

A Systems Approach to Improving Patient Flow at UVA Cancer Center Using Real-Time Locating System

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Abstract - Long wait times not only indicate costly inefficiencies for healthcare facilities, but they also influence patient satisfaction and outcomes. As healthcare systems transition from provider centric care to patient centric care, increasing efforts have been made to reduce patient waiting times. At the University of Virginia, the Emily Couric Clinical Cancer Center (ECCCC) has experienced a 30% growth in patients over the past 3 years, resulting in a visible increase in wait times. In an effort to reduce wait times, the ECCCC has recently adopted a Real-Time Locating System (RTLS) that monitors patients' and providers' transient locations throughout the facility. The objectives of this project were to 1) to develop a framework to utilize RTLS data with other electronic medical records (EMR), and 2) to demonstrate how combined data can be used to better understand the flow of patients, bottlenecks, and patient-provider interactions in order to improve ECCCC operations. We combined data sets from multiple sources and statistically analyzed the data from patient and provider perspectives. Results indicate that the East Waiting and first floor Waiting areas have the highest average wait times and thus were identified as bottlenecks. Other locations at the ECCCC such as the Registration area were found to have significantly high average dwell times. A regression model indicated that patients visiting the ECCCC in the mid-morning, 9 a.m. – 12 p.m., experienced longer length of stay than patients visiting at other times. Analysis of patient-provider interactions showed that providers are on average 48 minutes late to appointments. Recommendations include tailoring scheduling to prevent appointment delays and investigating processes such as registration. Future work includes intervention strategy testing through simulation of the entire multi-clinic ECCCC.

Index Terms – Patient flow, Patient tracking, Real-Time Locating System, Statistical analysis

INTRODUCTION

Patient satisfaction has become more important in healthcare because it affects not only patient outcomes but also healthcare organizations' financial incentives [1]. Excessive wait times negatively impact patients' experience and reflect system inefficiencies. Patient satisfaction has been found to

decrease as wait times increase [2]. Also, delays in appointments negatively impact employee satisfaction [3]. A better understanding of patient wait times can allow healthcare facilities to target issue areas and tailor strategies to improve patients' experiences and healthcare facility operations.

Real-Time Locating System (RTLS) technology tracks entities at all times throughout a facility by providing timestamps and information relating to an entities' location every couple of seconds. RTLS uses beacon technology in conjunction with wearable sensors to communicate data through radio frequencies or Wi-Fi. This real-time collected data is then stored in various databases [4]. As RTLS is constantly collecting real time information, these systems accrue millions of lines of data. Hospitals have implemented RTLS to track assets in order to decrease the time spent locating vital equipment [5]. More recently, the use of RTLS has been extended to track personnel via wearable badges to improve patient flow [6].

The University of Virginia's Emily Couric Clinical Cancer Center (ECCCC) has experienced a 30% growth in patients over the last three years. With an increase in the patient volume, the ECCCC implemented an RTLS, named Ekahau, in the past year to better understand patient and provider flow throughout their system.

Despite its implementation and use, the ECCCC has faced challenges in attempting to draw meaningful information from the data generated from Ekahau. Between August and December 2016, Ekahau collected over three million lines of data. The ECCCC wants to use this data to investigate and enhance the patient experience, but have yet to join this data with complementary data sets such as scheduling and provider information. The objectives of this study are two-fold: 1) to develop a framework to utilize RTLS data with other electronic medical records (EMR), and 2) to demonstrate how the combined data can be used to better understand the flow of patients, bottlenecks, and patient-provider interactions in order to improve ECCCC operations. The analysis may provide the ECCCC insights into the actual patient flow, which can help hospital managers plan interventions for better patient flow, such as a redistribution of resources and changes to the scheduling system. These operational decisions may positively influence patients' experiences and employee satisfaction.

I. Approaches Used to Study Patient Wait Times

Non-value-added activities are activities that do not contribute to the consumer’s desired outcome from a service. In healthcare, non-value-added times include the amount of time a patient spends in an exam room waiting for his or her medical provider [7]. Wait times have been a widespread source of patient dissatisfaction across healthcare [8]. To address prolonged wait times, studies have used various systems engineering approaches, including data-based statistical analysis, queuing theory, and simulation. For example, multivariate statistical analysis was used to reveal correlation between total wait times and appointment type [9]. In a simulation of the University of Kentucky’s emergency department (ED), what-if scenarios were used to identify bottlenecks and suggest improvements in specific congested areas of the ED [10]. Another study, aiming to optimize hospital pharmacy performance, modeled the queuing network to detect bottlenecks in flow [11].

II. RTLS in Healthcare

Previous studies have shown how RTLS can be used in healthcare settings to estimate the average wait times for specific locations across time frames. An outpatient clinic tested the feasibility of a RTLS as a means to improving patient flow. Statistical analysis of the data revealed bottlenecks and areas for improvement [12]. The research demonstrated RTLS’s applicability beyond asset tracking.

RTLS’s big data has also been used to determine patient and provider locations within predefined areas of an ED. A study showed how the use of this data can overcome limitations of electronic health record data and gain a greater understanding of patients’ visits [13].

This study extends previous research by incorporating the RTLS data with scheduling and provider data and investigating patient flow throughout a multi-clinic facility.

I. Observations

Observations and time-motion studies were conducted in the ECCCC to enhance understanding of the system. Researchers were paired with a patient and followed him or her throughout the center for the entirety of the patient’s visit. Data was collected on the arrival time, dwell time, and location of the patient throughout his or her stay.

II. Data Integration and Manipulation

The ECCCC uses a variety of information systems for different purposes such as RTLS, scheduling, and EMR. For this study, we used data obtained from these three systems: Ekahau, A2K3, and Epic. Epic and A2K3 data is populated by human entry, while Ekahau is generated every five seconds by the RTLS.

Before integrating the data sets, the Ekahau data was cleaned to remove inaccurate information. For example, Ekahau data between 9:00 p.m. and 4:59 a.m. were removed given the assumption that patients, even those who stay late for delayed appointments, would not be at the ECCCC at these hours. Data was also cleaned by accounting for “jumps,” or rapid movements of one badge between two locations. Using a threshold of 6-seconds, data points below this threshold were collapsed with their previous occurrence so that overall time spent in the ECCCC was not altered.

This study created new datasets by combining the three information systems, Ekahau, Epic, and A2K3 and analyzed the combined data from two perspectives: patient flow and patient-provider interactions. Figure I shows an example of how the data sets were integrated using the primary keys to develop one of the new, meaningful data sets. Furthermore, this figure details the key data points collected from each system.

Two other data sets were created by processing Ekahau patient data. The “Daily Patient Experience” data set provides the total dwell time a patient spent in each location throughout his or her stay, as well as the total number of

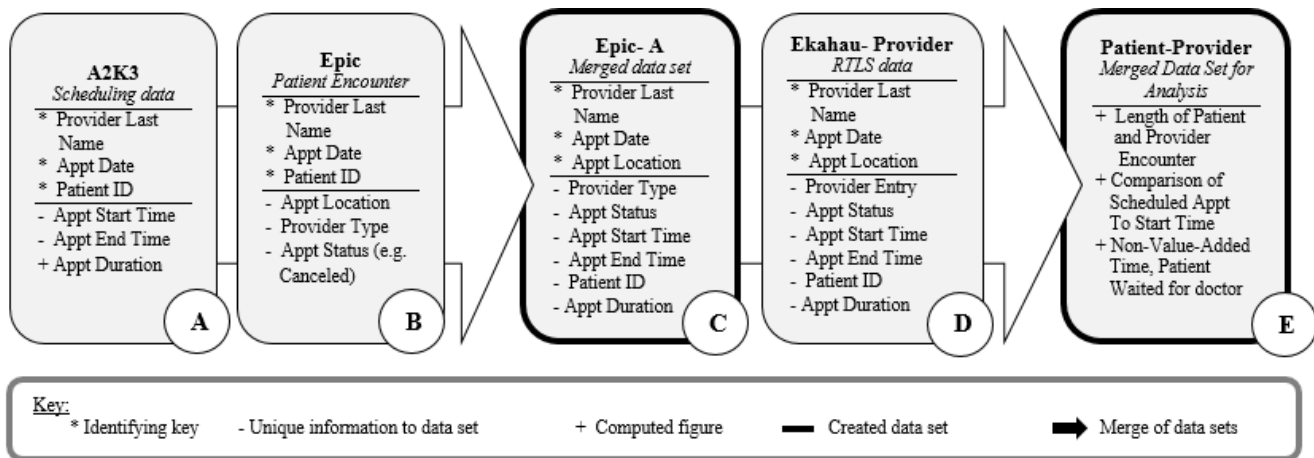


FIGURE I
DATA INTEGRATION ACROSS 3 SOURCES

locations and wait rooms visited. A patient may visit the same zone multiple times in one day. For this reason, the “Patient Locations” data set was created to calculate the time a patient spent in a zone upon each occurrence. The time a patient spent in each zone was updated by collapsing adjacent rows in Ekahau that had the same location designation, which occurs due to the nature of RTLS recording. Before collapsing occurred, Ekahau data was sorted by the patient ID, date, and arrival time. Figure II shows simplified logic used to create “Patient Locations.”

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For each data point recorded by sensor in Ekahau {
  if (the current patient is the same as the previous
    and the current day is the same as the previous) {
    if (dwell time < threshold) {
      Add current dwell time to previous dwell
      time in “Patient Locations”
    } else {
      if (the current location = previous location) {
        Add current dwell time to previous dwell
        time in “Patient Locations”
      } else {
        Create a new row in “Patient Locations”
        with new location and dwell time for
        patient
      }
    }
  } else {
    Create new row for new patient with a new
    location and dwell time in “Patient Locations”
  }
}

```

FIGURE II
CREATION OF PATIENT LOCATION DATA SET

III. Analysis of Patient Flow and Wait Times

“Patient Locations” and “Daily Patient Experience” were analyzed to identify and visualize bottlenecks in patient flow. For this study, we focused on assessing the length of stay (LOS) and waiting times with respect to location and time (e.g., time of day, day of week, and month). Because the ECCCC’s normal operation hours are Monday-Friday, only data for weekdays was evaluated. Also, outliers of data (e.g. dwell times of less than five minutes or longer than eight hours) were removed from analysis based on the assumption that short dwell times were indicative of suitable wait times and long dwell times were system errors (e.g. lost badge). To analyze waiting times and length of stay, the six specified waiting locations, a subset of “Patient Locations”, were considered: Waiting (first floor), Women’s Waiting, East Waiting, West Waiting, Lab/Imaging Waiting, and Infusion Waiting. Waiting times in exam rooms could not be quantified using the Ekahau patient data alone, thus were not included in general waiting times. However, exam room wait time is quantified in the patient-provider interaction subsection.

Statistical analysis was then performed on the extracted data. ANOVA and Kruskal-Wallis tests were performed to evaluate if wait times were statistically significantly different across the selected factors. Also, conditional probabilities were calculated using formula (1) to estimate the chance a patient waits longer than a certain time in various ECCCC waiting areas.

$$= \frac{P(\text{Wait times} > x | \text{Location } y)}{P(\text{Location } y)} \quad (1)$$

Hierarchical linear regression models were developed to understand factors associated with the total patient visit time and the total time spent in wait areas. Successive models were built by adding the number of locations visited, hour of arrival (binned by morning, mid-morning, afternoon, and evening), and the day of the week. Models were compared using AIC, BIC, and partial F tests to find the model of best fit.

IV. Patient-Provider Interactions

Based on data table E from Figure I, patient-provider interactions were investigated. To understand the interactions, we focused on three metrics. First, timeliness of arrival to scheduled appointments compared the actual arrival time of providers to the scheduled appointment start time. Second, the non-value-added time calculated the time that a patient spent in an exam room before the provider entered for the first time. Third, “overage” compared the time a provider spent in a room for an appointment, “their duration,” to the scheduled duration of an appointment. A provider’s duration was defined as the time between a providers’ first entrance to and last exit from an exam room.

Using these metrics, two ratios were computed to quantify patient-provider interactions. The *Patient-Provider Ratio* is the total time a patient is in a room after a provider first enters over the total time a patient is in a room. The *Intersect-Duration Ratio* is the total time a provider spends in the room with a patient over the total time a patient is in a room. The Intersect-Duration Ratio is less than the Patient-Provider Ratio because providers may leave and come back to the exam room at various points within an appointment.

RESULTS

I. Observations

Observations of the ECCCC revealed that the Ekahau data included badge activity during non-operational hours and movement between rooms in time intervals that did not reflect reasonable human action. These data points supported the ECCCC management’s concern of possible data inaccuracies.

II. Descriptive Statistics

This study used data obtained from Ekahau, Epic, and A2K3 from August to December 2016. During the period, 9,517 patients visited the ECCCC. 5,903 patients (48.5%) visited more than once and a total of 640 instances of patient-provider interactions were analyzed.

The jumping issue was detected in the Ekahau patient data. There was a total of 255,077 jump instances (8.5%) at a 6 second threshold. Sensitivity analysis showed that there were 854,950 data points between 5-6 seconds, whereas only 38,231 and 13,960 data points between 4-5 seconds and 6-7 seconds respectively.

III. Patient Flow and Wait Time Analysis

The average LOS for patients during operating hours (6 a.m. – 8:59 p.m.) was 3 hours and 15 minutes with a standard deviation of about 2 hours and 20 minutes. 39% of patients stayed at the ECCCC for 0-2 hours, 23% for 2-4 hours, and 48% for 4-8 hours. Also, 37% of patients visited 4-8 unique locations in the ECCCC, and 51% of patients visited 0-2 waiting rooms. On average, patients spent 9.4% of his or her time in a waiting room during their visit.

When ECCCC zones were grouped by location type, locations of designation “Other” (e.g. transit, bathrooms, and registration) averaged the longest dwell time, followed by Clinics and then Wait Rooms.

Figure III shows that the wait time distributions and the number of patient visits varied across waiting rooms. Four out of the six waiting areas showed fewer instances of wait times per longer binned time period. For example, Lab/Imaging Waiting, the area with the highest number of patient visits, showed 61% of patients waiting 5-10 minutes, 36% waiting 10-30 minutes, 2.6% waiting 30-60 minutes, 0.4% waiting 60-120 minutes and <0.4% waiting 2-8 hours. On the other hand, East Waiting showed low patient visits with 67% of patients waiting 5-10 minutes, 28% waiting 10-30 minutes, 2.3% waiting 30-60 minutes, 0.6% waiting 60-120 minutes and 2.9% waiting 2-8 hours.

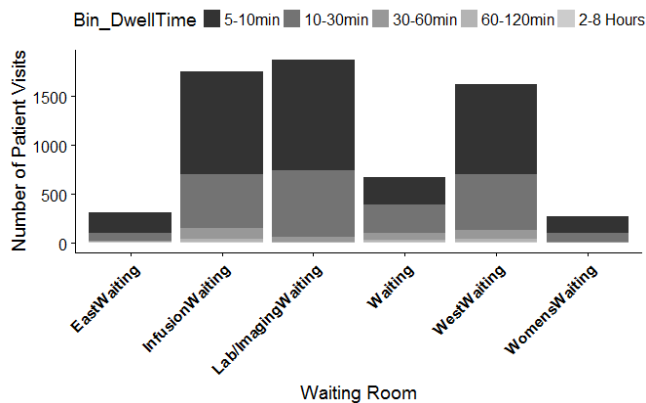


FIGURE III

NUMBER OF PATIENT VISITS BY DURATION IN WAITING AREAS

Patient flow analysis showed significant difference in wait times across waiting areas. The Waiting area had the maximum average wait time of about 20 minutes 30 seconds while the Women’s Waiting had the minimum at about 11 minutes and 30 seconds. Even though Women’s Waiting had the least amount of patient volume and the minimum average wait time, the number of visitors was not correlated with the average wait time across wait rooms. For example, East Waiting had about the same number of visits as Women’s Waiting but a significantly longer average wait time.

The results also showed that the likelihood of patients waiting more than 30 minutes or more than 2 hours varied across waiting areas. For example, Lab/Imaging Waiting had the minimum chance to wait more than 30 minutes at 3.87% whereas the Waiting area had the maximum at 14.02%. Similarly, Women’s Waiting had the minimum chance to wait more than 2 hours at 0% whereas the East Waiting had the maximum at 2.06%.

Figure IV shows a difference in wait times depending on the time of day a patient enters a waiting room compared with the number of patient visits across the time of day. The morning hours had more patient visits and less wait times compared to the afternoon hours. The Kruskal-Wallis test indicated that wait times were not uniform across hours at $\alpha=0.05$ ($p < 0.05$). The same statistical significance was true when analyzed with wait times greater than 30 minutes.

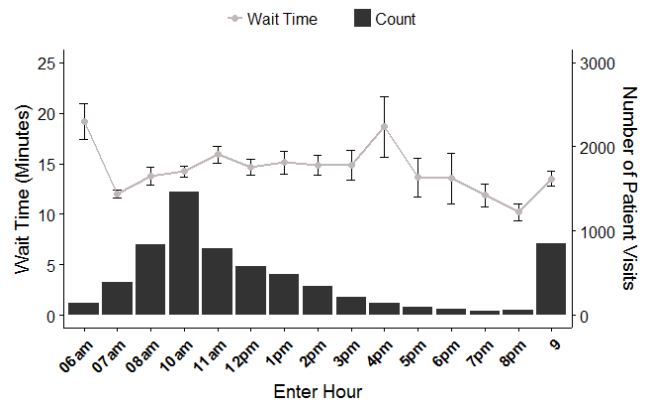


FIGURE IV

PATIENT TRAFFIC AND AVERAGE WAIT TIME ACROSS PATIENT ARRIVAL TIMES TO WAIT ROOMS

Hierarchical modeling found the linear regression models of LOS and time spent in waiting areas that included all variables to have the best fits. For both models, the partial F-test indicated that the coefficients of interaction terms were not equal to zero at $\alpha=0.05$ ($p < 0.05$). The model with two-way interactions of LOS had an adjusted- R^2 value of 0.3386, while the adjusted- R^2 of wait time was only 0.1027.

Table I showed the results of the full LOS model with interactions where the significant variables were highlighted in gray. The model passed tests for normality and homoscedasticity. Coefficients indicate that mid-morning times influence the LOS more than other times of day and

that patients who arrive for Thursday evening appointments after 5 p.m. encounter long LOS.

TABLE I

LINEAR REGRESSION: PATIENTS TOTAL LENGTH OF STAY

Estimate	Coefficient	p-values
(Intercept)	60.40	< 0.01
Number of Locations Visited	4.31	< 0.01
Monday	-4.09	0.68
Thursday	-2.11	0.79
Tuesday	0.88	0.92
Wednesday	12.05	0.13
Mid-morn	73.89	< 0.01
Afternoon	-8.29	0.50
Evening	-105.97	0.04
Number of Locations Visited * Tuesday	-2.74	0.01
Number of Locations Visited * Wednesday	-2.61	0.01
Number of Locations Visited * Mid-morn	8.76	< 0.01
Number of Locations Visited * Afternoon	13.79	< 0.01
Thursday * Evening	155.21	0.04

IV. Patient-Provider Interaction Analysis

The analysis between patients and providers' movements allowed us to understand providers' timeliness of arrival to scheduled appointments, non-value-added time patients spent in exam rooms, and actual encounter times as compared to their scheduled lengths. The results indicated that 14% of the time, providers arrived early or on time to appointments, whereas 86% of the time, providers were late, arriving an average of 48±1.8 minutes after the appointment was scheduled to begin.

About 75% of patients waited an average of 20.2±0.8 minutes, with a minimum wait time of 0 minutes and a maximum of 90 minutes, in an exam room before their provider arrived. When looking at the top 10% of non-value-added times, patients waited on average about an hour before they were seen by their provider.

Overage showed that providers spent 11.2 minutes less than the allotted time for each appointment on the appointment. The Patient-Provider Ratio is 0.61, indicating that 39% of the patient's time in an exam room was spent waiting for the provider to enter for the first time. The Intersect-Duration Ratio is 0.32, showing that 32% of the patient's time in an exam room was time spent with the provider in the room.

DISCUSSION AND CONCLUSION

I. Indications of System Shortcomings

Analysis showed jumping occurs frequently thus further calibration of the beacons within the RTLS could improve system accuracy. Jumps in the data result in patients appearing to be in locations for less time than they actually were which can skew the data when analyzed. Other system errors were recognized in extreme dwell times greater than 8 hours. While these were removed for analysis, they could be indicative of a patient losing his or her badge in the center, or more generally badges staying active in the ECCCC outside of operating hours. Management could employ more rigid processes for badge return, such as a checkout clerk asking

for the badge after the final appointment, instead of requiring the patient to drop it off him or herself.

II. Patient Flow and Wait Times

This study showed how to develop new data tables, "Patient Locations" and "Daily Patient Experience," from the original Ekahau data. This is important because they can be used to identify problems that are otherwise difficult to detect, and can analyze patient travel through a multi-clinic facility over time. The analysis pointed out bottlenecks in patient flow in the East Waiting and Waiting areas. The ECCCC can further investigate why these two waiting areas with the least patient volume have the highest wait times. Staff and resource allocation may be needed to be re-assessed. Since afternoon appointments had higher waiting times, reducing the number of morning appointments or expanding scheduling procedure to tailor appointment lengths could prevent afternoon back-up.

Using the results of patient flow analysis, the hospital manager may be able to inform patients of potential waiting times in different locations. For a patient who is told they have at a 10% chance of waiting more than 30 minutes, it would not be advised for the patient to leave the waiting area.

If a patient is late for an appointment in the morning, later appointments will be delayed. Delays not only create stress for the patient, but also for the provider who must make up lost time. Appointment delays are at least partially caused by the current scheduling system, showing further support for the need to alter scheduling procedures.

Patients spend the most time in other locations (e.g., transit, bathrooms, registration) indicating that improvement can be made not only in provider and waiting areas but also in other locations at ECCCC. Recommendations include improving signage throughout the ECCCC to hasten transit. Additionally, registration time could be reduced by increasing the number of staff or improving the human factors of registration forms.

Linear models showed significant factors associated with the LOS and waiting time for individual patients. Specifically, the ECCCC should investigate possible scheduling adjustments for mid-morning and Thursday evening appointments.

III. Patient-Provider Interactions

Combined RTLS data with scheduling and provider data provided insights into scheduling and non-value added times. In terms of promptness, most providers arrived over 45 minutes late for appointments, which may be attributed to delays in schedule. Improving scheduling processes by tailoring the time allotted for appointments by appointment type and provider may minimize wasted time in exam rooms and delays in provider workflow.

It is desirable for patients to spend the majority of their time in an exam room with a provider. However, the results indicated that 39% of a patient's time in an exam room (approximately 20 minutes) was spent waiting for the provider to enter for the first time. In addition, only 30% of a

patient's time spent in an exam room was spent with a provider. Overage indicates that providers are spending about 10 minutes less time with the patient than designated for a scheduled appointment. The improvements to the scheduling system should minimize the patient's time in an exam room waiting for his or her provider, ultimately increasing the percentage of time patients are in the exam room with their provider

IV. Limitations and Future Work

Limitations in the data and system implementation must be considered. The data, in particular scheduling data, we used included some human errors. For example, provider names included typos such as a number in a last name. This limits the ability to join data sets by matching provider names contributing to the low amount of provider data points. Increasing the number of data points within the patient-provider interaction data set would strengthen the study's statistical significance.

The Ekahau data included limited provider data because of RTLS badge acceptance issues. ECCCC management explained that only 1 in 20 patients refuse a badge, whereas providers are less likely to use a badge.

The system error, jumping, affected the accuracy of patient dwell times. While this study addressed the issue using generalized rules, the limitation still remains.

A future work of this project is to simulate a clinic and its associated waiting area to provide actionable recommendations relating to resource and employee allocation. After this initial simulation, a simulation of the multi-clinic ECCCC facility could be constructed to reveal interactions between clinics more clearly.

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