Coordinating Primary Care Operating Hours to Reduce Acute Care Visits

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1 Introduction

A challenge primary care providers face is administering care to their local populations to reduce acute care visits for low-complexity issues. The goal of this study is to understand how the operating hours of two clinics, A and B*, affect hospital use and to optimize those hours to reduce acute care visits.

1.1 Background

Emergency care for people who do not have urgent issues is an inefficient use of resources in the healthcare system [10]. As a result, having those visitors handled by primary care clinics is a priority for those managing healthcare spending. Provincial authorities in British Columbia have indicated that about a third of visits to St. Paul's Hospital in Vancouver are for non-urgent issues [9]. This is also reflected in the data for the population we consider of visitors to clinics A and B, for who 40% of hospital visits were for non-urgent care. When surveyed, patients attest that they go to the emergency room (ER) because they believe it to be their best choice for reliable, high-quality care, whereas they believe clinics offer a lower-quality alternative [5, 11]. In cases where patients had a regular family doctor, or had been with their clinic for many years, they saw a reduced reliance on ER, which suggests that familiarity with the services available at primary care clinics is a significant factor in reducing ER visits [6, 12].

Clinics A and B face the additional challenge of servicing people who are most likely to visit hospitals for low-complexity issues, such as the homeless, low-income patients, and people who do not have a regular primary care provider. By adjusting the opening and closing hours of each clinic, we may reduce the number of no-shows or cancellations so that utilization is closer to their total capacity. By running more efficiently, the clinics will be able to serve clients without additional resources such as additional staff hours. This will allow them to serve more people by making room for more appointments and walk-ins, resulting in fewer people having to resort to acute care for non-urgent issues.

1.2 Outline

This study is comprised of six sections: data, methods, assumptions and limitations, analysis, results, and conclusions. In the data sections, we discuss the source and nature of our data set. In the methods section, we provide an overview of the analysis methods we use to forecast clinic and hospital demand, model client behaviour, and optimize operating hours. The next section explains our simplifying assumptions and the limitations of the study. In our analysis, we proceed in the

*Names are redacted for confidentiality.

following way:

1. We use time-series data to create forecasting models that project future demand for the clinics and hospitals.

2. We create models of frequent clinic visitors to understand common client behaviour patterns.

3. We simulate client behaviours with varying rates of arrival to ensure clinic operations have acceptable wait times and staff levels for the proposed new operating hours.

We finish with a discussion of the results and recommendations. We conclude that diverting resources from weekends to weekday evenings will result in a 14% decline in low-acuity hospital visits per extended hour for a total decline in 2.4% in low-acuity hospital visits.

2 Data

This study uses anonymized data provided by Vancouver Coastal Health (VCH) who recently consolidated their databases into a system called the Vancouver Community Analytics Tool (VCAT). VCAT, for the first time, provides new opportunities for understanding by allowing us to follow patients as they navigate the healthcare system. From their fully integrated database, VCH extracted records of patients who met two conditions during the period from January 1st, 2014 to December 31, 2018. First, they had at least one visit to clinic A or clinic B and, second, at least one visit to an acute care facility. These two clinics are both located in the same area of the city and therefore have the same general patient base. Names and personal information have been removed.

VCH provided fields such as the location, time, and day the care took place as well as the provider code, acuity code, and whether or not each appointment was kept. The dataset contains a total of 459,130 clinic entries with 235,877 from clinic A, 223,253 from clinic B, and an additional 129,369 entries from acute care. It is structured in four different tables that are linked together by an identifier variable called StudyID, which ties the databases together. This is not the actual unique identifier but a replacement for the purposes of this project. The first two tables concern primary care. There is one table providing the information on appointments and another for clinic visits (encounters). The second two tables provide information on acute care. The first has data on admissions discharges and transfers (ADTC), and the second the emergency department (ED). Having primary care data that is linked to acute care data provides us the opportunity to draw conclusions about how primary care can reduce acute care usage. Of the 129,369 emergency department records, 103,868 were for patients with an acuity score of 1,2 or 3. These scores correspond to serious conditions best suited to acute care. The remaining 25,501 entries are acuity scores of 4 or 5 which are candidates for substitution by less costly primary care.

3 Methods

3.1 Forecasting Demand

A common technique used to predict future demand is a time series analysis model. Time series analysis is a statistical technique suitable for studying data listed according to points in time. The resulting model accounts for the seasonal variations or trends one can expect in data tied to time. The autoregressive integrated moving average model (ARIMA) is a standard tool for time series analysis that we use in this study [3]. ARIMA characterizes the demand for clinics using historical demand data and projects future demand based on historical patterns. The objective is to predict the numbers of visitors to the clinics and hospitals by day of the week and operating hour interval.

In order to make accurate projections based on historical data, the ARIMA model uses the time series data to produce values for the model parameters. ARIMA is sometimes expressed as "ARIMA(p,d,q)" where p, d, and q refer to the parameters. The parameter p represents the autoregressive nature of the model and expresses the number of periods in our data based on the growth and decline cycles within the data. The parameter d represents the degree of differencing required to make the data stationary (a time series that hovers around a predefined mean). The parameter q represents the size of the moving average. The values for these terms allow us to produce a forecast. To check the validity of the forecasts, we use the Box-Ljung test. Box-Ljung is a tool to examine the residuals, the difference between the observed values and fitted values, after the ARIMA model is fitted to the data. The Box-Ljung test provides us with a p-value. If the p-value is more than 0.05 we conclude the model does not show significant lack of fit.

One factor to consider is potentially biasing the parameters with data that contains a step-change in mean or variance. This is not a concern for the hospital data due to the uniformity in how hospitals operate and how infrequent significant changes are to those operations. In fact, researchers who have used the ARIMA approach to forecast hospital demand have found it useful and accurate [7, 8]. However, medical clinics operate differently from hospitals. Operational characteristics can be quite different among clinics and changes to clinic operations happen frequently. Appointment density data for clinics A and B can be used to reveal when there were changes to their operations. It was learned through interviews with clinic officials to expect variation in the 2015 data for clinic A as a result of massive operational changes at that time. While the data for clinic B shows a consistent density from 2012 to 2018, the data for A demonstrates a pronounced increase in appointment density in 2015 corresponding to the operational changes described.

In this study, we have eliminated the data preceding the 2015 change at clinic A to bypass the issue of biased data altogether. This avoids the abrupt change in the 2015 data and the more recent data will provide a more accurate reflection of how the clinics operate today for better demand projections moving forward. Major clinic changes also occurred in summer 2018 when clinic B relocated to a new location in the city and clinic A moved to a new team-based operational model. There is not enough data to draw conclusions about how these changes will affect future demand, therefore, 2018 was also excluded from the ARIMA models. This approach results in three years of valid time series data which remains sufficient for the ARIMA model to make useful projections.

3.2 Patient Models

To model patient behaviour, we split the data into three categories - appointments, walk-ins, and emergency visits. We then considered each of these categories separately for the purposes of our patient models. Afterwards, we split patients into various categories representing their behaviour. For example, patients who frequently failed to show up for scheduled appointments were placed into a particular category. We then used MATLAB to generate histograms to measure patient behaviours and to filter patients into more specialized categories.

With respect to emergency room visits, patients were categorized based on their potential to improve cost-efficiency. Patients who more frequently used emergency room care for low-complexity reasons were considered to be higher potential. Similarly, patients who were categorized as frequently failing to attend appointments were judged to be high potential. Higher potential patients represent more frequent usage of non-urgent acute care that could potentially be substituted by less costly primary care.

3.3 Simulation

Simulations were done in AnyLogic, specialized software for doing simulations [4]. Five flow models were created: S1, S2, S3, S4 and S5.

1. S1 simulates patients arriving for their appointments at clinic A.

2. S2 simulates patients arriving for their appointments at clinic B.

3. S3 simulates patients walking-in to clinic A with no appointment.

4. S4 simulates patient walk-ins to clinic B during the appointment period.

5. S5 simulates patient walk-ins to clinic B during the walk-in period.

The flow diagram for S1 appears identical to S2 but they operate on different parameters. The flow diagram for S1/S2 can be seen in Figure 1. Patients show up at the "source" node and leave at "sink" node. Patients wait for service at "queue" nodes and receive service at "service" nodes. The "select" nodes decide where patients go and the "resource pool" nodes indicate the presence of staff.

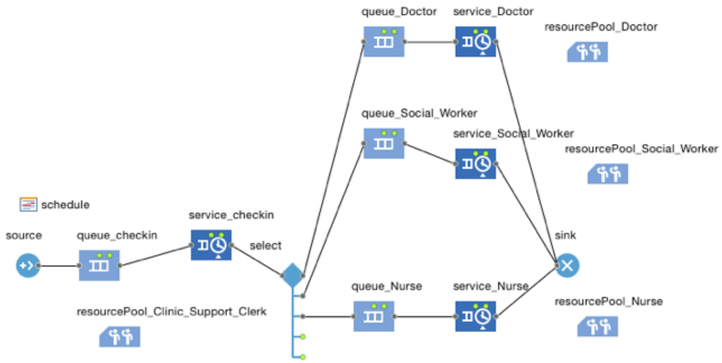

Figure 1: **Flow chart showing patients arriving for appointments (S1 and S2)**

The flow diagram for S4 can be seen in Figure 2. It shows patients without an appointment walking-in to clinic B during the appointment period (8:30 to 12:00) when walk-ins are not accepted unless they are urgent. If urgent, they make the next availble appointment. If not, they return later for a walk-in visit.

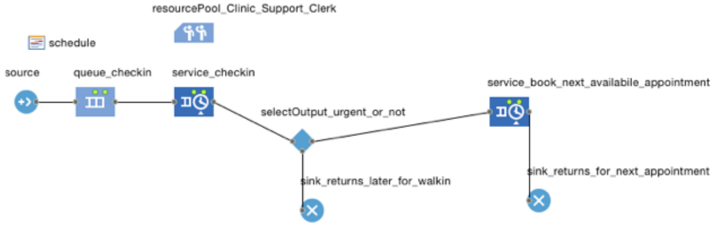

Figure 2: **Flow chart of walk-ins to clinic B during the appointment period (S4)**

Like S1 and S2, the flow diagram for S3 and S5 are visually identical but differ in their parameters.

S3 and S5 simulate walk-ins to clinic A and clinic B, respectively. Clinic A accepts walk-ins all day while clinic B accepts them from 12:00 to 16:30. The flow diagram can be seen in Figure 3.

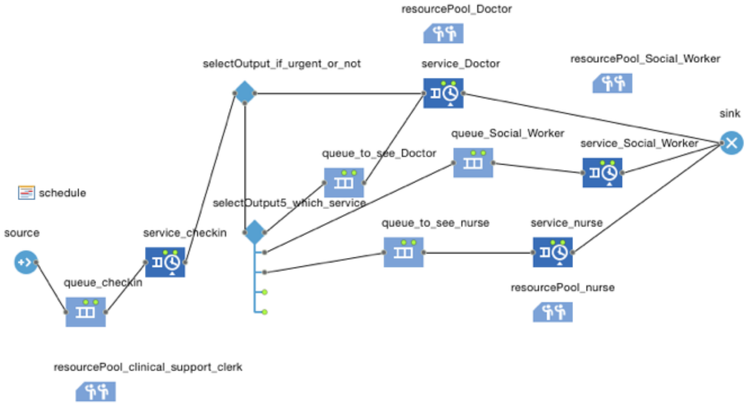

Figure 3: **Flow chart of walk-ins to clinic A and clinic B during the walk-in period(S3 and S5)**

To run these simulations, a number of parameters are required:

1. The rates at which patients arrive at the clinics.
2. The time required for a clinic support clerk (CSC) to check-in a patient.
3. The percent of total patients who require urgent care.
4. A probability parameter representing which service the patient requires.
5. The time patients spend with care providers.

4 Assumptions and limitations

There were several assumptions and limitations to consider based on the completeness of the data we had access to and other operational factors at the clinics. The assumptions and limitations allowed us to simplify our models while still retaining the ability to generate useful results.

ARIMA Models:

1. *No-shows and cancellations are excluded.* People who canceled or did not show up for their appointment are not considered in the ARIMA models.

2. *Data before 2015 and after 2018 are excluded.* As a result of numerous operational changes before 2015 and after 2018, data from these periods are excluded from the ARIMA models.

3. *Incomplete entries in the dataset were removed.* There were 132,442 incomplete entries in our dataset. For the purposes of our ARIMA model, these were removed.

4. *Improperly-labelled entries* Clinic B has many appointments during hours where they supposedly are not open for appointments. We believe that these are due to improperly-labeled phone call entries. We have not filtered out these appointments from our dataset for the purposes of our ARIMA model.

   Patient Models:

5. *Time-Focused visitors prefer only one time period.* People who have multiple time preferences to visit a clinic are not considered in the patient models. For instance, patients who prefer one of 12:30 or 16:30 for an appointment are not categorized differently to those who only prefer 12:30.

6. *Physician-Focused visitors prefer only one physician.* Multiple physician preferences are not considered in the patient models. For instance, patients who prefer one of Physician A or Physician B are not categorized differently to those who only prefer Physician A.

7. *Patients who rarely come to a clinic are not modelled.* We excluded all patients with less than 20 appointments or 10 walk-in visits.

8. *Patient treatment is never incomplete.* Patients are not considered to immediately revisit the clinic due to an incomplete treatment.

9. *Patient complexity is not considered.* We were unable to obtain any patient complexity data. Therefore, this factor is not considered in our model. If patient complexity data could be obtained, a much more complete model could be made.

   Flow Model:

10. *Visitor arrivals are independent*. Patients do not arrive in groups to the clinics.

11. *Each patient visits only one care provider per visit*. The simulations do not consider patients who visit multiple clinic staff.

12. *Service times are averaged.* We assume the time patients spend with a nurse, social worker, or doctor is the average time all patients typically spend with these staff members.

13. *No distinction between different types of nurses.* The dataset is in inconsistent about differentiating between RN and LPN nurses. Although, LPN nurses can only do a subset of the tasks RN nurses can do we treat all nurses as RN nurses in the flow models.

14. *It takes the same amount of time to check-in each visitor.* We assume each visitor spend 3 minutes with a CSC for an assessment on whether their case is urgent.

15. *First time visitors are not treated differently.* When a person visits a clinic for the first time, they have a more elaborate check-in experience, which is not considered by the flow models.

16. *Urgent walk-in visitors to clinic B arriving during appointment-only hours each spend the same amount of time booking the next available appointment.* We assume each of these visitors spends 5 minutes booking the next available appointment. Non-urgent walk-ins who visit during appointment hours are told to come back during the walk-in period in the afternoon and are not considered in the flow model.

17. *No distinction is made between opioid replacement therapy (ORT) visits and regular visits.*

5 Analysis

5.1 Demand Forecast Models

Three sets of ARIMA models were created for each clinic, one to forecast weekday appointment demand and two more to forecast weekday and weekend walk-in demand. The time series data for each of the three categories were different enough to warrant their own models to ensure the most accurate projections. Hospital emergency department visits were also modelled.

The process of producing the ARIMA models involves using the auto.arima function in R, the statistical computation software used in this study, to produce candidate models each with their own set of parameters: p, d, and q. An autocorrelation function (ACF) plot is then used to compare lagged versions of the time series to the original in order to determine if the historical data is useful to predicting appointment or walk-in visits in the future. The q parameter of the ARIMA model, representing the moving average, is adjusted until the lags in the ACF plot are not significantly different from zero.

5.1.1 Clinic A

The time series data for clinic A reveals that the number of appointments the clinic accepted between 2015 and 2018 has grown steadily. This time series was cleaned to remove outlier data below a threshold of 25 from 2016 to 2017 and 50 from 2017 to 2018, representing slow days. Some of these outliers indicated zero appointments on some days, these were when the clinic was closed for holiday. Removing outliers improves the accuracy of the projection by eliminating bias.

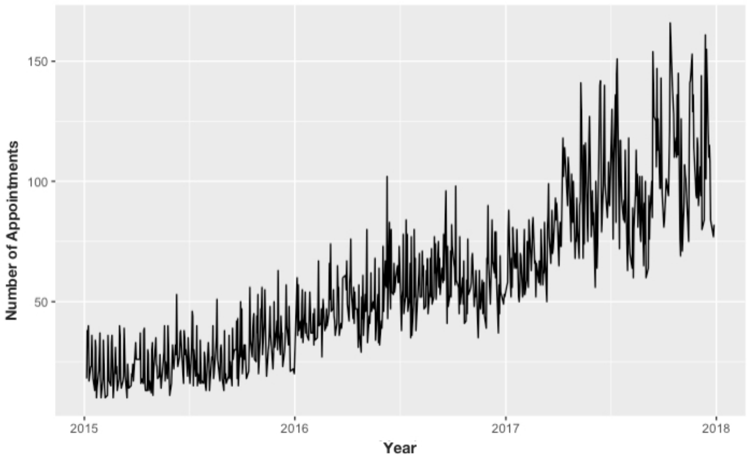

Figure 4: **Daily number of appointment visits for clinic A (weekdays)**

Using the time series, the model process produced an ARIMA(3,1,11) model in Figure 5. The model projects out 35 days into 2018 that, within an 80% confidence interval, the demand for appointments will range from 75 to 125 per day. The Box-Ljung test provides us with a p-value of 0.9813 indicating a valid projection.

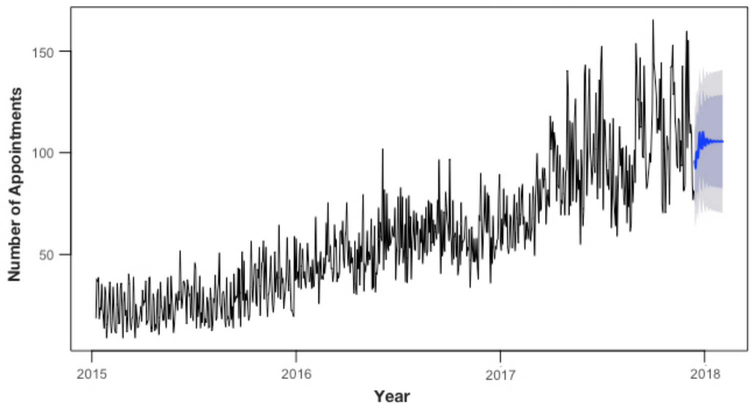

Figure 5: **Daily 2018 appointment demand forecast for clinic A (weekdays)**

Weekday walk-in visits, however, were more consistent over the years. Figure 6 shows visits between 2015 and 2018 are concentrated between 20 and 30 every day. No outliers were removed from this time series.

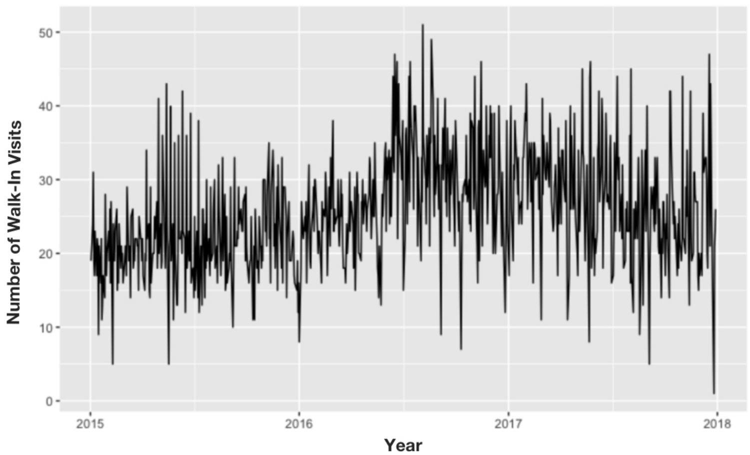

Figure 6: **Daily number of walk-in visitors to clinic A (weekdays)**

The weekday walk-in time series for clinic A resulted in the ARIMA(2,1,10) model in Figure 7. The model projects out 30 days into 2018 that, within an 80% confidence interval, the demand for walk-ins will range between 15 and 35. A p-value of 0.812 validates the projection.

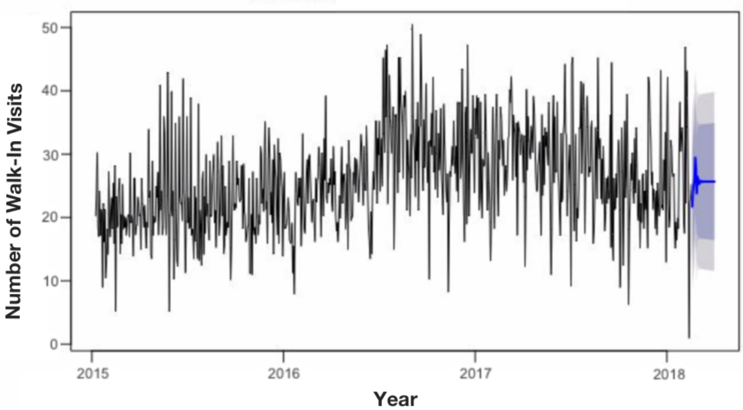

Figure 7: **Daily 2018 walk-in demand forecast for clinic A (weekdays)**

For weekend walk-ins, data from 2017 to 2019 were considered for the time series. The density of walk-ins saw a step-change in 2017 and, as a result, prior years were excluded to produce a more accurate projection. Outlier data above a threshold of 25 visits were also removed from the time series.

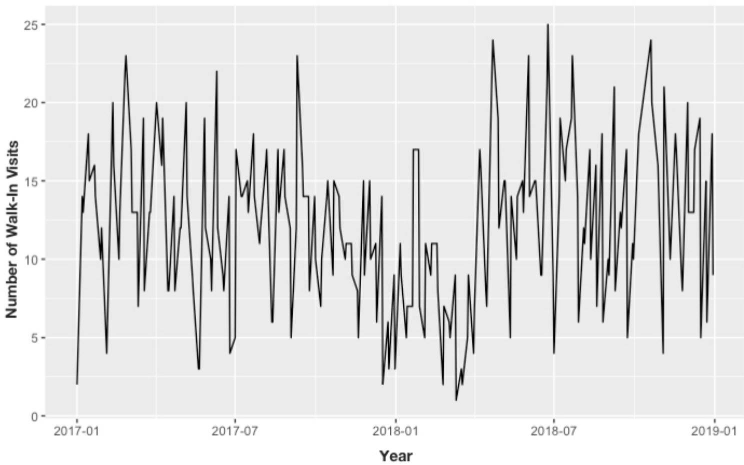

Figure 8: **Daily number of walk-in visitors to clinic A (weekends)**

The weekend walk-in time series produces the ARIMA(1,0,4) model in Figure 9. The model projects out 5 weekends in to 2019 that, within an 80% confidence interval, demand for weekend walk-ins will range between 5 and 20 clients. A p-value of 0.9147 validates the projection.

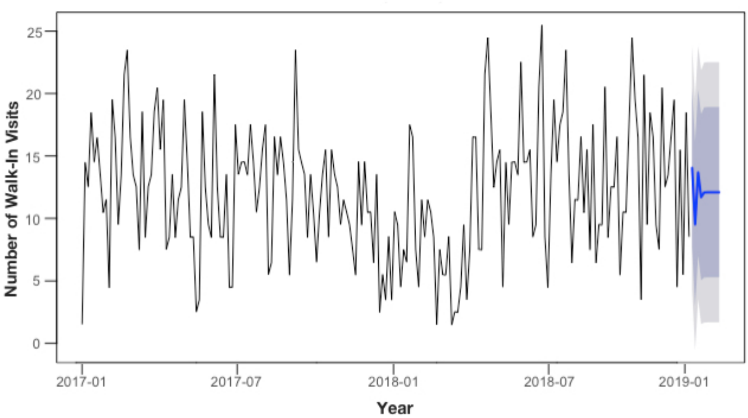

Figure 9: **Daily 2019 walk-in demand for clinic A (weekends)**

5.1.2 Clinic B

Like in clinic A, the number of appointments at clinic B grew steadily between 2015 and 2018. For clinic B, the outlier thresholds were 10 from 2015-2016, 25 from 2016 to 2017, and 50 from 2017 to 2018.

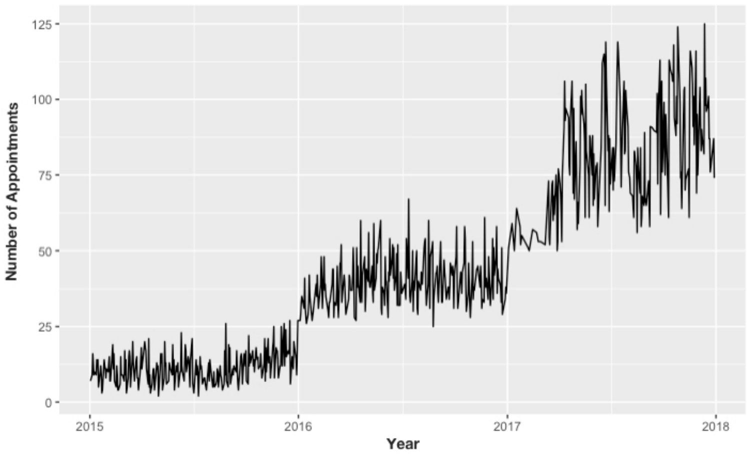

Figure 10: **Daily number of appointments for clinic B (weekdays)**

Based on the time series, the model process produced the ARIMA(1,1,7) model in Figure 10. The model projects out 25 days into 2018 that, within a 80% confidence interval, the demand for appointments will range from 60 to 100 per day. A p-value of 0.9955 validates the projection.

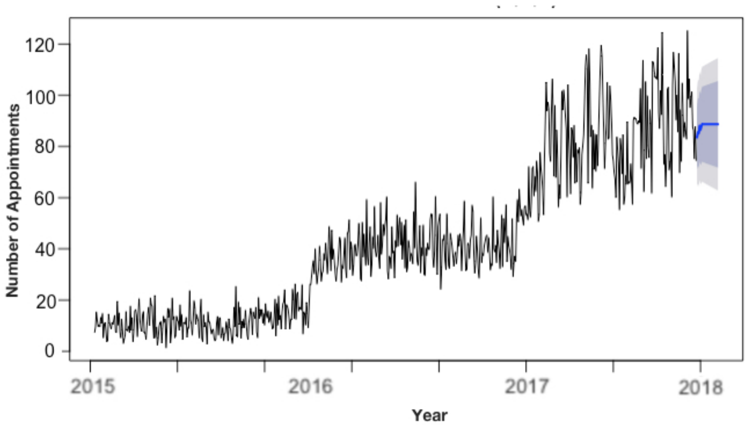

Figure 11: **Daily 2018 appointment demand forecast for clinic B (weekdays)**

The number of weekday walk-in visitors, like clinic A, have been largely consistent from 2015-2017 at clinic B, as seen in Figure 12. The number of people who walk-in to the clinic without an appointment is typically between 10 and 20. No outliers were removed from this time series.

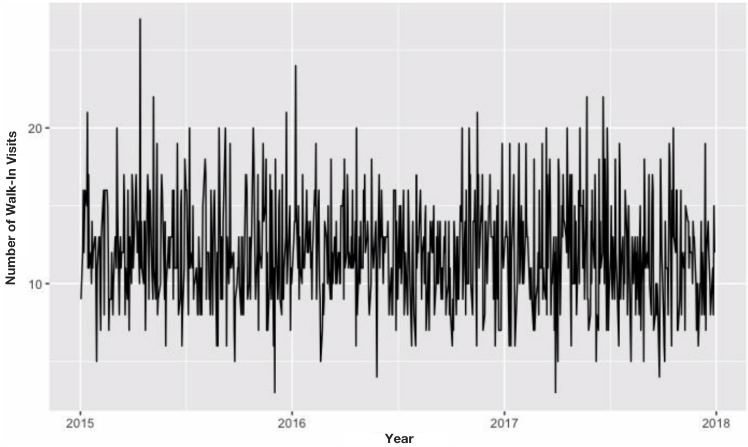

Figure 12: **Daily number of walk-in visitors to clinic B (weekdays)**

The weekday walk-in time series for clinic B resulted in the ARIMA(1,0,6) model in Figure 13. The model projects 30 days into 2018 within an 80% confidence interval, wherein the demand for weekday walk-ins will range between 8 and 18. A p-value of 0.9998 validates the projection.

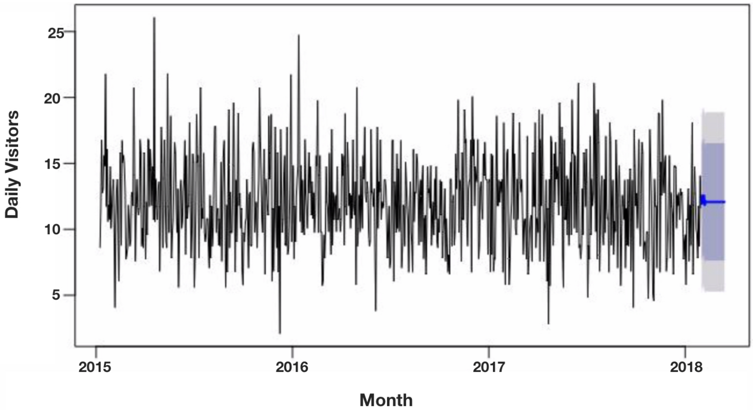

Figure 13: **Daily 2018 walk-in demand forecast for clinic B (weekdays)**

As with clinic A, data from 2017 to 2019 was considered for the weekend walk-in time series. In this case, 30 or more visits were considered outliers and were removed.

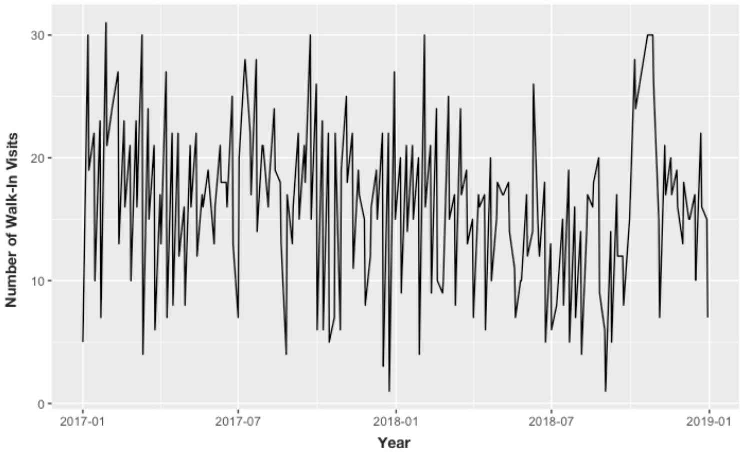

Figure 14: **Daily number of walk-in visitors to clinic A (weekends)**

The weekend walk-in time series produced the ARIMA(1,1,2) model in Figure 15. The model projects

10 weekends into 2019 that, within a 80% confidence interval, demand for weekend walk-ins will range between 5 and 20 clients. A p-value of 0.5645 validates the projection.

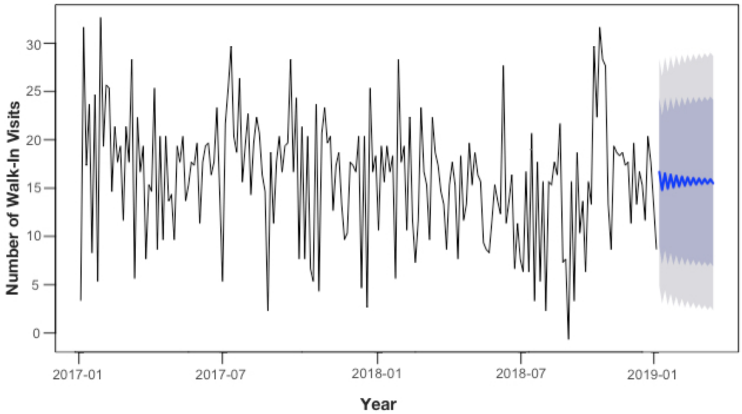

Figure 15: **Daily 2019 walk-in demand for clinic B (weekends)**

5.1.3 Hospitals

The time series reveals hospital emergency department visits have been consistent from 2015 to 2019. This corresponds to the fact that hospitals do not change their operations as frequently as clinics do.

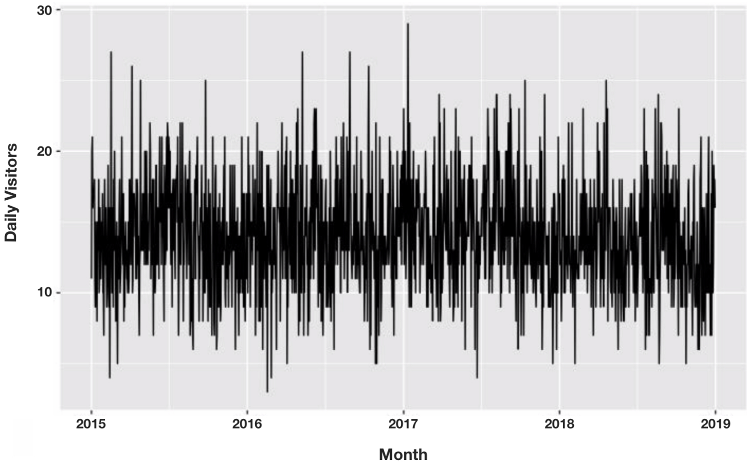

Figure 16: **Daily number of acuity 4 and 5 visits to hospital emergency departments (weekdays)**

The time series produced the ARIMA(1,1,6) model in Figure 17 shows a steady 35 day projection into 2018 with between 13 to 18 visitors to the hospital with an 80% confidence interval.

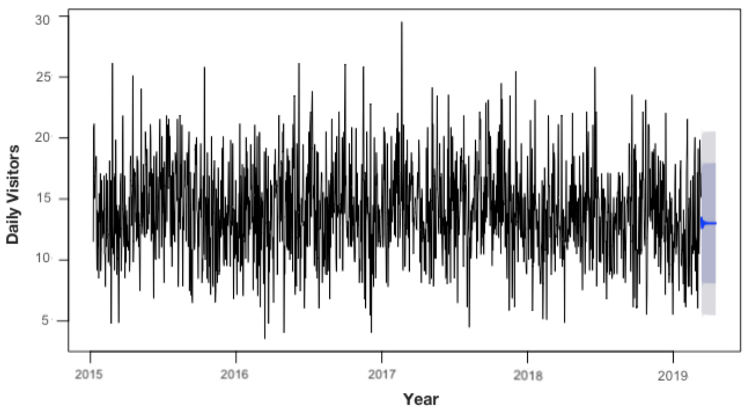

Figure 17: **Daily 2019 demand forecast for hospital emergency departments from acuity 4 and 5 visitors**

5.2 Model of High Use Patients

5.2.1 Appointments

From our initial dataset of 19,619 patients making 360,424 appointments, we identified patients who booked at least 20 appointment within the range of the data as "appointment seekers". Appointment seekers were classified into one of several categories depending on their characteristics. Among all patients who had made appointments, 4,605 patients (23.47%), making up 298,519 (82.82%) appointments, were included in this category.

Time-Focused Patients with more than 50% of their appointments taking place within 30 minutes of a given time were considered to be time-focused patients. Among our appointment dataset, 466 patients (10.12% of appointment seekers) were found to be time-focused and they made 26,360 appointments (7.31% of all booked appointments).

Physician-Focused Patients with more than 75% of their appointments taking place with a particular physician were considered to be physician-focused, 959 (20.83%) patients were found to be physician-focused and they made 50,645 appointments (14.05%).

Multi-Focused Patients satisfying both the conditions for time and physician focus were considered to be multi-focused, 203 (4.41%) patients were found to be multi-focused and they made 8,867 appointments (2.46%).

No-show Patients with more than 30% of their appointments being marked as “no-show” were categorized as no-shows. We found 871 (18.91%) patients to be no-shows and they made 62,747 appointments (17.41%).

Irregular Patients not fitting into any other category were grouped into this additional category, 2,666 (57.89%) patients were categorized as irregular and they made 195,827 appointments (54.33%).

Frequent Patients with more than 200 appointments are frequent visitors, 134 (0.49%) of all patients are frequent visitors, making a total of 38,458 appointments (10.67% of all appointments). Among frequent users, 20, (14.93%) were found to be in the no-show category. This is a lower percentage than the aforementioned 18.91% of appointment seekers. Appointment seekers and frequent visitors had roughly equal proportions of no-show appointments, at 19.15% for appointment seekers and 19.51% for frequent visitors.

5.2.2 Walk-ins

From our initial dataset, we identified any patient who attended at least 10 walk-in visits as a "walk-in". Walk-ins were classified into one of two additional categories depending on their characteristics. Among all patients who made a walk-in visit, which not every client does, 2,412 (11.69%) were found to be in the walk-ins category, making 51,737 walk-in visits (52.42% of all walk-in visits).

Time-Focused Walk-In Patients with more than 50% of their walk-ins taking place within 30 minutes of a given time were considered to be time-focused patients. Among our walk-in dataset, 702 patients (2.56% of all patients) were found to be time-focused walk-ins, and they made 15,179 walk-in visits (15.38%).

Irregular Walk-in patients not falling into any other category were grouped into this additional category. We found 1,710 patients (6.25%) to be irregular walk-ins and they made 36,558 walk-in visits (37.04%).

5.2.3 Emergency

Among emergency visits, we considered only patients with a acuity score of 4 or 5 to be non-urgent patients. We categorized emergency visitors into one of four categories:

Low-Potential Patients with 5 or fewer emergency room visits were considered to be low-potential, 11,540 patients (80.73% of all 4 and 5 emergency patients) were placed in this category and they made 19,947 emergency room visits (39.17% of all 4 and 5 emergency room visits).

Mid-potential Patients with more than 5 but less than 15 emergency room visits were considered to be mid-potential, 2,228 patients (15.59%) were placed in this category and they made 16,783 emergency room visits (32.96%).

High-Potential Patients with 15 or more emergency room visits, or no-show patients with between 5 and 15 visits, were considered to be high-potential, 711 patients (4.97%)

were placed in this category and they made 15,664 emergency room visits (30.76%).

Top-Potential No-show patients with 15 or more emergency room visits were considered to be top-potential, 72 patients (0.5%) were placed in this category and they made 1,914 emergency room visits (3.76%).

Among all emergency room patients, an average of 3.56 visits per person were made. Among emergency room patients who were also no-shows, 6.67 visits per person were made. A similar difference does not appear for time or physician-focused individuals, suggesting that no-shows more frequently use the emergency room for non-urgent matters.

5.3 Simulation Parameters and Operation

5.3.1 Parameters

For the simulations, visitors of clinic A see a doctor, social worker or nurse with probability 0.5457, 0.03874 and 0.4155, respectively. Visitors of clinic B see a doctor, social worker or nurse with a probability of 0.75773, 0.01073 and 0.23154, respectively. These probabilities were acquired from examining the frequency of patients known to be visiting a doctor, social worker or nurse, compared to the total number of visits for each clinic.

At clinic A, visiting a doctor takes 25.8 minutes, a nurse takes 35.2 minutes and a social worker takes 60.16 minutes. At clinic B, visiting a doctor takes 24.6 minutes, a nurse takes 40.0 minutes and a social worker takes 57.3 minutes. These times were acquired by taking the average time for each type of visit at each clinic. Walk-ins are urgent with a probability of 0.01076 at clinic A and 0.000355 at clinic B. This was calculated by dividing the number of urgent walk-ins at each clinic by the total number of walk-ins. At both clinics, we assume a CSC takes 3 minutes to check-in a visitor.

5.3.2 Simulation Operations

S1 simulates people arriving at Clinic A for an appointment and has visitors arrive at an average rate that changes throughout the day corresponding to the figures below. First, visitors see a CSC and then, as soon as one is available, they see either a doctor, nurse or social worker. Notice the high levels of appointments. This is believed to be due to classifying phone calls as appointments, which is skewing the data.

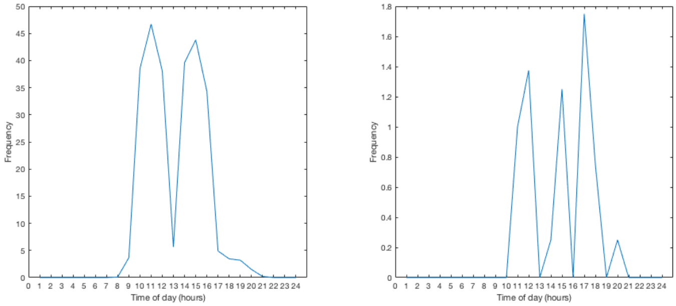

Figure 18: **S1: Clinic A expected appointment arrival rate on weekdays (left) and weekend (right)**

S2 simulates people arriving at Clinic B for an appointment and has visitors arrive at an average rate that changes throughout the day corresponding to the figures below. First, visitors see a CSC and then, as soon as one is available, they see either a doctor, nurse or social worker but with different probabilities and service times than S1 because this is simulating a different clinic.

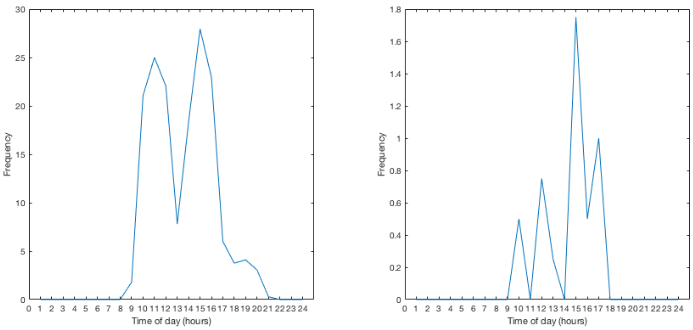

Figure 19: **S2: Clinic B expected appointment arrival rate on weekdays (left) and weekends (right)**

S3 simulates people walking-in to clinic A. It has visitors arrive at an average rate that changes throughout the day corresponding to the figures below. First, visitors see a CSC. If urgent, the visitor goes straight to the doctor. If not, as soon as one is available, the visitor sees a doctor, nurse or social worker.

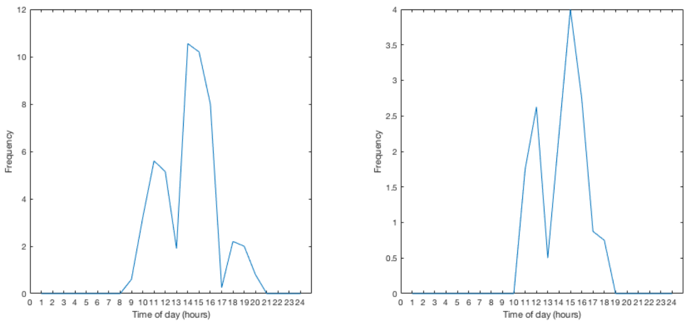

Figure 20: **S3: Clinic A expected walk-in arrival rate on weekdays (left) and weekends (right)**

S4 and S5 simulate people walking-in to clinic B. They have visitors arrive at an average rate that changes throughout the day corresponding to the figures below. S4 simulates before noon, during the appointment period. It has visitors first see a CSC. If urgent, the visitor books the next available appointment to see a doctor. If not, the visitor leaves to return later for a walk-in after the appointment period is over. S5 simulates the afternoon, after the appointment period is over. Here, visitors first see a CSC and, if urgent, the visitor goes straight to the doctor. If not, as soon as one is available, the visitor sees a doctor, nurse or social worker.

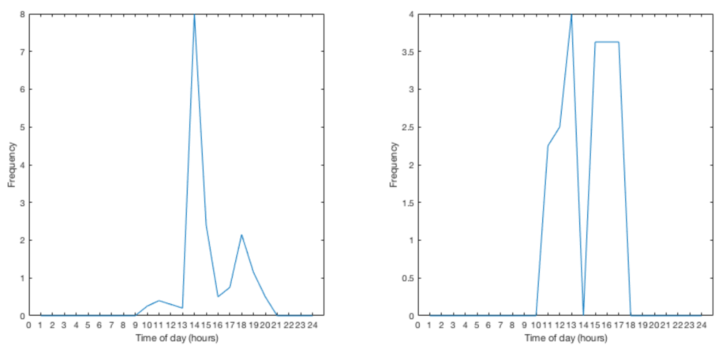

Figure 21: **S4 & S5: Clinic B expected walk-in arrival rate on weekdays (left) and weekends (right)**

6 Results

6.1 ARIMA Models

The time series plots show that clinic demand has been increasing with time. The ARIMA models project that this demand will remain at high level. Daily appointments to clinic A averaged approximately 25 visitors per day in 2015 and the projection estimates it will be more than 100 moving forward. For clinic B daily appointments went from 10 on average to more than 80 moving forward. However, appointment data may be skewed by phone calls. Historically, more visitors to clinics has not resulted in fewer clinic patients going to the hospital for low-urgency issues, which has remained at approximately 12 patients from 2015 to 2018. The ARIMA projection estimates that this figure will continue in to the future unless changes are made to specifically address the issue. The stability in hospital visits allows us to use it as a baseline against which to compare the results of our recommendations.

The ARIMA models also allow us to understand how previous operational changes at the clinics have affected acute care use. The ARIMA model in Figure 17 shows how hospital visits for acuity 4 and 5 patients has been very stable. Prior to September 11, 2016, clinic B was not open on Sundays. After that date, they started opening on Sundays to little discernible effect on hospital demand for low-complexity patients. This suggests that removing operating hours on Sundays should not significantly impact acute care use.

6.2 Operating Hours

Examining acute care visits with acuity scores of 4 or 5, from January 2, 2018 to April 11, 2018, (a typical and relatively recent 14-week period) it appears that weekdays have a higher potential for cost-reduction than weekends. Weekdays are busier overall, with 5,130 low-priority acute visits compared to 2,035 on weekends. On weekdays, 2,967 of the visits occurred during the hours the clinics were closed, versus 1,203 on weekends. This suggests that increasing operating hours on weekdays has a higher potential for reducing acute care visits than doing so on weekends. Those low-priority acute care visits would be substituted with primary care clinic visits.

In order to determine the effect that clinic opening hours had on acute care usage, we looked at the one-hour periods before and after the clinics opened (7:30-8:30 and 8:30-9:30, respectively). From 7:30 to 8:30, there were 38 low-urgency acute visits to the hospital out of 175 total visits (21.7%). From 8:30 to 9:30, 52 visits out of 208 (25%) were low-urgency. Similarly, we looked at hospital visits one hour before the clinics close (15:30-16:30) and one hour after closing (16:30-17:30). From 15:30-16:30, 48 out of 285 (16.9%) of acute care visits were low-priority. From 16:30-17:30, 53 out of 271 (19.6%) were low-priority.

During that same 14-week period, we examined acute care usage on weekends. One hour before opening, from 8:00 to 9:00, 19 of 84 (22.6%) acute care visits were low-urgency. From 9:00 to 10:00, 22 of 94 (23.4%) were low-urgency. One hour before closing, from 16:00-17:00, 23 of 120 (19.2%) acute care visits were low-urgency. From 17:00-18:00, 16 of 102 (15%) were low-urgency.

There are many extraneous factors at play in these time periods, making these observations less reliable than would be optimal. Rush hour, among other things, could have a significant effect on hourly visitors at these times of day. Nonetheless, our findings suggest that additional operating hours on weekday evenings would be more effective at reducing acute care usage than operating hours on weekend mornings or evenings. Additional weekend evening hours would reduce acute care usage by roughly 14% (16.9% versus 19.6%) per extended hour compared to the same time period with no clinic hours.

On the other hand, weekend evening clinic hours show no particular effect in reducing non-urgent acute care usage, potentially even increasing acute care usage. One mechanism to explain this, if accurate, is that weekend evening staff tend to direct walk-in staff towards the emergency room, who would otherwise not have gone. Assuming our observations to be accurate, this would suggest that moving resources away from weekend evenings and towards weekday evenings would reduce low-urgency acute care usage.

One possible concern about closing the clinics on weekends is that there may be some clients who are only able to visit the clinic on weekends. By removing weekend operating hours, those weekend-only people may be motivated to go to acute care for low-priority reasons. This is unlikely to be the case, however. We observed that in the previous 5 years, of the 27,380 unique individuals who walked-in or had appointments at both clinics, 7,978 of them made use of the clinic on a weekend. However, only 1,419 of those made use of the clinic exclusively on weekends. Furthermore, those 1,419 weekend-only patients made a total of 1,861 visits to the clinics over the 5 year period, averaging out to 1.31 visits per patient, with 1,338 patients visiting only a single time. Of those 1,861 visits, 1,650 were walk-in visits. The vast majority of weekend-only visitors are individual walk-ins, who visit once and never return. By contrast, weekday-only visitors make up 19,402 individuals and 193,433 visits, just under 10 visits per visitor. This being the case, we believe that moving hours from weekends to weekdays would improve, rather than diminish, the number and variety of patients able to be seen.

6.3 Validation Simulation

The simulations were used to validate that patient wait times and clinic staffing levels remain at acceptable levels if weekend resources are redirected to weekday evenings or to adding more staff during peak hours.

The most important simulations in the validation process are S3 and S5. These simulations model walk-ins to clinic A at any hour and walk-ins to clinic B after the morning appointment-only period ends. They are important because they model the most unpredictable aspect of clinic operations, the arrival rates of walk-ins during non-appointment periods. These are unpredictable because there is more uncertainty when preparing to serve walk-ins than for people scheduled to arrive for appointments.

We broke down the arrival rates into one-hour sections where each hour was simulated with a different arrival rate. The arrival rate for each hour was found differently for appointments than for walk-ins but both used a representative four-week period from September 30, 2017 to October 27, 2017 to determine arrival rates. This period is a good representative sample because there are no holidays or operational changes during those weeks or immediately before them. For appointments, we considered only people with 20 or more appointments in the 5-year data set. For walk-ins, we considered only people with 10 or more walk-ins during the 5 years. This is because people who have rarely visited the clinics are not going to have a major impact on its use[†]. The simulations confirm that reallocating resources from weekends to weekdays is feasible by staggering shifts.

6.4 Patient Categorization

Among all appointment-seeking patient categories, there were no particular differences in the distribution of usage rates throughout the morning. The ratio between morning and afternoon appointments did have significant differences between categories. Physician-Focused patients booked less appointments in the mornings than in the afternoons, and vice-versa on weekends. Time-Focused patients booked more appointments in the mornings, and equal amounts on weekends.

As seen in the figures below, in walk-in patient categories, Time-Focused walk-ins were much more likely to visit immediately at the start of the walk-in period than the general walk-in population (corresponding to those patients with greater than 10 walk-ins over the course of the data). We suspect that these walk-ins represent patients who would prefer to visit at earlier hours and are made to wait until the walk-in period begins. Therefore, they could benefit from allowing walk-ins throughout the entire day.

[†] In the dataset, the number of appointments was unreasonably high. It is possible phone calls were recorded as appointments.

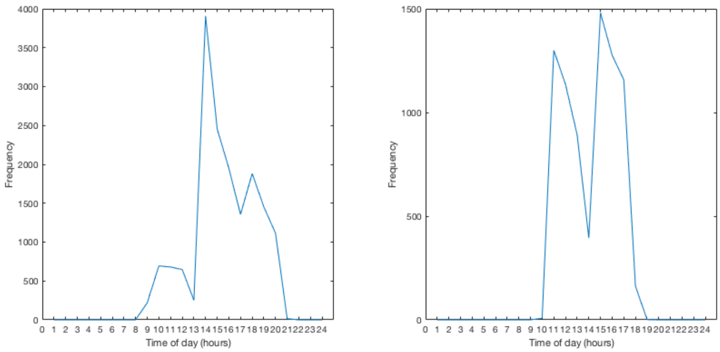

Figure 22: **Walk-In demand on weekdays (left) and weekends (right)**

‡

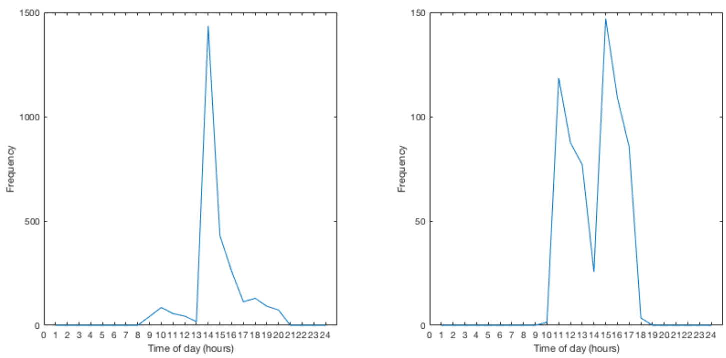

Figure 23: **Time-Focused walk-In demand on weekdays (left) and weekends (right)**

In previous studies, the majority of emergency room visits have been found to take place during the day, between the hours of 07:00 and 17:00, with additional activity between 17:00 and 21:00 [1, 2]. This is also reflected in our data as seen in the figure below.

‡Sharp decline in the afternoon hours may represent a lunch break.

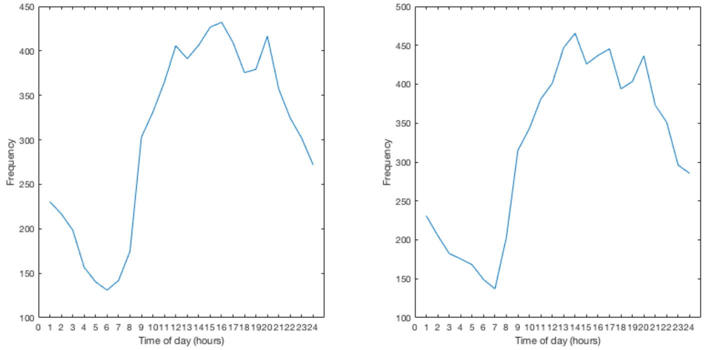

Figure 24: **Hourly emergency demand on weekdays (left) and weekends (right)**

Among Time-Focused, Physician-Focused, Appointment-Seeking, No-Show, Low-Potential, and Medium-Potential populations, none differ significantly in distribution from the above graph of total emergency department demand. They differ only in total scale of visits. However, high-potential and top-potential patients do show slightly different distributions, as seen in the figures below.

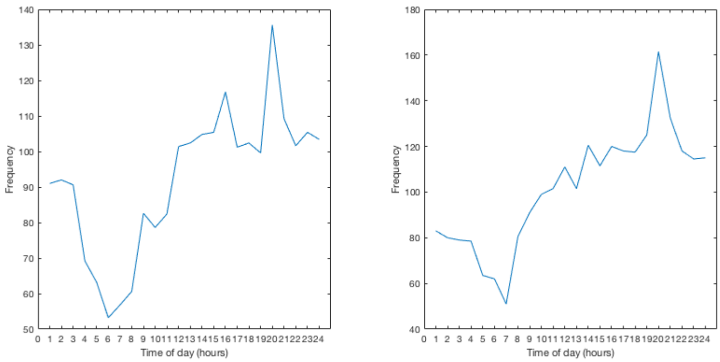

Figure 25: **High-Potential hourly emergency demand on weekdays (left) and weekends (right)**

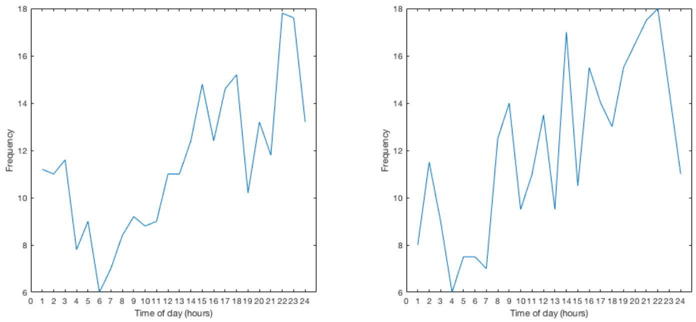

Figure 26: **Top-Potential hourly emergency demand on weekdays (left) and weekends (right)**

High and Top-Potential patients have a much larger spike in usage near the end of the day, with a much smaller usage during clinic hours. We initially conjectured that, since these patients were more likely to fail to show up for appointments, they would follow up their no-show appointments with emergency room visits. While we were unable to make any relevant observations regarding that question, it seems that the opposite, or similar, may be true. If these higher-potential patients are showing up for acute care more regularly than average outside of clinic hours, this suggests they are using clinic hours as a substitute for acute use. We speculate that when this category of patient has a low-urgency emergency, instead of going to the emergency department, they often phone the clinic to book an appointment, and fail to show up to that appointment when their emergency passes. However, a more detailed study is needed to confirm this suspicion.

Ultimately, we were unable to find many significant links between our different patient categories and their emergency room usage. High and Low-Frequency patients who are attached to particular physicians, and patients who are attached to particular times, do not show any significant difference from the average ER usage.

7 Recommendations

Our findings on acute care use and patient variety on weekdays and weekends suggest that reallocating resources from weekends to weekdays would reduce non-urgent acute care use and improve the clinics' ability to meet their patient needs. Those resources could be used to extend operating hours later into the evening on weekdays, to increase staffing during peak periods, or some combination of both.

Reallocating resources from weekends to weekdays helps reduce acute care use in two ways:

1. Extending operating hours into the evenings on weekdays allows the clinics to offer extended walk-in and appointment hours. Time sensitive people will have more opportunities to visit the clinic outside of business hours. There will also be additional resources to fully staff the clinics at these hours. Currently, clinics run reduced staff numbers in the evenings, limiting opportunities to meet patient demand at those hours.

2. More staffing during peak hours will allow clinics to reduce the number of patients who check-in but leave before their turn because the wait was too long. The clinics do not track how frequently this happens, but clinic officials suspect it to be a significant problem.

Eliminating weekend hours has the additional benefit of no longer having to fill those shift hours. Clinic officials have expressed that finding people for those shifts can be difficult and time consuming. This time can now be directed towards more productive areas.

Below, we present a comparison between the current emergency demand and the predicted emergency demand should normal operating hours be extended by a further four hours on weekdays (from 16:30 to 20:30). This comparison is made given that our estimate of 14% reduced acute use from weekday evening clinic hours is accurate.

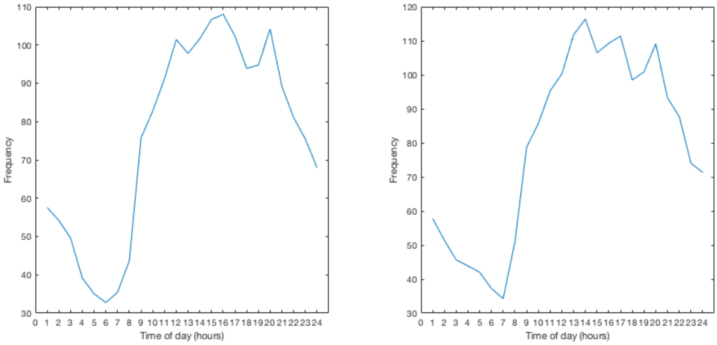

Figure 27: **Hourly emergency demand on weekdays (left) and weekends (right)**

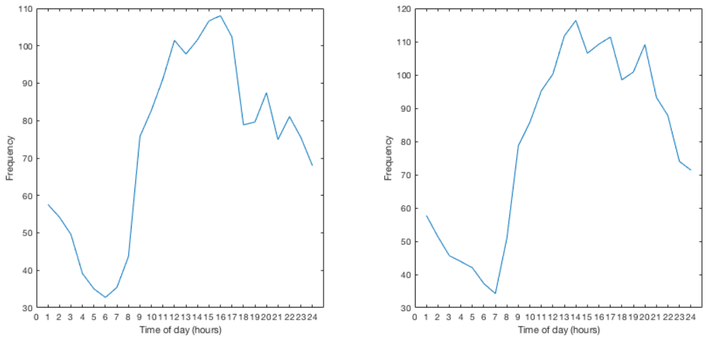

Figure 28: **Adjusted hourly emergency demand on weekdays (left, reduced) and weekends (right, unchanged)**

Based on our emergency demand projections from the month of September 30, 2018 to October 27, 2018, this represents a decrease of 2.4% in low-urgency acute care usage.

8 Conclusion

VCH has identified reducing acute care use for non-urgent issues as a priority. To do this, the high-acuity score hospital visitors will have to be serviced by primary clinics. For this to happen, it is important to understand who goes to hospitals versus primary clinics and why.

To answer these questions, this study began with an ARIMA analysis to understand the context under which the clinics and hospitals operate and what they can expect in the future. We have seen that the number of clinic visitors grows every year but low-complexity hospital visits stays relatively stable. We then profiled the clinic patients by grouping them into categories to understand their hospital use patterns. We found that High and Top-Potential people were less likely to visit a hospital during clinic hours. Otherwise, there were no significant connections between patient categories and emergency room use.

We determined that the best approach to reducing acute care visits for non-urgent patients was to redirect resources from weekends to weekday evenings. We then simulated this change to determine whether it was feasible with current staffing levels and found that by staggering shifts it was possible to provide more care on weekday evenings.

A key limitation of this study is the absence of patient complexity data at the clinics. Without this data we were unable to draw connections between why a patient chooses to go to a clinic versus a hospital. Another important limitation relates to uncertainties in the data, especially concerning appointments. Several assumptions had to be made in how data was grouped together which will affect the accuracy of the models. A future study, should begin with a deeper understanding of the data that incorporates both clinic complexity and hospital acuity scores.

In summary, engaging stakeholders to determine how more staffing resources can be redirected to weekday evenings in clinics A and B, even if it means redirecting those resources from weekends, can potentially reduce acute care use among low-acuity clinic patients by up to 14% per hour.

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