Improving Patient Flow in a Healthcare Clinic Post COVID-19: A Data Validation and Exploratory Analysis Approach

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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Improving Patient Flow in a Healthcare Clinic Post COVID-19: A Data Validation and Exploratory Analysis Approach

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***Abstract*— Since the beginning of the COVID-19 pandemic, healthcare clinics have faced increased inefficiencies due to an influx of patients returning to clinical care. The strain on nursing resources leads to long patient waiting times, which can lead to provider burnout and more stressful patient care. Here we compare the electronic medical record (EMR) timestamp data with observational data to understand better the current patient flow at the University Physicians of Charlottesville (UPC) clinic, a primary care clinic within the UVA Health System. Our overarching goal for this study is to propose data-driven solutions to improve clinic efficiency and reduce stress for providers, nurses, and staff. We implemented a two-phased analysis approach. The first phase involved cross-checking the EMR timestamp data with observed data to validate the consistency and reliability of the EMR timestamp data and thus allow us to confidently identify areas of improvement within the clinic, such as peak waiting periods. In the second phase, we used the validated data to analyze the distribution of delays during different appointment stages. Using a discrete event simulation, we recommend solutions that could improve the patient experience and reduce stress on medical personnel. The findings are further supported by graphical analyses of the delays in patient rooming depending on the time of day, length of the appointment, and provider. Overall, the two-phased approach will provide the clinic with a holistic understanding of the causes behind delays in patient care.**
Keywords- Primary Care, COVID-19, Patient Flow, Electronic Medical Records (EMR)

I. Introduction

The COVID-19 pandemic has posed a significant challenge for healthcare systems worldwide, with increased patient demand often surpassing healthcare providers' capacity. Additionally, primary care facilities were forced to rely on telemedicine, resulting in a loss of revenue and creating new bottlenecks in patient care [1–3]. The University Physicians of Charlottesville (UPC), a primary care clinic within the UVA Health System, also faced similar challenges during the pandemic. In response, the UPC clinic implemented various measures to enhance its operations. Nevertheless, as the world emerges from the pandemic, UPC and other clinics are expected to operate at their pre-COVID and normal capacity. Here we identified areas for improvement post-Covid at UPC that sought to improve workflow and mitigate factors that could lead to provider and nurse stress. The goal here was to support the clinic by offering actionable recommendations to improve the quality of care and the patient experience.

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II. Project Background

We build upon the work conducted by Korte et al. [4] and Dozier et al. [5] that focused on the same clinic during the pandemic. However, we examine the clinic post the height of the pandemic. Because of many COVID-19 restrictions on in-person observations, previous studies were more limited in scope and provided a general overview of the patient flow process, explored patient cancellation behaviors, and capacity utilization in specialty care outpatient clinics. In addition, in the study of Dozier et al. [5] the authors analyzed appointment times, lengths, and types to extract metrics averaging the patient cycle times. Their results showed a steady decline in cycle times after March, the start of the COVID-19 pandemic, with a general trend of decreasing cycle times in the early morning, which increases in the late morning. This work laid the foundation for this study, especially regarding the importance of the distribution of timestamps and what causes delays in patient rooming throughout the patient care process.

This research focuses on analyzing data from UPC's electronic medical record (EMR) system, consolidating patient data onto a single server. The EMR system includes features such as health templates, patient medical history, and referrals to ensure healthcare providers can deliver the best patient care. Along with patient care features, the EMR system also collects data on certain events, such as when the patient checks into the clinic, when the nurse retrieves the patient from the waiting room, when the nurse and patient enter the examination room, when the nurse logs into the EMR system on the computer, when the nurse leaves the examination room, when the provider enters the examination room, when the doctor exits the examination room, and when the patient checks out of the clinic.

Timestamp data was archived in two EMR reports. One report contained information on patients' appointment scheduling, which provides valuable information when matched with the EMR timestamp data. The two primary data sources were validated using in-person observations. These observations also yielded qualitative information to provide a holistic understanding of clinic processes and workflows.

To structure our analysis, we studied published literature on various aspects of clinical efficiency. Mesko et al. [6]

identified issues in a high-volume radiation oncology clinic using metrics such as cycle times, waiting times, and rooming times. They implemented the Patient Flow Analysis (PFA) system to optimize the workflow of consultation visits in the clinic. Their study revealed long rooming times, inefficient communication, duplicated tasks, and unclear clinic roles and to address these issues, they intervened to enhance the patient experience, reduce staff burnout, prioritize financial savings, and identify opportunities to expand clinical capacity [6]. This work provides a valuable framework for our study and informs our approach to analyzing clinical efficiency in the post-pandemic context.

III. Methods and Design

Our approach consisted of (1) collecting observational data in-person at the UPC clinic, (2) cross-matching the observational data with the recorded timestamp EMR data, and (3) running a simulation of clinic operations. The team observed the nurses and providers at the UPC clinic over the course of five months and at different times throughout the day (i.e., morning, 8-11 am; afternoon, 1-3 pm). During data collection, all team members used a template that listed the timestamps of interest to make data collection consistent across observers.

An essential part of the data collection process is the dotting system used in the clinic. The dot system shows where patients are throughout the clinic cycle. Once the patient checks in, a dot appears, which indicates that the patient is ready to be roomed. A yellow dot indicates that the patient checked in. A green dot indicates that the patient is with the nurse and is ready to meet with the provider. A blue dot indicates the patient has pending orders that are needed before they leave, such as an EKG. A red dot indicates that the patient needs radiology care. A black dot indicates the patient completed the visit, while the white dot indicates the patient missed their appointment.

The dot system comes into play throughout the patient appointment process, similar to previous work [5]. Initially, the scheduling staff keeps track of the patient's arrival at the clinic and changes the colors dot in EMR system to inform the nurses and doctors of the patient's status. The nurse then retrieves the patient from the waiting room, which is immediately followed by certain personal information checks such as birth date, weight, vaccination status, and COVID-19 booster status. The nurse then escorts the patient to the examination room and logs into the EMR. The nurse begins to edit the patient's chart details, such as measuring the patient's vitals and checking medication history. Once the nurse's responsibilities have been completed, the nurse changes the patient's dot status, indicating to the provider that the patient is ready for their consultation. Next, the provider enters the room and confidentially provides care to the patient. Once the provider is finished, the patient exits the clinic to checkout. Sometimes there are additional tasks that the nurse needs to complete, such as helping another nurse or provider. This can impact the patient cycle time and cause unwanted errors in the time stamp collection process. Another factor that can skew time stamps is the delay when a patient arrives at their appointment. This can create a domino effect that can affect when other patients can be roomed, the provider availability, and overall appointment lengths. Depending on the type of patient visit, appointments can be 20 minutes or 40 minutes in length. They usually alternate 20 and 40-minute appointments, resulting in the providers having 14 appointments per day on average.

During the data collection process, in the months of September and October, the clinic was short-staffed with only three nurses, and many patients were seeking care at UPC to get the Covid vaccine. Each team member observed one nurse at a time, collecting data on each patient's rooming process. Despite each nurse following the same procedure, there were differences in their actions that prompted time stamps to record inconsistently. For instance, when charting patient information in the examination room, some nurses would sign into the EMR before getting the patient, while others would sign in after the patient was in the room.

In the months of January and February, there were five nurses and five providers in the clinic. The clinic implemented a new workflow process where a nurse would be matched with a provider, meaning that the nurse would preferentially perform responsibilities for the provider they are matched with for the day. This one-on-one pairing would vary from day to day, allowing nurses to work with different providers. This new process of provider-to-nurse matching improved patient throughput.

IV. Analysis and Results

A. Combining and Cleaning the Dataset

Our team cross-matched the observational data with the archived data in the EMR. We noticed several mismatches in the data while processing the data in Excel. First, we used a combination of appointment date and time and the provider's name to ensure that the right appointments were being compared with the two datasets. Through the xlookup Excel function, we joined the timestamp data from multiple datasets to create one table with the same appointment date and time for easy comparison. The xlookup function requires three arguments, the lookup value, the lookup array, and the return array. We also used the CSN number, which is unique to each patient encounter.

We found differences of a couple of minutes between data collected in person and recorded timestamps. We also identified some illogical timestamps, such as appointment completion timestamps recorded ten hours after the start time. To prepare the dataset for analysis, we removed rows with missing data. A significant point of confusion was ambiguity regarding the meaning of some data variables. For instance, 'BEGIN CHECKIN DTTM' and 'CHECKIN DTTM' refer to the same timestamp; however, some of their data entries were different. Instead of removing these rows, we decided to use the more accurate variable name for consistency.

After cleaning the database, we used an if statement, which returns a boolean response within Excel, to check if the appointments had the same provider. We then filtered the table to show observations with 'yes' as a response. This created a filtered table with the EMR and observational data for all the appointments we witnessed during shadowing. Following this, we compared the metrics within this singular table to see which ones matched. For instance, the variable 'Nurse Room Time' from the EMR was matched with 'Nurse Swipe In Time' in observational. We explored various factors and identified key points by plotting the differences between similar metrics using graphical displays. Some factors we looked at included the difference between the 'Nurse Room Time' and 'Nurse Swipe In', which results in the difference between the observed swipe-in time by the nurse and the actual recorded room time by the EMR.

B. *Data Analysis*

To further analyze the data, we created graphical representations to determine the current status of the clinic's efficiency. This allowed us to recommend changes to improve the patient experience. First, we looked at general demographics within the clinic. For the first five months, we created a gender breakdown by sub-setting all the patients to see if gender was a significant factor. We found that there we no significant difference in gender among the patients seen. In Figure 1, we sub-setted the Age category of the dataset to understand the age distribution of the patients at UPC. The pie chart showcases that very few patients are between the ages of 18-39, meaning that over 90% of the patients in the clinic were at least the age of 40. This finding can be attributed to the primary care population of the clinic. Since this is an internal medicine clinic that serves adults with chronic conditions, it is fitting that a large majority of its patients are middle age to elderly.

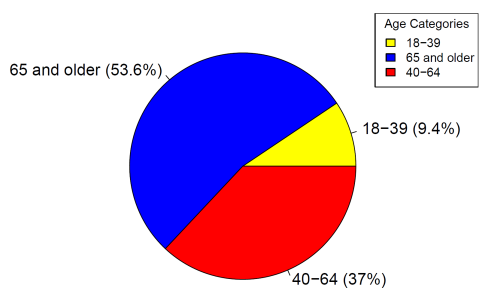

Fig. 1. Age distribution of the patients seen during February 2023 from Fontaine Data

Once we examined patient demographics, we analyzed the timestamp data from October to identify sources that caused delays at the clinic. The reason behind inspecting October data was because it was the month with the most observational data and hence, resulted in the most matches. To understand why the patients had to wait so long for their appointments, we compared their appointment times with when the nurse roomed them. First, we converted the date and time datatype of these columns to a numeric data type and then subtracted the roomed time column from the appointment column. The values that we obtained were either positive, negative, or zero. Positive values meant that the patient was roomed early, negative meant they were late, and zero meant they were on time. Upon counting these values, we found that 79 patients were roomed before appointment time, 151 were roomed after appointment time, and only 2 were roomed on time. This analysis confirms that 65% of the patients faced delays in their appointments from the beginning of the rooming process.

We looked at the breakdown of the time of day and how delays are distributed across different times to see whether this causes delays. As seen in Table I, the majority of the patients with appointments in the mornings (i.e., 9-11 am) were roomed after their scheduled appointment time. Of the 232 patients' appointments in the data, only one patient was roomed on time. The same conclusion was found for afternoon time appointments, indicating that the time of the day did not have an influence on delays.

Expanding the analysis on rooming delays, we also looked at the UPC providers specifically to understand the average amount of time they took to visit their patients' rooms. Seven providers saw a wide range of appointment types, and one provider had an average time of 18 minutes, while another was almost similar, with an average time of 17 minutes. The provider who took the least amount of time to see their patient had an average of 5 minutes.

TABLE I
ROOMING TIME BY SESSION TYPE

Time of Day	Before Appt	On Appt	After Appt
Morning	43	1	76
Afternoon	36	1	75

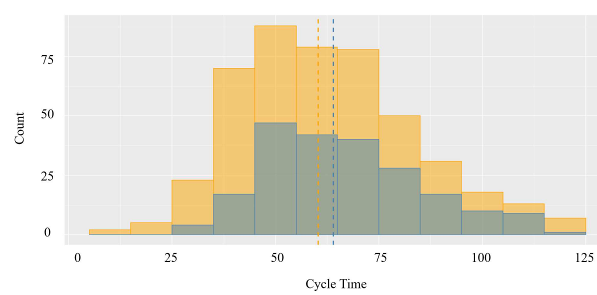

Fig. 2. Comparison of cycle times distributions between 20-min (orange bars) and 40-min (blue bars) appointments for October. The corresponding colored dotted lines are the mean cycle times for each distribution.

The cycle times for 20 and 40-minute appointments from October are shown in Figure 2. The overall average between both types of appointments was 64 minutes. The orange bars show the distribution of cycle times for 20-minute appointments, whereas the blue bars show the distribution for 40-minute appointments. The mean cycle time for 20-minute appointments was 63 minutes, which is signified by the orange dotted line. Similarly, the mean cycle time for 40-minute appointments was 67 minutes, which is signified by the blue dotted line. Note how the means for the 20-minute and 40-minute appointments are similar at 62.9 minutes and 66.9 minutes, respectively. This indicates that the 20- and 40-minute appointments are not significantly distinguishable, as both result in the patient spending over an hour in the clinic on average.

C. Simulation

We also created a discrete event simulation to analyze different nurse-to-provider combinations and optimize patient throughput. The layout of simulation components can be seen in Figure 3. To start the creation process, the group used the validated metrics of CheckIn, NurseEnter, ProviderEnters, and CheckOut. The experimental distributions for time intervals between these validated metrics were then recreated using Monte-Carlo simulation for days when three nurses and three providers were at the clinic. The group then inputted the discovered probability distributions that best fit the experimental data into the full simulation built in Simio, along with various other parameters such as patient inflow rates. The patient flow inputted within the simulation was created using historical data, which allowed the patient flow per provider to be found. The average patient number for five providers was eighty-two patients per day, while for four providers, the average patient number was seventy-two. This allowed the team to input the patient flow per hour within the simulation from 8 AM-5 PM. The simulation measured the following metrics: cycle time, time waiting for the provider, and time waiting for the nurse. The comparisons of interventions can be seen in Figures 4, 5, 6, and 7 below.

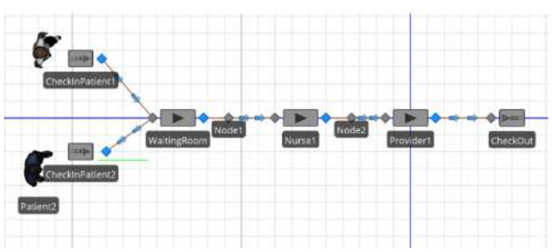

Fig. 3. Clinic Simulation Design for Simio

The group validated the simulation's ability to replicate the patient cycle times for different combinations of nurses and providers with the EMR data. When comparing the cycle times, the difference was found to be 10%, with the average cycle time being about 62 minutes while the average simulation cycle time was 56 minutes. The simulation results of patient total cycle time, time spent waiting for the nurse, and time spent waiting for the provider with the optimal scenario of five nurses and five providers were all compared and validated using the EMR's data. The difference between the patient waiting time was greater with the EMR data (mean = 9 min) than the simulation (mean = 5 min)–a 56% difference. Lastly, the patient time waiting for the provider was compared with the EMR data averaging eight minutes, and the simulation results averaged three and a half minutes resulting in a 78% difference.

We also tested other what-if scenarios the UPC clinic providers wanted to predict. The main factors explored with the simulation were the ratio of nurses to providers and the number of patients a provider would see in a given time. Here we were interested to see if there was significant justification for hiring another nurse to retain a 1:1 ratio between nurses and providers (i.e., five nurses and five providers). The comparison in cycle times can be seen in Figures 4 and 5, with a differentiation in patient appointment times. Type 1 and Type 2 patients are scheduled for 40 minute and 20 minute long appointments, respectively. When the number of nurses and providers was equal, the average cycle time was 60 minutes or less for both patient types. Decreasing the number of nurses from four to three with four providers resulted in a 33% increase in cycle time. When decreasing from five to four nurses, at a level of five providers, we noticed an increase of about 17% in cycle time. When the nursing staff was further decreased to three with five providers, cycle time increased by 70 minutes on average compared to a level of five nurses. The simulation shows that a 1:1 ratio of nurses to providers is ideal, but the clinic can operate sufficiently with one less nurse than a provider. The latter is suboptimal but does not increase cycle times by more than 33%.

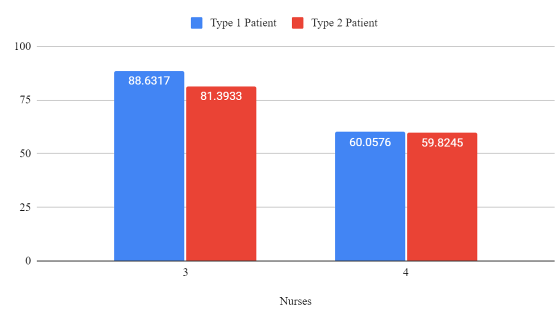

Fig. 4. Cycle Time for Type 1 and Type 2 Patient Types for 3 and 4 Nurses for 4 Providers

The simulation was also beneficial in exploring the necessity of a limit on how many patients a provider can see in a session. The sessions are defined as a four-hour time block in the morning and afternoon, with two sessions per day. Administrators are pushing for the clinic to increase the number of patients they see per session. According to historical data from December and January, providers currently see an average of eight patients per four-hour session. Increasing this number of patients per session to twelve will increase patient cycle times by 35-50%, as seen in Figures 6 and Figure 7.

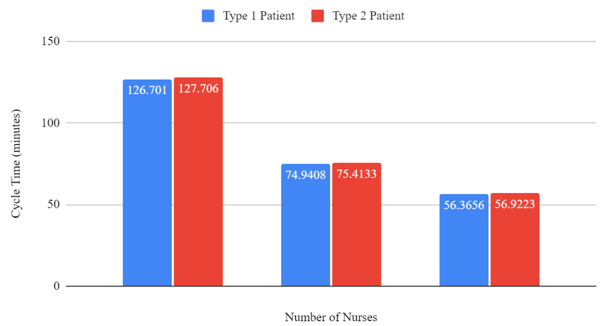

Fig. 5. Cycle Times for Type 1 and Type 2 Patient Types for 3, 4, and 5 Nurses for 5 Providers

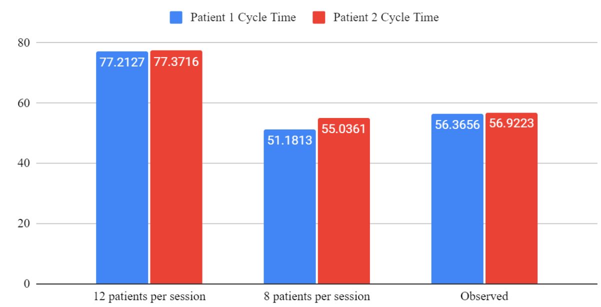

Fig. 6. Patient Cycle Time for 5 Nurses and 5 Providers with Varying Patient Loads

V. Discussion and Limitations

A. Discussion

This study aimed to build on previous work [4, 5] to better understand the clinic's needs emerging from the height of the pandemic. The analysis of patient demographics showed that a significant majority of the clinic's patients were over the age of 40. This could be because the age of the patients may require longer appointments and more procedures that need to be performed. To this end, we performed additional analyses to understand factors that could cause delays during an appointment. We found that the majority of the patients experienced delays during their appointments, starting even with the rooming process. This could be attributed to the extra time nurses took to get patients from the waiting room to the exam room and the mobility of the patient to move between rooms. We also sought to see whether the time of day played a role in whether rooming occurred on time, as there is a cascading effect due to delays. We found that the length of delays was fairly similar across morning and afternoon appointments.

Next, the team investigated the time nurses took to room patients. In Figure 2, we clearly noted no rooming procedure standardization between nurses. As a result, there were large discrepancies between when nurses entered the room and when they swiped into the EMR system. Had the rooming procedure

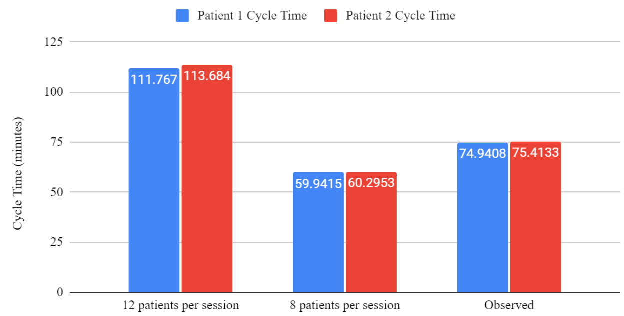

Fig. 7. Patient Cycles Time for 4 Nurses and 5 Providers with Varying Patient Loads

for when nurses swiped into the room been standardized, the data collected for rooming times would be more consistent for the data analysis portion of this study. This prompted us to recommend when nurses should swipe in the EMR system mid-way through this study to improve our data validity.

After determining the cause behind delays, we analyzed the length of the appointments to see if 20-minute appointments had more delays since they were significantly shorter than 40-minute appointments. We found no significant differences between both appointment lengths, and surprisingly, they took an average of over an hour to complete. Patients were spending 67 minutes on average in the clinic. This inflated appointment duration may primarily be due to when the clinic was short-staffed during one of the busiest times of the year when the demand for vaccines was at its highest. The clinic then implemented changes to the vaccine procedure in an effort to reduce cycle times. Initially, the nurses would escort the patient to the examination room and then ask whether they would like to receive a vaccine, then go to draw the vaccine, administer the vaccine, and document the process after completing the rooming procedure. This process took 12 minutes from when the nurse would leave the examination room to when they completed the documentation. Over time this would result in a significant amount of time spent just on vaccines, causing the patient to remain in the clinic longer. For instance, if ten vaccines were administered in the first three hours of the clinic, this would be approximately two hours spent just on vaccine administration. Thus, the clinic decided to pre-draw the vaccines to save time. As a result, the nurse would ask the patient during weigh-in if they would like to receive a vaccine. If yes, then the nurse could retrieve a vaccine from the storage unit, which was located adjacent to where the weight check is performed. This greatly improved efficiency and patients could receive their vaccine while they were waiting for the provider. However, the vaccine administration process still took between 6 and 11 minutes. There were some instances where the patient would wait until after meeting with the provider to then ask for the vaccine, causing further delays.

Given that 20- and 40-minute appointment procedures took, on average, the same amount of time, we did not find it significant enough to include this factor in the simulation. Our analysis validated the data collected, which then allowed the team to create a simulation to develop and provide the clinic with actionable data-driven recommendations to improve patient throughput. Two main interventions were used to drive the analysis. First, the team changed the nurse-to-provider ratio within the simulation to find overall cycle times, time spent waiting for the nurse, and time spent waiting for the provider. The results indicated that cycle times and wait times and patient time spent waiting for the nurse decreased significantly with each additional nurse added. The optimal combination of nurses and providers is one where the number of nurses staffed is equal to the number of providers staffed (i.e., 1:1 ratio). When the number of nurses was one less than the number of providers, the cycle times would not increase by more than 33%. However, when the number of nurses was two less than the number of providers, that is when cycle times were estimated to increase by 70 minutes. To avoid the risk of falling into this situation, if the clinic has one less nurse than the providers on staff, hiring another nurse should be a priority. This decreases the risk of long cycle times and creates a buffer in case a nurse is not able to come in.

Next, the team changed the number of patients within the simulation by comparing eight and 12 patients per session. The simulation was used to find the cycle times for each patient per session scenario and compared to the historical EMR data. The results from the simulation indicated that increasing the patient flow to 12 patients per hour would result in a significant increase in cycle times. This is in support of capping the number of patients a provider can see within a given session.

B. Limitations

The EMR data were used throughout the analysis portion of this work. Ensuring the data was accurate posed to be a challenge as there were outliers in the data and these had to be removed prior to data analysis. Only variables from the EMR data that were validated by observations were used in the data analysis; however, this decreased the sample size of the data used.

The length of patient visits also likely has seasonal components, with appointments lasting longer in the fall because it is the start of the flu season. Seasonality was not a factor taken into consideration in the analysis for this paper. However, the simulation data from the months of November and February did include the fact that there was a different number of nurses working during flu season.

VI. Conclusion

This study used observations, data analysis, and a simulation to provide a greater understanding of UPC's specific patient flow and how it can be used to improve the in-clinic experience as we transition into a post-pandemic society. Future work should explore how timestamps are triggered. This will allow for a more accurate portrayal to assess nurse and provider workflows. Additional analysis of the UPC clinic should also look into how seasonality affects patient flow at the UPC clinic and recreate the simulation from times of the year with similar patient wait times. The distributions to recreate this new simulation should come through either eliminating seasonality components in time series analysis or physical experimentation of changing the number of nurses within the same month. While the physical experimentation data may prove more useful, limiting the utilization of the primary care facility by limiting the number of nurses may prove counterproductive. Another future effort revolves around surveying the nurses and providers to understand their satisfaction with the clinic's procedures. UPC relies heavily on its staff to administer efficient care, and their stress levels and work ethic can significantly impact patient care procedures. Hence, anonymously soliciting feedback can help improve overall care. As future study directions, the implementation of captivating concepts such as applying machine learning techniques to forecast needed staff and arriving patients, as discussed in [7], can have a substantial impact on clinic planning. The interventions implemented, such as a new appointment scheduling system, patient flow mapping, and staff training programs, as discussed in [8] resulted in a significant reduction in wait times, increased provider productivity, and improved staff and patient satisfaction.

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