Exploring Discrepancies: Analyzing Electronic Medical Records Data Against Direct Observations

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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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***Abstract*— An Electronic Medical Record, or EMR, is a digital way to keep track of patient information. EMRs are used by healthcare providers for diagnosis, treatment, and clinic decisions. There are several factors that impact the accuracy of EMRs, including data entry accuracy, backend configuration, and the time of documentation. This project aims to improve the patient and worker experience in primary care clinics, focusing on the influence of EMR. Through observations at the University of Virginia's University Physicians Primary Care Clinic, appointment milestones were recorded to create a dataset for comparison with the EMR dataset. Discrepancies between in-person observations and EMR data were noted. Metrics were applied to analyze decision implications based on each dataset. This paper underscores the importance of accommodating discrepancies for reliable healthcare information and decision-making.**

Keywords: Electronic Medical Records, Electronic Health Records, Primary Care

I. INTRODUCTION

Delivering high-quality healthcare to numerous patients, while simultaneously dealing with risks of disease exposure as well as managing regulations and other requirements, is a difficult feat for any healthcare institution. However, UVA Health is committed to putting the patient at the center of everything they do. That mission reigns true for their University Physicians Clinic of Charlottesville (UPC) primary care clinic. Navigating challenges following the COVID-19 pandemic, this clinic hopes to optimize their patient flow in order to provide optimal care. The UPC clinic has been affected by the national nursing shortage crisis and experienced difficulties with the reliability of their electronic medical records (EMR) system, so our team addressed these needs in a specific way. Currently, data from the clinic's EMR system is used to make decisions involving patient scheduling and physician clinic assignments. However, through in-person observations our team discovered that the EMR-provided data is not accurate and skews expectations of what patient flow will be in the clinic. Since this data is crucial for clinic decision-making, it has become evident that the EMR system used at the UPC clinic is making it more difficult for the clinic to improve their patient experience.

II. PROJECT BACKGROUND

The UPC Clinic has been attempting to optimize their patient flow since the onset of the COVID-19 Pandemic in 2020. We built upon the work of Korte et al. [1], Dozier et al. [2], and Jain et al. [3]. In the initial years, during the height of COVID-19, research delved into the clinic's response to the pandemic. Then the focus shifted towards post-pandemic operations. Korte et al. navigated restrictions, focusing more on the overall patient flow process. Dozier et al. prioritized data analysis, looking at different appointment types, timings, and durations. Their work laid the foundation for extracting metrics to analyze patient cycle times.

Jain et al. focused on analyzing data from the electronic medical record (EMR) system. This system collects timestamps 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 provider exits the examination room
- When the patient checks out of the clinic

These timestamps allow metrics to be collected such as total rooming time and how much time the patient spends at the clinic. They implemented a Patient Flow Analysis (PFA) system to optimize the flow of patients in the clinic, and focused on pain points in the system, such as long rooming times, inefficient communication, duplicated tasks, and unclear clinic roles. Changing these factors can result in enhancing the patient experience, reducing staff burnout, prioritizing financial savings, and identifying opportunities to expand clinical capacity.

Many of the past research studies with the UPC Clinic focused on consolidating the results from the electronic medical record (EMR) system in order to provide recommendations regarding patient flow. However, after our team began in-person observations in this clinic, we began to notice an issue that hindered us from offering clear recommendations about the EMR data: there were large discrepancies in the data the EMR provided and the data we collected through our observations. Therefore, the research conducted throughout the duration of this project focused on analyzing the differences between the UPC's EMR system and the collected observations. By analyzing where these discrepancies were most often taking place, it would provide physicians and nurses with specific target areas where the EMR system was vulnerable. As the pandemic was a few years in the past and in-person observations were able to be conducted, the remnants from the disruption the pandemic caused were not as notable. Rather, other issues contributed to there being issues with the way the EMR system collected data. For example, the UPC clinic faced a significant amount of nurse turnover this year, so it was important to be able to teach the nurses how to use the EMR system, in order to provide the clinic with the most accurate data possible.

In this paper, we will understand the patient flow of the University Physician Care (UPC) Clinic through various data analyses. Having gone through an explanation of the current background of the project, we will then detail the methods and designs used in this research. The following section will detail the results of our data collection, and will include a thorough analysis of the data from the EMR as well as the observations. Then, we will go into our discussion of our results, including any limitations. In summary, the goal of this paper is to detail the differences between the data collected from the UPC through observations, and that of the EMR provided data. The inaccuracies between the EMR data gives the clinic an skewed expectation of patient flow, which hinders the clinic's ability to make important scheduling decisions.

III. METHODS AND DESIGN

Our methodology is structured into three main parts. In Part 1, we gathered observational data by conducting in-person visits to the UPC clinic to understand the current patient flow process spanning from check-in to check-out. In Part 2, we compared the timestamps obtained through our observations with those recorded in the EMR system to identify any disparities or inconsistencies. In Part 3, we conducted analyses to evaluate the variance in the timestamps recorded in the EMR system regarding appointment durations and physician scheduling. The insights gained from Part 2 clarified the numerical findings to reveal potential data-related issues and deepened our analyses in Part 3.

Part 1: In-Person Observational Data Collection at UPC Clinic

From August to November, the team shadowed one nurse at a time to observe patient flow, rooming processes, and interactions with nurses and providers. We focused on weekdays during the morning hours from 8 to 11 am, conducting two-hour sessions each. For the data collection process, every team member used a standardized template outlining key timestamps for consistency in recording observations. Key timestamps include rooming of the patient, provider's entry to the room, and patient checkout. Using these timestamps, data statistics like provider wait time, time with nurse and provider, and total appointment duration was calculated. The collected data was compared to the EMR data to find any discrepancies using the programming language R. We also investigated how data cleaning could help reduce the influence of outliers and inaccuracies on the data's statistics, which the clinic relies on for its decision-making processes.

A. Patient Receiving Process

Currently, the UPC clinic has a standardized method for receiving and seeing patients. Patients sign-in on the first floor of the medical building at reception and are directed towards the elevator to go to the third floor where the Primary Care Clinic is located. They then exit the elevator and enter a door on their right, where they check-in with the clinic receptionist and are given paperwork to complete prior to their appointment. Behind the scenes, nurses prepare the patient's room before their scheduled time and scan their badges to log into the computer program EMR, which houses the patients charts and records patient data. Once the room is prepped, the nurse will walk to the waiting room door and call out the patient's name. They will then guide the patient to the scale to record their birth date, weight, height, and preference for receiving the yearly flu and covid vaccines, before leading them to their assigned room. The patient's forms will then be checked and validated with the information in EMR; updates to allergies and medications are made in the charts. The nurse takes the patient's vitals, including blood pressure and temperature, and administers the flu and/or covid vaccine per clinic protocols.. The nurse will then scan their badge to log out of EMR and exit the patient's room. The provider will then enter the patient's room, conduct the necessary tasks and tests privately, and then exit the room while giving the nurses any additional orders for vaccines or tests. The patient then exits their room and speaks with a separate receptionist by the examination rooms before leaving the clinic through the elevator they entered in.

Part 2: Comparative Analysis Between Observations and EMR Records Timestamps

While their current patient flow process has been sufficient up to this point, there have been various difficulties in recent years with the accuracy of both the EMR data and patient scheduling. Appointment durations are typically set for 20 or 40 minutes depending on the type of patient visit. Providers schedule an average of 8 back-to-back appointments per 4-hour session, alternating between 20 and 40-minute slots. However, our observations indicate persistent delays, as both 20 and 40-minute appointment durations consistently overrun their expected timeframes, potentially triggering a domino effect on following patients' rooming, provider availability, and appointment lengths. This highlights the EMR's accuracy issues because it may be incorrectly documenting appointments that run over and potentially skew timestamps that healthcare professionals rely on to make informed decisions about patient care, treatment plans, and resource allocation. Another contributing factor is that, despite nurses following the same procedure in seeing patients, variations in their actions led to inconsistencies in the recorded timestamps. For instance, some nurses signed into the EMR before bringing in the patient, while others did so after the patient had entered the room. This variability was also observed among providers, as the care provision process for each patient differed.

Other issues the clinic has faced is in their nurse staffing. High demand for traveling nurses, influenced by seasonal variations and fluctuations in patient volume, combined with lower pay for staff nurses, may cause experienced nurses to seek better opportunities elsewhere or in becoming traveling nurses. Stress and burnout from demanding schedules and environments can further add to staff turnover and shortages. [4]

Part 3: Assessment of EMR Timestamp Variance for Appointment Durations and Physician Scheduling

Our team assessed the EMR records by beginning with a comprehensive filtering process that targeted outliers and instances of missing data. This process selectively retained in-person appointments with recorded check-ins and nonzero total appointment times for further analysis. Additionally, appointments with unusually long durations were standardized to mitigate potential data discrepancies within the EMR system. The resulting dataset underwent comparison with the unfiltered dataset to evaluate the effectiveness of cleaning in improving data quality through statistical measures. Additionally, appointments were subsetted based on their scheduled lengths of 20 and 40 minutes to examine variances in appointment times and the impact of appointment duration on physician schedules. This included analyzing the average number of appointments assigned to each physician daily and whether they were scheduled back-to-back, meaning consecutive without any gaps in between the appointments.

The overarching objective of this study was to provide a foundation for our concluding recommendation that the clinic should improve its data collection process through the EMR system to enhance the accuracy and reliability of the data for future analyses and decision-making.

IV. ANALYSIS AND RESULTS

A. Observational Data and Matching Process

Our team's initial data analysis surrounded the data collected through in-person observations between August and November. Sixty appointments were observed between 8:00 am and 11:30 am on Tuesdays, Wednesdays, and Thursdays and established observational metrics to compare the raw EMR data to for discrepancies. These comparisons were created by matching the corresponding EMR appointment data with the observational data via appointment date, scheduled appointment time, and physician in Excel and Tableau. After removing rows with incomplete or inconsistent data, such as rows indicating a total appointment time of zero, our team analyzed 42 rows of matched data. Incomplete rows occurred when appointments ran past scheduled observation times, resulting in the end of longer appointments not being recorded. The cleaned observational data has an average of 39.14 minutes for the total appointment time, as opposed to the matched EMR data which displayed an average time of 34.08 minutes for the same appointments. Both values are slightly larger than the overall average for the raw EMR data which has an average appointment time of 28.33 minutes. The time spent with a nurse during our team's observations was on average 6.76 minutes, with the matched EMR data determining these appointments include on average 10.27 minutes spent with the nurse (p-value = 0.0458). The time spent waiting for a physician to attend to the patient was 8.13 minutes in our observations, but 15.94 minutes on average in the EMR data for the same appointments (p-value = 0.005). For the in-person observations, we concluded that doctors on average spend 23.88 minutes with their patients, as opposed to 15.18 minutes as indicated by the EMR data (p-value = 0.0072).

Although these three differences between observational and EMR measurements are statistically significant, these numbers differ drastically for each of the clinic's eight clinicians. For example, Clinician Two was observed for 17 appointments to spend on average 17.08 minutes with their patients. However, the EMR data severely underreported this value, showing an average time of only 3.84 minutes. This could be attributed to the physician not following the standard operating procedures with the EMR system, resulting in triggers not occurring until much later than intended. These discrepancies can be seen in Figure 1 below. The orange bars represent the average minutes physicians spent with their patients according to the matched EMR data, and the blue bars show these averages according to the observed data.

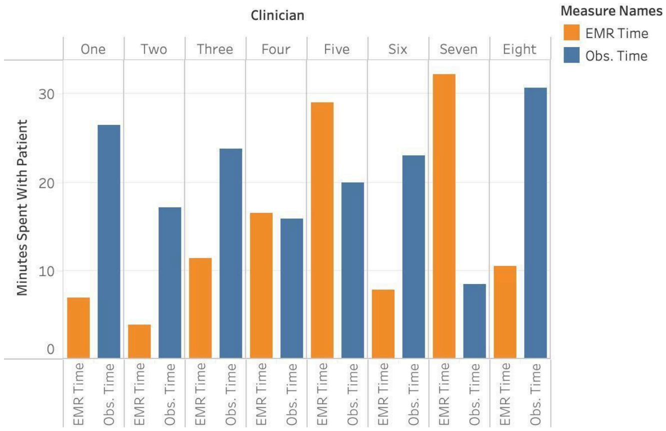

Fig 1. Comparison of the time spent with patients for all eight physicians from the observational and EMR data.

B. Dataset cleaning

To further analyze the overall data, the entire EMR dataset was filtered and cleaned to deal with outliers or absences. Only in-person appointments with recorded check-ins and nonzero total appointment times were kept. Additionally, appointments with appointment lengths of zero were removed to account for trigger misfirings in the EMR system. For the variable that tracked patients' times waiting to be roomed, all values below the first quartile and above the third quartile were replaced with the values of the first and third quartile values, respectively. Next, for variables that tracked patients' time with the nurse, time waiting for the physician, and time with the physician, any values above the third quartile for the respective category were set to that category's third quartile value.

The appointment length or duration was calculated as the sum of the time spent with a nurse, time spent waiting for the physician, and the time spent with a physician during a patient's appointment. Compared to the average appointment duration for the entire uncleaned dataset, which had an average of 35.78 minutes, the cleaned and filtered EMR data showed appointments take on average 23.69 minutes. Dividing these appointments into their scheduled lengths of 20 and 40 minutes, we further saw how the raw EMR data underestimates appointment times. While our observed 20 minute appointments had an average duration of 31.23, the overall raw EMR data had an average of 40.17. After cleaning and filtering the data, the average decreased to a value of 21.58 minutes. Similarly for 40 minute appointments, the average for the cleaned dataset decreased to 25.65 minutes from 45.17, compared to the observed average of 30 minutes. Therefore, it can be seen in the cleaned EMR data that there is little difference in the total appointment length between appointments scheduled for 20 or 40 minutes. However, this analysis indicates that 20 minute appointments run longer than their anticipated times, which can impact subsequent appointments.

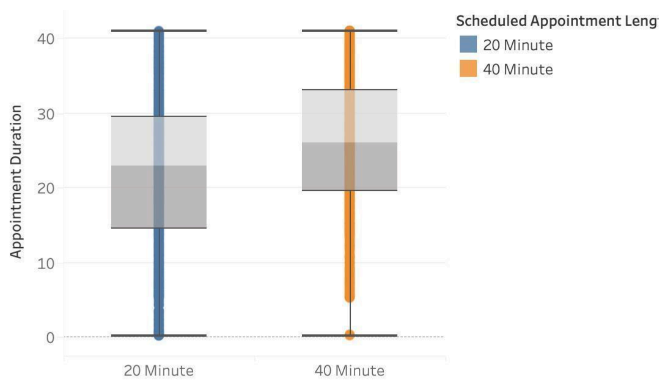

Fig 2. Comparison of the duration of appointments in minutes for scheduled 20 and 40 minute appointments from the cleaned EMR data.

Our team next investigated the number of appointments assigned to each physician daily on average, and if these appointments were scheduled back-to-back. A back-to-back appointment is when the scheduled start time of one appointment is the same as the scheduled end of the previous appointment for the same physician (i.e. an appointment scheduled to start 20 minutes after the start time of a 20 minute appointment). If the appointments are back-to-back, these 20 minute appointments that run longer can disrupt the schedule for the remainder of a physician's schedule. Out of 2,878 morning appointments, 70% of appointments were scheduled as back-to-backs, as well as 65% of the 2,318 afternoon appointments. The average number of appointments for each physician did not differ if the appointments were scheduled as back-to-backs or not, and ranged from 4.74 to 7.5 appointments on average. Clinician Two, who was assigned the most appointments between August and January, had the highest daily average of 7.5 appointments scheduled during their morning shifts. As previously mentioned, this physician's time spent with patients was severely underreported.

Additionally, when comparing the number of appointments that exceed their scheduled time, Clinician Two had the highest percentage of appointments run over time: 51.55% of time. Decisions regarding physician daily appointment capacity are therefore being overestimated, resulting in appointments running longer than scheduled. Specifically, 20 minute appointments make up 95.15% of overrun appointments, further demonstrating that the clinic's usage of the EMR dataset for clinic capacity is not reflective of real life.

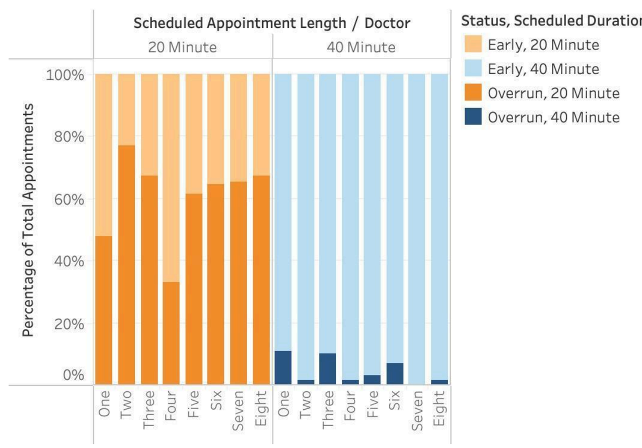

Fig 3. Percentage of 20 and 40 minute appointments that run longer than the scheduled time.

V. DISCUSSION AND LIMITATIONS

A. Discussion

From the analysis, the team was able to better understand the flow of primary care appointments at the UPC. Overall, the team's understanding relies on translating the qualitative and quantitative data on the clinic's processes and comparing it to the actual data obtained from the EMR. The team first compared quantitative observational data to the actual data and noted outliers and where the two datasets did not match. The qualitative data and knowledge of patient flow through the clinic were used to understand and quantify the differences in the two datasets. A data cleaning process was developed to handle the outliers in the EMR data, and this cleaned EMR data was compared again to the observed data. Ultimately, it was found that the observational data still captured the most accurate representation of patient flow compared to the EMR dataset, even when it was cleaned. Observational data consistently modeled the patient flow most accurately.

The work completed in this project illustrates the difficulty of optimizing patient flow at a larger clinic such as the UPC. Since unfiltered and uncleaned EMR data is used to make decisions regarding appointment length and other parts of scheduling, there is room to improve the EMR data collection process and thus the scheduling decisions. If further steps were taken to standardize the EMR data collection and cleaning procedures, the resulting appointment lengths may more accurately match the observational data recorded at the clinic. Decisions like these may not only increase clinic efficiency but also alleviate doctor and nurse burnout, since appointments that run past schedule result in delays and situations where doctors or nurses rush to input closing appointment information.

B. Limitations

It should be noted that the data used to reach these conclusions was primarily observational data. Although time-stamped patient data was provided in the EMR dataset, inconsistencies in the data required a data cleaning process to make the data more representative of real patient flow. However, the cleaned dataset showed similar discrepancies to the observed data and still could not be deemed an accurate representation of the clinic's patient flow. It is possible that both human error and the manner in which the data collection system is set up are contributing to these differences, but the exact extent is not known. If time or ability to change system parameters were not obstacles, those would have been the next variables to be changed in data collection.

VI. CONCLUSIONS

Performance metrics for Primary Care clinics, like the average patient wait time in the clinic, average time with provider, average time to room a patient, overall cycle time, etc., are each important to the clinic staff and personnel of the clinic, the health system in general, and patients of the clinic. Each specific performance metric will matter to these groups to varying degrees. These performance metrics can reveal areas where improvement is needed, as well as areas the clinic is meeting or exceeding a certain expectation. This paper underscores the importance of ensuring that EMR systems are collecting timestamp data that is accurate to the true system. Calculating performance metrics using inaccurate data can lead to mischaracterizations of certain processes and erroneous conclusions. The goal of every system should be one seeking continuous improvement, but it is necessary to correctly characterize with the most accurate data possible what is actually happening in the system. For EMR systems where timestamp data is collected, the triggering action that records the timestamp value should be clear to the personnel that "trigger" the timestamp to occur, and the timestamp values recorded in the EMR should be verified through in-person data collection before the data collection system is used for operational decision making.

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