Patient Flow Management
Combining Analytical and Observational Data to Uncover Flow Patterns

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Abstract: **Background:** Hospitals must improve patient flow to achieve better efficiency and improve patients' outcomes. Recent advancements in real time monitoring have provided immediate feedback for clinicians to address any bottlenecks. However, root causes of delays remain embedded in the details of clinicians' activities. This work presents an observational study of a clinical pathway within a heart unit at a community hospital in North America. Observational data is correlated with multiple sources to uncover flow patterns.
Materials and Methods: We observe heart patients as they arrive in at the heart unit and throughout their care up until their discharge. Data is correlated with electronic healthcare records and paper trails to enhance data reliability and accuracy.
Results: Single data source alone is not sufficient to uncover process patterns. In our study, we discovered a negative correlation between the number of patients arriving at the hospital, and the total wait time each patient has experienced. We also identified key inefficiencies in the first and last hours of work shifts.
Conclusion: Correlating multiple data sources can provide insights into details of process activities and uncover patterns and inefficiencies.

1! INTRODUCTION

Efficient flow of patients within hospitals is crucial for multiple factors. There is a strong correlation between patient wait times and clinical outcomes, the longer the wait, the worst the outcome (Meier-Kriesche et al, 2002), (Zheng el al, 2008). Long wait time is also costly for hospitals, and is not conducive of quality of care.

Care Process Management is an emerging domain where Business Process Management technologies are deployed inside hospitals to analyze care processes. Analysis can recommend reengineering of care processes to enhance patient flow and reduce wait times. This has proved very effective in multiple ways. First, hospitals can simulate patients' flow and can analyze the impact of any process reengineering before deployment. Second, by representing care processes in explicit steps, this helps clinicians achieve some levels of systematic consistency in patients care delivery. For example, one issue we observed is that many heart patients are not diagnosed early in the process. Their diagnosis is delayed, it seems, because those patients were not identified within a risk group of heart diseases, and hence, appropriate tests were not ordered in time.

Our prior work in patient flow management focused at presenting real time dashboards showing current state of patients as they flow along the clinical pathways (Badreddin and Peyton, 2013). Clinicians use such dashboards to respond to excessive delays or take action to resolve potential bottlenecks. This work did not consider the fine grained steps that clinicians perform to complete the care process tasks. Our intuition was that a significant amount of time is consumed by such micro activities that are too fine-grained for process modeling.

This paper presents an observational study of heart patients from admission to discharge at a community hospital in North America. The observational data is correlated with electronic healthcare records and paper trail records to enhance data reliability. Our findings revealed distinctive patters and variations of patients wait times and flow efficiency.

This paper is organized as follows. We first present related work followed by an overview of the identified clinical pathway for heart patients. The outlines of the observational study of heart patients is presented in section 4. In section 5, we present the data and analysis. In section 6, we present out findings and recommendations. Threats to validity and a discussion are then presented, followed by a conclusion of the main findings of the work.

2! RELATED WORK

The value of patient flow monitoring is widely recognized to have significant impact on patient wait times (Aladdin et al, 2013), positive care outcome (Middleton el al, 2009), and reduction in associated hospital costs. There is also wide recognition that electronic healthcare records (EHR) alone are insufficient to provide any meaningful flow monitoring (Baffoe et al, 2013). This is because patient flow monitoring requires fine-grained data that is typically unavailable in modern EHRs. Clinicians' practice of using paper trails and batch processing data entry at end of the shifts mean that 1) data is not available until at least the end of the shift, 2) the data time stamps do not reflect actual clinical events and care delivery for patients. In fact, many hospitals provide reports on patient flow only weeks and months after the fact (Badreddin et al, 2014). This is because hospital data must be transferred to data warehouses where multiple sources are combined and correlated to provide information on the big picture.

EHR systems are mainly concerned with supporting clinical operations and storing patient records. They are much less concerned with the real time management of patient flow (Badreddin et al, 2014). This fact has prompted multiple researchers to investigate additional untraditional sources of data, such as location and movement data of patients and clinicians (Aladdin et al, 2012). In such work, the researchers investigate how to correlate disparate sources of data, including data from the hospital records, location and movements of patients and clinicians, as well as external data sources, to infer key patient states along clinical pathways.

Our approach correlates observational data and paper trails with EHR data to gain insights into patient flow within the heart unit at an urban hospital. The use of observational studies within the medical community is relatively common and wide utilized. The majority of such studies focus on identifying treatment effectiveness, patient outcomes, or to support investigations into clinical decisions.

Tessler et al have conducted an observational study of patient flow in the post anesthesia care unit (Tessler et al, 1999). Their objective of the study is to investigate whether patients are being transported into the care unit only when the patients are ready. They recorded the flow of 336 patients recording key events and wait times. They conclude that patients are waiting unnecessarily for multiple reasons. Tessler's study, however, did not use EHR records as a data source in their analysis, and relied exclusively on observational data. Observational data are unstructured by nature and the analysis is typically qualitative.

Tang and Carpendale have conducted an observational study to guide the development of an information system (Tang and Carpendale, 2007). Their focus was observing information flow and communication during nurses shift change. The key objective of the study is to drive the development effort of an intra-hospital communication tool.

3! HEART PATIENTS CLINICAL PATHWAY

Our first objective of this study is to identify the key care process steps and verify with clinicians that the identified process reflects as closely as possible what happens to patients as they are admitted into the hospital. The care process documentation steps were performed by the researcher, in close collaboration with the hospital staff members.

The following figure summarizes the high level steps in the care process. Clinicians agreed on an expected average for each of the steps. This is important to help us in identifying which steps are particularly time consuming.

As a patient arrives at the unit, an admission nurse takes vital sign measurements and checks-in the patient into the hospital system that creates a visit ID. The patient then waits until the nurse completes some admin tasks, and for the care provider to perform an initial assessment. The provider completes the patient chart and may request some blood tests to be performed. Typically, a follow up appointment is schedule to discuss the test results with the patient and/or to perform additional examinations. At this step, the patient may be admitted to the hospital or may be recommended for discharge.

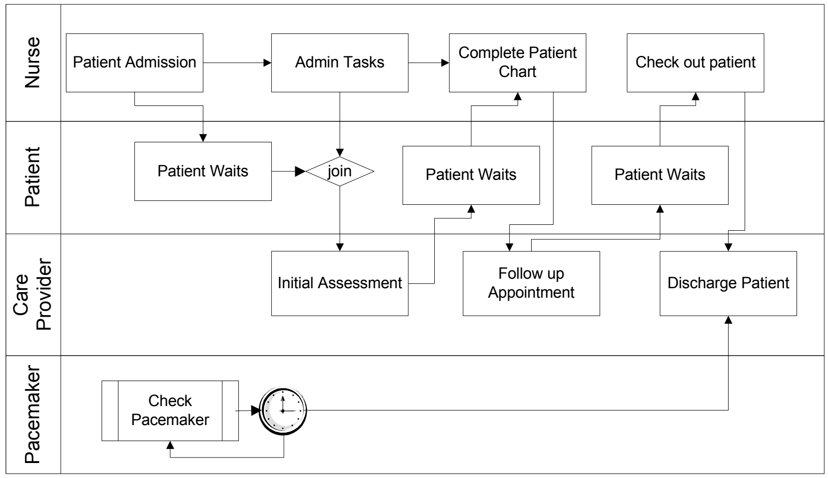

Figure 1: Top Level Heart Patient Process.

If the patient is recommended for discharge, he is first checked out of the hospital electronic system and a discharge request is initialized. The details of the discharge activities are out of scope of our analysis, and we use the check out time stamp as an approximation for patient discharge

There are significant variations and overlapping steps in the care process. For example, if the patient happened to have a pacemaker, he will be scheduled for a regular pacemaker check throughout the visit time. The frequency of the check varies from one patient to the other, but it is typically performed around every 20 minutes.

4! OBSERVATIONAL STUDY OF HEART PATIENTS

Our observations started on January first, 2014 and lasted until March 14th of the same year. In this period, we have observed 137 patients. There were two observers who observed the same patients over the same period. Their observation notes were consolidated at end of every day. The observers were not familiar with the care process and documented their observations on paper. At the end of the observation period, the observers transcript their observation data into a semi-structured format. The data also included free text where the observers documented any incidents of interest.

In addition to the observation data, we also collected data from Athena system (Athena, 2014), the electronic healthcare record system in use at the hospital under the study. We used this data to enhance our confidence and accuracy in the collected observational data. When discrepancies were identified, we referred to the observers for validation. Occasionally, we involved healthcare providers to interpret the data for us.

The observational data did not identify any care provider or any patient identify. The identity of the principle cardiovascular physician is disclosed in the report published in the hospital. In this paper, we refrain from identifying any participant to comply with the ethical conduct requirements. The observational study was limited in scope to specific pathways and care providers to limit variations in treatment from one provider to the other.

5! DATA CORRELATION AND ANALYSIS

Three key sets of data were collected. The first is observational data that included detailed time stamps of every event. The second is a data collected from Athena records. The third is paper trails of patients and clinicians collected at end of the shift. We correlated the data sets and created a synthesized data set. The purpose of the correlation is as follows.

Data from Athena alone is not reliable, because the time stamps in the system do not reflect, within any reasonable accuracy, the events timing. This is because there is a significant time gaps from the moment the event has taken place, and the time the clinician has updated the system data. This is despite our observation that many clinicians updated the system after, or during, each patient encounter. For purposes of this study, fine-grained measures are key for the analysis.

Complexities in the clinical process sometimes make electronic records inaccurate. For example, some heart patients who have a pace maker, require a routine pacemaker check every 20 minutes. This activity overlaps with whatever clinical activities are taking place. In addition, sometimes a care provide starts to examine a patient, but then put the examination on hold until test results has been received, or to attend to another urgent patient. Such events mean that we cannot rely on electronic records alone to have insights into fine-grained events along clinical pathways.

The second reason for the correlation is to enhance our confidence in the observational data accuracy. The observers were not allowed to interact or communicate with clinicians at any time. Occasionally, observers were not able to identify some events happening for some patients. For example, some of the observations noted that the nurse walked the patient into another assessment room for no apparent reasons. Such anomalies were documented and at end of the day were correlated with system data and clinicians' input was obtained when needed.

6! FINDINGS AND RECOMMENDATIONS

We present the analysis for the correlated data using electronic healthcare records, observation data, and paper trails. The findings are presented in two steps. We first present the findings on number of appointments and average duration of appointments over days of the week and over hours of the day. Next, we present findings on how long patients have been waiting from admission to checking out. As we show in Figure 2, the patient is checked out before being discharged. The discharged process is relatively more complex, and patients are delayed at discharged for a variety of reasons, some of which are outside of scope of the heart unit. We therefore measure the total time patient spent inside the hospital by measuring the time from admission to check out. Discharge processes at hospitals are known to be excessively time consuming (Haraden and Resar, 2004), and they are not the main scope of out study.

6.1! Number and Duration of Appointments

Figure 2 illustrates the average appointment duration by time of the day. The figure plots the appointment duration against the hours of the day (starting from 8 am to 4 pm). This is shown as percentage of the time allocated for the appointments. For example, Acute Coronary Syndrome appointments are scheduled for 20 minutes. If the care provider spends only 16 minutes with the patient, this means the appointment consumed 80% of the allocated time.
Figure 3 summarizes the number of appointments by time of day. Number of appointments tends to follow an almost perfect bell distribution, with exception of the noon appointments.

Analyzing the data along the day of the week reveals that Wednesday is the busiest day of the week. Interestingly, appointments on that day took the least amount of time (Figure 4). This negative correlation between number of patients and appointment duration was evident in all weeks over the duration of the analysis.

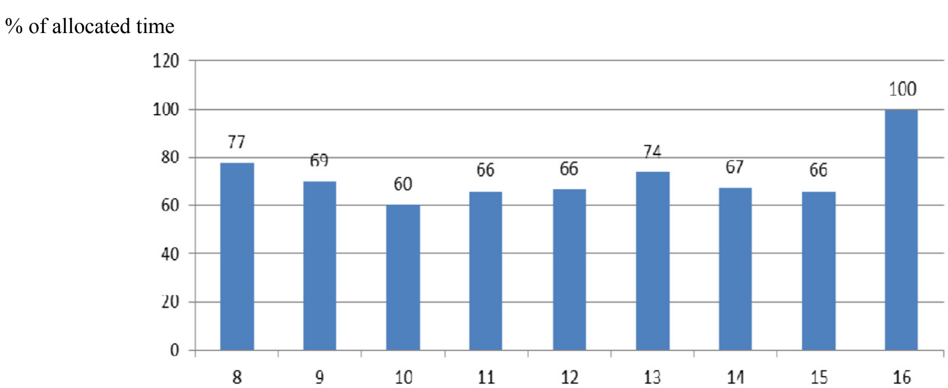

Figure 2: Average appointment duration per hour of day.

Number of appointments:

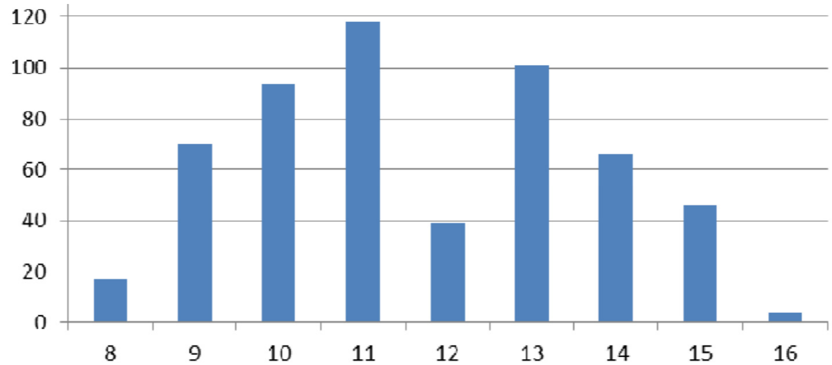

Figure 3: Number of appointments by time of the day. [1]

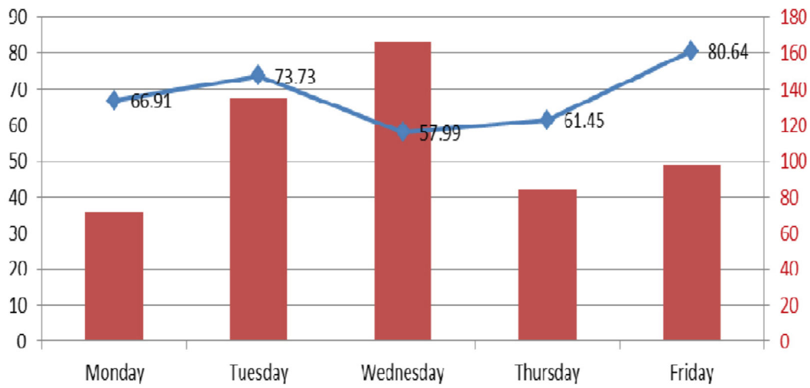

Figure 4: Average Appointment duration and number of patients per day of the week.

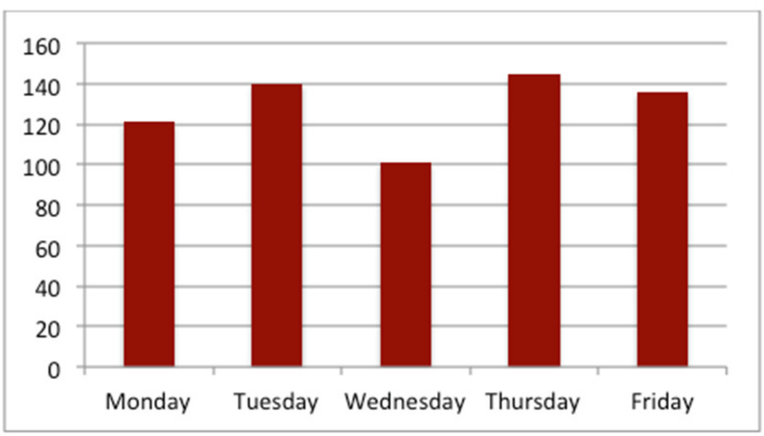

Figure 5: Total visit duration by day of the week.

[1] Number of appointments are calculated by the start time. For example If an appointment started at 10:45 and ended at 11:10, this appointment falls under hour 10 in the graph.

6.2! Total Visit Duration

Patients overall did not face significant variations over day of the week analysis. However, patients seem to have spent less time inside the hospital on Wednesdays, which are also the busiest day of the week.

6.3! Care Provider Effort

Care providers spent on average between 5 to 15 minutes with the patients. This includes the time to update patients' records. The average time spent with the patient is 6 minutes. Care providers spent on average between 57 and 80 minutes (Figure 4). This translates to efficiency between 7.5% and 10.5%. Our observation indicates that this low level of efficiency is not due to lack or resources, but rather, is due to significant variations in patients flow and service times. This results in uncontrollable variations in patients wait times.

This observation is in contrast to the general belief that lack of hospital resources is the main root cause of excessive patients wait times. There is also the belief that adding hospital resources may help address capacity and patients wait times. Our observations seem to suggest that understanding flow variations is key in improving efficiency and increasing hospital capacity.

Silvester et al has proposed four hypotheses to explain long wait times for patients; 1) demand is simply greater than capacity 2) Fundamental mismatch between variations in demand and variations in capacity 3) Queues actually keeps the utilization of scarce resources at 100% 4) Queues discourages people from using what is perceived to be scarce resource (Silvester et al, 2004). Silvester provides theoretical analysis to dismiss all hypotheses, except for the second. Our observations in this study support Silvester's findings.

7! STATISTICAL ANALYSIS OF THE DATA

We analyzed the data using multiple statistical analysis tools to uncover any hidden patterns. For example, we wanted to investigate whether patients face more unpredictable visit duration on busy days. To that end, we analyzed the standard deviation of patients visit during the busy days as compared to days where fewer patients visited the unit. We did not find any significant difference in the standard deviation of the data. For example, analyzing the data for Wednesdays (the busiest day of the week) against all other weekdays, using a two-tailed student test, there was not significant difference in the standard deviation of the data. We obtained the same result when using the Levene's test for equality of variance.

Testing for significance for total visit duration for Wednesday on one hand, and the average of the rest of the week on the other hand, a two-tailed student test shows that Wednesday data is significantly lower than the rest of the week ($p = 1.35*10^{-7}$).

We tested the same data using Mann-Whitney (U-test), a non-parametric test in case of a significant departure from the normality requirement of the t-test. U-test indicate that Wednesday data is still significantly lower than other days of the week ($p = 7.1*10^{-4}$), with W value of 1721.

Similar studies with relatively similar data and tests (Dixon and Mood, 1946) have utilized a sign-test, which checks pairs of the data points. We applied the sign test to pairs of patients' visits on Wednesdays and other patient visits on other days of the week. A visit on Wednesday had a 91% chance of being shorter than corresponding visits on other days.

These tests suggest that the difference in data values for Wednesday cannot be attributed to random occurrences alone.

8! THREATS TO VALIDITY

In this section, we discuss some of the key threats to validity of this study.

8.1! External Validity

The study was conducted within a Heart Unit, similar studies in other units, or other hospitals, may give different results. Care providers at that unit did not list limited resources or staff to be a concern. The hospital is located in a relatively smaller city, with relatively small population size. Other hospitals with different resource allocation may exhibit different patterns.

8.2! Bias towards the Time of the Year

This study was conducted mostly in the first quarter of the year. We have no information on how resources are allocated for the rest of the year, or if there are any significant changes in patterns of patients' arrival during the rest of the year.

Our discussions and interactions with hospital staff do not indicate that this threat is significant. We have electronic records for the entire year, and our preliminary analysis do not indicate any significant change in patterns. Average number of patients, beds and staff were very similar throughout the year.

8.3! Observers Making Systematic Errors in Data Logging

There is a threat that a systematic error was occurring during the observation study. This is possible especially that observers were required to remain completely passive, and not interact with patients or care providers at any time. Observers marked their concerns when they could not interpret the sequence of events, or when they could not explain a specific scenario with a patient.

We addressed this threat by first utilizing multiple data sources and ensuring that any significant discrepancy is explained. In addition, at end of every shift, we reviewed our synthesized data with hospital staff to ensure accuracy. The study also involved two observers in every observation session. Two observers mean that it is less likely that a systematic error was occurring.

9! DISCUSSION

The data and tests seem to suggest that patients arriving on a busy day are more likely to spend less time in the hospital. One can speculate that maybe care providers tend to work more efficiently when there are more patients.

This study is exploratory by nature. One can consider the hypothesis that "clinicians work more efficiently when there are more patients during a specific day". However, this requires another study to investigate the validity of such hypothesis.

One should consider such a study in the light of key hospital objectives. Hospitals typically want to reduce re-admission rates, and attain high patient satisfactions. Reducing patient wait times is only a secondary objective to providing quality care. A study may look into re-admission rates and analyze the day on which the patient was examined. There may be a relationship between the patient flow and re-admission rates.

A key challenge in conducting such a study is that it requires multiple data sources and extensive manual data correlation. This requires a multi-disciplinary team with diverse expertise. In our study, we needed participation of social scientists who are more familiar with conducting observational studies. In addition to information scientists who are required to query and process health care records.

Despite the findings of this paper seems to be intuitive, care providers work more efficiently when facing higher rates of patients flow, the significance of this basic observation is significant. If we consider the objective of reducing the time patients spend inside the hospital, then scheduling more patients during one half of the day may in fact serve achieving such objective.

CONCLUSIONS

This paper presents a study where multiple data sources were utilized to infer key events along clinical pathways within a Heart Unit in a community hospital. The study utilized observational data, electronic healthcare records, and paper trails. The resulting synthesized data reveals some patterns of patients' arrival and appointments durations.

Patients' appointments in the first and last hour of every shift take the longest amount of time. For our subject hospital, Wednesday was the busiest day of the week, and also the day where patients visit duration was the shortest. The study also observed that the time utilization of care providers is very low. This is due to the nature of the process and how appointments are scheduled.

The study does not explain the reasoning behind the emergent patterns. However, the study functions as a basis for future studies to examine and explain such patters. The study can also feed efforts of re-engineering of the clinical pathway to achieve better efficiency.

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