E_T3_15 min_DB			E_T4_15 min_DB		
Patient type	Appt time	Time	Patient ty	Appt time	Time	Patient ty	Appt time	Time	Patient ty	Appt time	Time
2	8.50	10	2	8.50	15	2	8.50	15	2	9.00	15
2	8.67	10	2	8.50	15	2	8.50	15	2	9.00	15
2	8.83	10	2	8.75	15	2	8.75	15	2	9.25	15
2	9.00	10	2	9.00	15	2	9.00	15	2	9.50	15
2	9.17	10	2	9.00	15	2	9.25	15	2	9.50	15
2	9.33	10	2	9.25	15	2	9.50	15	2	9.75	15
2	9.50	10	2	9.50	15	2	9.50	15	2	10.00	15
2	9.67	10	2	9.75	15	2	9.75	15	2	10.00	15
2	9.83	10	2	10.00	15	2	10.00	15	2	10.25	15
2	10.00	10	2	10.00	15	2	10.25	15	2	10.50	15
2	10.17	10	2	10.25	15	2	10.50	15	2	10.50	15
2	10.33	10	2	10.50	15	2	10.50	15	2	10.75	15
2	10.50	10	2	10.75	15	2	10.75	15	2	11.00	15
2	10.67	10	2	11.00	15	2	11.00	15	2	11.00	15
2	10.83	10	2	11.00	15	2	11.25	15	2	11.25	15
2	11.00	10	2	11.25	15	2	11.50	15	2	11.50	15
2	11.17	10	2	11.50	15	2	11.50	15	2	11.50	15
2	11.33	10	2	11.75	15	2	11.75	15	2	11.75	15
2	11.50	10	2	12.00	15	2	12.00	15	2	12.00	15
2	11.67	10	2	12.00	15	2	12.00	15	2	12.00	15
2	11.83	10									

E_T5_15 min			E_T6_15 min_DB			E_T7_10 min_DB		
Patient ty	Appt time	Time	Patient ty	Appt time	Time	Patient ty	Appt time	Time
2	8.00	15	2	8.00	15	2	9.00	10
2	8.25	15	2	8.00	15	2	9.00	10
2	8.50	15	2	8.25	15	2	9.17	10
2	8.75	15	2	8.50	15	2	9.33	10
2	9.00	15	2	8.75	15	2	9.50	10
2	9.25	15	2	9.00	15	2	9.50	10
2	9.50	15	2	9.00	15	2	9.67	10
2	9.75	15	2	9.25	15	2	9.83	10
2	10.00	15	2	9.50	15	2	10.00	10
2	10.25	15	2	9.75	15	2	10.00	10
2	10.50	15	2	10.00	15	2	10.17	10
2	10.75	15	2	10.25	15	2	10.33	10
2	11.00	15	2	10.50	15	2	10.50	10
2	11.25	15	2	10.75	15	2	10.50	10
2	11.50	15	2	11.00	15	2	10.67	10
2	11.75	15	2	11.25	15	2	10.83	10
2	12.00	15	2	11.50	15	2	11.00	10
2	12.25	15	2	11.75	15	2	11.00	10
2	12.50	15	2	12.00	15			
2	12.75	15	2	12.00	15			

APPENDIX 8: TEMPLATES GENERATED FOR ORTHO

O_T1_15 min			O_T2_15 min_DB			O_T3_15 min_DB		
Patient type	Appt time	Time	Patient typ	Appt time	Time	Patient typ	Appt time	Time
1	9	15	1	9	15	1	9	15
1	9.25	15	1	9	15	1	9.25	15
1	9.5	15	1	9.25	15	1	9.5	15
1	9.75	15	1	9.5	15	1	9.5	15
1	10	15	1	9.75	15	1	9.75	15
1	10.25	15	1	10	15	1	10	15
1	10.5	15	1	10.25	15	1	10.25	15
1	10.75	15	1	10.5	15	1	10.5	15
1	11	15	1	10.75	15	1	10.75	15
1	11.25	15	1	11	15	1	11	15
1	11.5	15	1	11.25	15	1	11.25	15
1	11.75	15	1	11.5	15	1	11.5	15
1	12	15	1	11.75	15	1	11.75	15

O_T4_15 min_DB			O_T5_20 min			O_T6_20 min_DB		
Patient typ	Appt time	Time	Patient typ	Appt time	Time	Patient typ	Appt time	Time
1	9	15	1	9	20	1	9	20
1	9	15	1	9.33	20	1	9	20
1	9.25	15	1	9.66	20	1	9.33	20
1	9.5	15	1	10	20	1	9.66	20
1	9.75	15	1	10.33	20	1	10	20
1	10	15	1	10.66	20	1	10	20
1	11.25	15	1	11	20	1	10.33	20
1	11.25	15	1	11.33	20	1	10.66	20
1	11.5	15	1	11.66	20	1	11	20
1	11.75	15	1	12	20	1	11	20
1	12	15	1	12.33	20	1	11.33	20
1	11.75	15	1	12.66	20	1	11.66	20
1	12	15	1	13	20	1	12	20

O_T7_20 min_DB			O_T8_20 min_DB			O_T9_20 min			O_T10_20 min		
Patient typ	Appt time	Time	Patient typ	Appt time	Time	Patient typ	Appt time	Time	Patient typ	Appt time	Time
1	9	20	1	9	20	1	9	20	1	9	20
1	9.33	20	1	9	20	1	9.33	20	1	9.33	20
1	9.33	20	1	9.33	20	1	9.66	20	1	9.66	20
1	9.66	20	1	9.66	20	1	10	20	1	10	20
1	10	20	1	10	20	1	10.33	20	1	10.33	20
1	10.33	20	1	10.33	20	1	10.66	20	1	10.66	20
1	10.33	20	1	10.66	20	1	11	20	1	11	20
1	10.66	20	1	11	20	1	11.33	20	1	11.33	20
1	11	20	1	11	20	1	11.66	20	1	11.66	20
1	11.33	20	1	11.33	20	1	12	20	1	12	20
1	11.33	20	1	11.66	20	1	12.33	20			
1	11.66	20	1	12	20	1	12.66	20			
1	12	20	1	12	20						

APPENDIX 9: REPLICATION OUTPUT FOR BASE CASE SCENARIO

	Scenario Properties				Control	Responses		
	S	Name	Program File	Reps	Num Reps	waitingroom	total time in system	System.NumberOut
1		Ortho_BASE	13 : Sim_Mas	10	10	0.067	0.278	7.000
2		Ortho_Scenario1	1 : Sim_Mast	10	10	0.548	0.745	13.000
3		Ortho_Scenario2	1 : Sim_Mast	10	10	0.710	0.907	13.000
4		Ortho_Scenario3	1 : Sim_Mast	10	10	0.797	1.007	13.000
5		Ortho_Scenario4	1 : Sim_Mast	10	10	0.515	0.716	13.000
6		Ortho_Scenario5	1 : Sim_Mast	10	10	0.185	0.384	13.000
7		Ortho_Scenario6	1 : Sim_Mast	10	10	0.562	0.747	13.000
8		Ortho_Scenario7	2 : Sim_Mast	10	10	0.502	0.688	13.000
9		Ortho_Scenario8	1 : Sim_Mast	10	10	0.460	0.646	13.000
10		Ortho_Scenario9	2 : Sim_Mast	10	10	0.184	0.382	12.000
11		Ortho_Scenario1	1 : Sim_Mast	10	10	0.178	0.382	10.000

	Scenario Properties				Responses		
	S	Name	Program File	Reps	total time in system	waitingroom	System.NumberOut
1		ENT_BASE	17 : Sim_Masters	10	0.362	0.213	15.000
2		ENT_Scenario1	1 : Sim_Masters_	10	0.244	0.111	21.000
3		ENT_Scenario2	1 : Sim_Masters_	10	0.214	0.082	20.000
4		ENT_Scenario3	1 : Sim_Masters_	10	0.220	0.082	20.000
5		ENT_Scenario4	1 : Sim_Masters_	10	0.248	0.114	20.000
6		ENT_Scenario5	1 : Sim_Masters_	10	0.148	0.010	20.000
7		ENT_Scenario6	1 : Sim_Masters_	10	0.178	0.041	20.000

Double-click here to add a new scenario.

Appendix 10: Discrete Event Simulation Model