# Utilization of Automated Location Tracking for Clinical Workflow Analytics and Visualization

by

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ABSTRACT

The analysis of clinical workflow offers many challenges to clinical stakeholders and researchers, especially in environments characterized by dynamic and concurrent processes. Workflow analysis in such environments is essential for monitoring performance and finding bottlenecks and sources of error. Clinical workflow analysis has been enhanced with the inclusion of modern technologies. One such intervention is automated location tracking which is a system that detects the movement of clinicians and equipment. Utilizing the data produced from automated location tracking technologies can lead to the development of novel workflow analytics that can be used to complement more traditional approaches such as ethnography and grounded-theory based qualitative methods. The goals of this research are to: (i) develop a series of analytic techniques to derive deeper workflow-related insight in an emergency department setting, (ii) overlay data from disparate sources (quantitative and qualitative) to develop strategies that facilitate workflow redesign, and (iii) incorporate visual analytics methods to improve the targeted visual feedback received by providers based on the findings. The overarching purpose is to create a framework to demonstrate the utility of automated location tracking data used in conjunction with clinical data like EHR logs and its vital role in the future of clinical workflow analysis/analytics. This document is categorized based on two primary aims of the research. The first aim deals with the use of automated location tracking data to develop a novel methodological/exploratory framework for clinical workflow. The second aim is to overlay the quantitative data generated from the previous aim on data from qualitative observation and shadowing studies (mixed methods) to develop a deeper view of clinical workflow that can be used to facilitate

workflow redesign. The final sections of the document speculate on the direction of this work where the potential of this research in the creation of fully integrated clinical environments i.e. environments with state-of-the-art location tracking and other data collection mechanisms, is discussed. The main purpose of this research is to demonstrate ways by which clinical processes can be continuously monitored allowing for proactive adaptations in the face of technological and process changes to minimize any negative impact on the quality of patient care and provider satisfaction.

# DEDICATION

To Sarah

To my parents

To my grandparents

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ABBREVIATIONS

| | |
|---|---|
| ED | Emergency Department |
| EHR | Electronic Health Records |
| IOM | Institute of Medicine |
| RFID | Radio-Frequency Identification |
| ALT | Automated Location Tracking |
| RTLS | Real-Time Location Sensing |
| CPOE | Computerized (or Computer-assisted) Provider Order Entry |
| CMS | Centers for Medicare & Medicaid Services |

# CHAPTER 1

# INTRODUCTION

The pursuit of quality and improved patient safety through the refinement of clinical practice has been one of the primary goals of medicine throughout modern history. In the $19^{th}$ century, Dr. Ignaz Semmelweis discovered that incidence of puerperal fever ("childbed fever") could be reduced significantly by the introduction of hand disinfection in obstetrical clinics (Best & Neuhauser, 2004). In the $20^{th}$ century, the use of mathematical and statistical models created from data collected in clinical environments increasingly gained acceptance contributing to the creation of the field of Biomedical Informatics. While early works in the field (Ledley & Lusted, 1959; Warner & Cox, 1964) dealt primarily with the diagnostic aspect of practice, the fundamental feature of these methods, and one of the lasting impacts of these seminal works, was that data generated in medical practice could be used to refine and improve quality of patient care.

Subsequently, the introduction of technology into clinical environments further solidified the need to research the impact of these technologies on patient care and clinical practice. In the year 2000, the Institute of Medicine (IOM) released the report "To Err is Human" (Institute of medicine & Committe on Quality of Health Care in America, 2000) which estimated that between 44,000 and 98,000 lives were lost annually in the United States from preventable medical errors. These startling findings shed further light on the need for healthcare to consistently analyze and refine their processes to reduce preventable errors. In a subsequent report (Institute of Medicine & Committee on Quality of Healthcare in America, 2001), IOM provided broad recommendations for the future of the healthcare stating the need for systems to “safe, effective, patient-centered, timely, efficient, and equitable”.

The reports led to a variety of interventions being introduced into medical practice throughout the country, but an important lesson learnt was the need to treat the medical environment as a system that combines human factors (social, organizational) with technology and other processes. While it may be convenient to blame human error on those findings, it is not a view shared by the majority of patient safety researchers (Henriksen, Dayton, Keyes, & Carayon, 2008). A more accepted view is to consider a medical environment to be a complex system and errors are typically caused by one or more aspects of the system failing leading to a sequence of failures which ultimately impact patient safety. Errors occur more due to our lack of understanding of the environment and its bottlenecks rather than any specific individual in the environment. To that end, it become clear that the analysis of clinical environments relies heavily on the tracking and assessment of clinical workflow.

**Workflow in complex clinical environments**

Workflow is the description of a sequence of activities performed independently or collaboratively by the various agents/entities in the system (M. Vankipuram, Kahol, Cohen, & Patel, 2011). The agents in a clinical system include, but are not limited to, clinicians, technologies, and care delivery processes. Analysis of the causes of clinical error that compromises safety, has always been a complex proposition.  Since healthcare is a complex and collaborative system, the study of clinical activities and interactions with healthcare professionals and support systems, can help us better understand the care delivery process and consequently, the workflow.

However, a meaningful analysis of workflow is a time and task intensive process, the complexity of which scales in relation to the complexity inherent to the observed environment (M. Vankipuram et al., 2011). Traditionally, workflow analysis involved the use of one or multiple methods by means of a human observer to capture various streams of data in the environment of interest. The most widely used method has been ethnography (Laxmisan et al., 2007; Malhotra, Jordan, Shortliffe, & Patel, 2007; V. L. Patel, Zhang, Yoskowitz, Green, & Sayan, 2008). Ethnography in clinical environments is the study of individuals in the setting and how their interactions, including their biases, impact clinician performance and patient care outcomes. Ethnographic studies most often focus on aspects of clinical workflow and related behaviors rather than attempt to model a global state. These aspects can range from the actual tasks being performed within the environment to the mental perceptions, models of the providers and associated clinical staff or some combination of both.  Mental models are an abstraction of the thought process of individuals performing tasks being tracked. An analysis of those tasks relies strongly on their conceptualizations of the task (Norman, 1983), and are therefore vital in workflow analysis.

Jiang et al. (2017) examined the impact of an electronic handoff tool on the shared mental models within patient care teams. The goal of this study was to assess discrepancies in the mental models of the team members pre and post implementation of the electronic handoff system. They found that the electronic handoff did not have the desired impact of reducing discrepancies and was at times associated with an increase in discrepancies specifically in relation to dosages and patient symptoms. Mamykina et al. (2017) studied the purpose of interruptions within a PICU and the opportunities to reduce them. They found that physicians were interrupted 11.9 times per hour and others 8.8 times an hour. The most common reason for interruptions was determined to be information seeking or sharing (46.3% of the time). They also determined that 29.5% of the interruptions could be resolved using information displays or computer-mediated communication. Malhotra et al. (2007) conducted a study leveraging ethnographic techniques to model clinical workflow in an intensive care unit, using both observed activities and an inferred understanding of the underlying cognitive processes of clinical personnel. The goal of their work was to create models of ICU workflow that could be used in the identification and classification of medical errors. Similarly, Laxmisan and colleagues (2007) conducted ethnographic observations in the ED to study cognitive burdens imposed on clinicians in the work environment. They found that multi-tasking, interruptions, and gaps in information were potentially causing heavy cognitive load. In another context, Gralla and colleagues (2005) studied the impact of a 16-MDCT scanner on workflow in the emergency department. They recorded the time intervals of various tasks during examinations and found that the use of the scanner resulted in shorter examinations times even in the case of multiple body region exams. One of the advantages of incremental studies on aspects of clinical workflow, as described here, is that a survey of literature can give us a much better view of the state-of-the-art. The goal of any single researcher is rarely to find a global truth of workflow. As an example, Niazkhani & Pirnejad (2009) surveyed literature to find the impact of CPOEs on clinical workflow based on a conceptual framework and found that CPOE has a positive impact on legibility of orders, remote accessibility, and order turnaround times but suffered from concerns about usability, enforcement of predefined relationships between clinical tasks and providers. An alternative advantage of workflow analysis is the ability to generate best practices and guidelines that can seamlessly integrate into workflow to enhance efficiency and quality. Tu and colleagues (2004) developed a method to integrate decision support systems into clinical workflow based on a deployment-driven methodology of identifying usage scenarios, disambiguation of relevant knowledge, formalization of data elements and vocabulary, and encoding the usage scenarios into the guideline. They evaluated their methodology by simulating the deployment of an immunization guideline in a clinical information system. Their results suggested the potential for sharable executable guidelines that allow seamless workflow integration.

The studies described thus far have mostly dealt with clinical workflow analysis from a cognitive or behavioral perspective. An alternative or supplemental approach involves capturing the tasks or activities within the environment as a function of time. These methods help create a dynamic view of the clinical workflow. Time-motion studies are commonly used to map processes as well as associated tasks and their temporal relationships in complex environments. Such studies are considered a gold-standard for clinical workflow analysis. These studies most often involve use of qualitative observations (Sinsky et al., 2016a; Westbrook, Li, Georgiou, Paoloni, & Cullen, 2013), recording tasks in the environment, along with recordings of sequence and duration, using time stamps. While time-motion studies are an invaluable part of workflow analysis, Zheng et al. (2010) found that such work has consistently found the impact of health IT implementations on workflow to be negligible, where other qualitative methods have suggested negative end-user perceptions, as is the case for EHRs discussed earlier. They speculate that a reason for the discrepancy may be due to the nature of the time-motion study design being used and the reported outcome measures. In their paper, they propose a new set of analytical methods and visualizations derived from time-motion studies that they suggest could enrich future workflow analysis efforts.

Ethnographic techniques share some common propensity for erroneous observation or inference or are logistically problematic. Furthermore, the inferences made from the data can be difficult to generalize. An example of this is that human observers need to capture a significant amount of information within the complex environment. This can be cognitively taxing to the point of information loss or erroneous capture. Additionally, to maximize coverage of a clinical environment, several human observers may be required adding to the cost involved. To that end, several kinds of automated techniques have been developed to refine data collection in clinical environments. These techniques help either to provide human observers a streamlined mechanism of data capture or as a standalone method of supplementing information captures within the environment. The first of these techniques is the use of workflow simulations. Wang (2009) implemented an agent-based simulation to better identify bottlenecks in the ED workflow. His system was used to identify and subsequently modify parameters associated with triage and radiology processes that could achieve an improvement in mean patient wait times, thus reducing their length of stay. Wang et al. (2013) used a conceptual model of the ED to simulate the impact of modifying physician behavior on several performance metrics including the number of new patients seen per hour, and the length of stay.  Such techniques are a good way to simulate complex environments where the data collected may not always be consistent. However, the simulation models are typically created through expert opinion, which while valuable, are at times insufficient. Incorporating real world data into the creation of these models would go a long way towards developing consistent quantitative metrics.

There are certain other limitations to ethnographic methods as well. Specifically, they rely heavily on single or multiple human observers processing multiple, at times concurrent, streams of information (M. Vankipuram, Kahol, Cohen, & Patel, 2009). Increasing the number of observers can help in such situations, but it can become disruptive to the clinical environment.  Additionally, logistical issues, such as the need to train the observers to collect consistent data with high reliability, may be a cost-intensive. These issues are exacerbated in the emergency department (ED) (Brailsford, Lattimer, Tarnaras, & Turnbull, 2004), and it consequently poses a significant challenge for researchers. The tasks performed in the ED are typically, complex, distributed, and non-linear (Kannampallil et al., 2011). Therefore, to supplement ethnographically derived metrics, healthcare organizations have turned to automated data collection techniques, freeing the researchers to devote more time to data analysis and interpretation in context.

**Impact of EHRs on clinical workflow**

The Health Information Technology for Economic and Clinical Health (HITECH) Act, passed as part of the American Recovery and Reinvestment Act (ARRA) of 2009, introduced incentives for healthcare organizations to adopt and use EHRs (Blumenthal & Tavenner, 2010). This has led to a significant increase in EHR adoption and as of 2015, 96% of US non-federal acute care hospitals reportedly possessed certified EHR technology and 84% had adopted a basic EHR which was up from 9.4% in 2008 (Henry, Pylypchuk, Searcy, & Patel, 2016). The EHR systems have introduced a new dimension to clinical workflow. This, combined with the quality reporting requirements under “meaningful use” (Centers for Medicare & Medicaid Services (CMS), 2010) have seen organizations adopt a variety of protocols and techniques to collect and quantify clinical workflow to aid in reporting of measures. However, recent research has shown that the impact of EHRs into clinical workflow has not been without some significant drawbacks ranging from a lack of patient engagement to a negative impact on physician productivity (Furukawa et al., 2014; Mennemeyer, Menachemi, Rahurkar, & Ford, 2016; Middleton et al., 2013) suggesting the need for a thorough exploration of EHRs impact on workflow. Problems with EHR integration have also shown to negatively impact workflow (Ash, Berg, & Coiera, 2004; Koppel et al., 2005).

Noblin et al. (2013) studied clinician perspectives regarding a newly introduced EHR system in an ED and found that the users were, as a group, divided on its overall impact on patient flow and clinician satisfaction. Makam and colleagues (2013) conducted a survey of primary-care providers in 11 internal medicine practices, asking about their use of the EHR on typical tasks such as documentation, ordering, problem lists, etc.  They found that the decision-support features such as reminders were a source of frustration due to the usability concerns. Additionally, over half of those surveyed felt that the problem lists, while important, were unreliable and potentially inaccurate. They also found that the clinician subjects were spending at least an extra hour beyond normal work hours on the EHRs, contributing to burnout. In a comprehensive study of 223 providers in one academic healthcare system during adoption of a commercial EHR, Krousel-Wood and colleagues (2018) found a significant decrease in the overall satisfaction and perceived productivity of providers. A significant decrease in perceived time spent with patients or coordinating patient care was also reported. In summary, the introduction of an EHR alters workflow in that it introduces cognitive load, increases physician time at the workstation, (Arndt et al., 2017; Sinsky et al., 2016b) and thus reduces time spent a more direct patient care.

### Automated Data Collection in Clinical Environments

As previously mentioned, to supplement traditional approaches to clinical workflow analyses, organizations have begun to rely on data from a variety of automated sources. Automated sources refer to mechanisms in a clinical environment that track activities, events, movement, etc. of clinically relevant entities within the environment by way of sensors or other logging mechanisms built directly into medical systems. The goal of these systems is to provide a computational approach to the tracking of human activities and behaviors while accounting for the inherent complexity therein. Zheng and colleagues (Kai Zheng, Hanauer, Weibel, & Agha, 2015) define the concept of computational ethnography as "a family of computational methods that leverages computer or sensor-based technologies to unobtrusively or nearly unobtrusively record end users' routine, in situ activities in health or healthcare related domains for studies of interest to human–computer interaction.". The goal of computational methods used in ethnography or social sciences at large is to add a measure of objectivity to the more traditional approaches while also refining the otherwise burdensome process of data collection as described previously. The authors define the various data sources form the backbone of computational ethnography. These include: computer logs (activity, event logs), screen activities, eye tracking, motion capture, real-time location sensing (RTLS) etc. Each type of data source requires a separate set of technological, logistical, and ethical considerations. However, a clinical system fully capable of automated analysis of the workflow and process within will likely have some combination of the above methods and technologies implemented within the environment. Our goal as researchers is to demonstrate value for each of the methods and as a combination whenever possible to give medical organizations an empirical basis for increasing adoption of these technologies. In this research the focus (through the two aims) will be on two of the computational ethnographic methods: automated location tracking and EHR logs.

The first of these is RTLS. There are a variety of RTLS technological solutions available, the most common among them is Radio-Frequency Identification (RFID) which is also the tool used in this research. The value of automated environmental capture techniques in healthcare is described by Vankipuram and colleagues (M. Vankipuram et al., 2011), as being analogous to a black-box in aviation. The black-box continually captures internal performance and environmental data of the air-craft. This data can then be used in performance assessments and reliability checks as well as error analysis in the case of failures. Such technologies are best utilized in a similar manner and when combined with tried and tested qualitative measures, they can be used to capture workflow with greater fidelity. While, automated data collection techniques cannot independently provide the descriptive depth achievable using qualitative techniques, they are able to complement human observation or provide a means to find potential areas of concern that can be subsequently studied thoroughly through a combination of traditional and modern techniques.


Figure 1: RTLS Tags. top-left: ZigBee (Wikipedia.org); top-right: Bluetooth (Estimote.com); bottom-left: RFID (Midmark.com); NFC (Wikimedia.org)

Several technologies exist for the purpose of location tracking including, but not limited to, Wi-Fi (Youn et al., 2007), Radio Frequency Identification (RFID), Bluetooth (Han, Klinker, Ostler, & Schneider, 2015), ZigBee (Tung et al., 2014). Sensor-based technologies are based on a transmitter-receiver model where a transmitting tag is placed on the entities being tracked and a receiver collects the information when the tag is within a required range. The receivers can range from proprietary stations created for the technology to any desktop or mobile device capable of receiving the transmitted signal either natively or using an external USB receiver or other attachments.

In the context of clinical quality or performance analysis, ALT can help streamline the process. As an example, positional tracking can be used to derive additional metrics that may function to benchmark emergency room performance. The Center for Medicaid and Medicare Services (CMS) enacted several performance measures that needed to be enacted beginning in 2012 (Blumenthal & Tavenner, 2010).

The measures that can be analyzed using location tracking data include:

- Door to Diagnostic Evaluation by a Qualified Medical Professional
- Median Time from ED Arrival to ED Departure for Discharged ED Patients
- Median Time from ED Arrival to ED Departure for Admitted ED Patients
- Admit Decision Time to ED Departure Time for Admitted Patients

Welch and colleagues (2011) elucidated, in detail, the performance measures for emergency rooms and the salient timestamp or time-interval measures were as follows:

- Treatment space time: Time taken to acquire a bed or room
- Provider contact time
- Arrival to provider time (door-to-doc)
- Arrival to treatment space time
- Length of stay: Arrival to departure

Continuous tracking of these attributes can provide emergency rooms with the ability to continuously monitor and improve their processes.

**Radio-Frequency Identification (RFID)**

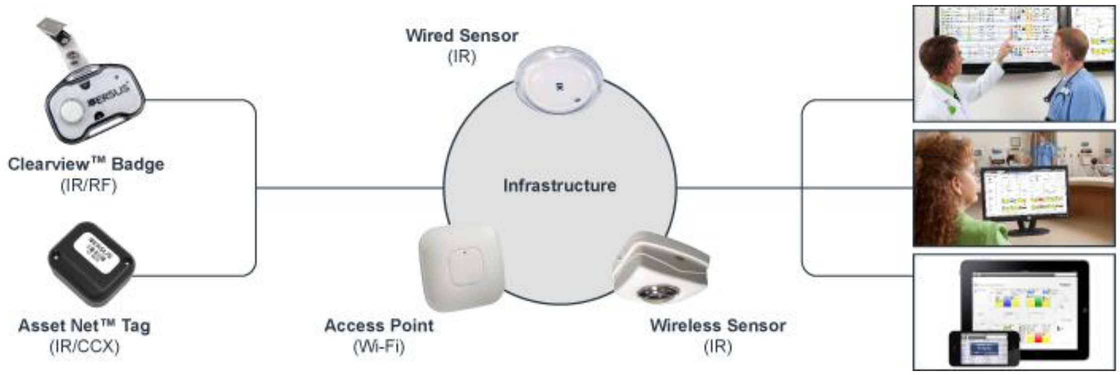



Figure 2: RFID system architecture (Versus Technology)

RFID is amongst the most popular technologies utilized for continuous location tracking in environments. RFID systems have been used in medical environments in a variety of ways. There are two main categories of RFID technology: active and passive. Active RFID tags have an internal power source and are continuously transmitting a signal. This increases their range of detection over the passive systems. An active RFID tag can be detected at distances of over 100m. However, the batteries need to be replaced at regular intervals. Passive RFID tags have no internal power source and therefore have a much longer single usage life that active systems. They derive their power from the receivers themselves. Their detection range is typically small (approx. 10m). Passive tags only activate when they are within the range of the receiver.

RFID can be potentially leveraged to track entities within the environment to study the workflow of its users. These tracking methods have been implemented in a variety of domains for the purposes of operations/workflow analysis. Fry and Lenert (2005) implemented a system called MASCAL that used RFID technology to track personnel, patients, and equipment in mass casualty events such as natural disasters and other catastrophes. MASCAL involved the use of 802.11g RFID tags in combination with receivers set around the hospital to track the various resources in real-time at times of emergency. Ajami and Rajabzadeh (2013), in their review of RFID and its impact on patient safety found that the use of RFID-based analysis integrated into workflow reduced “medical, medication, and diagnosis errors”. In the context of the ED, Kannampallil et al. (2011) presented a set of methods to formalize the investigation of clinical activities using RFID tags. They propose the use of entropy or the “degree of randomness” as a quantifiable metric that can be computed from tag-based data. The purpose of this techniques was to create a quantifiable mathematical abstraction of the nature of clinical workflow. An alternate technique was proposed by Vankipuram et al. (2009). Their activity tracking relied on the use of Hidden Markov Models (HMM) to probabilistically derive the underlying hidden activities that could be associated with a set of observations from the RFID tags. HMMs are primarily used for predictive modeling. In an ideal case, we may be able to predict the succeeding actions or tasks performed by the clinician based on the created model. This could potentially yield ways to simulate the clinical environment or for real-time error detection.

One of the primary limitations of RFID is its potential for interference. The interference of wireless RFID signals can be divided into two classes: interference that prevents correct data from being transmitter or received by the RFID system and the risk of incorrect interpretation of signals from other systems as being valid for the current system (“RFID and Interference - The Risks of Interference,” 2015). RFID systems can be affected by the medium through which the signals must pass i.e. when tags are mounted on metals and liquid. Due to this, interference may happen when signals pass through the human body. However, recent developments in tag and antenna design have helped mitigate this issue. The second type of interference occurs with Wi-Fi and Bluetooth networks. However, this is considered to be a fairly rare occurrence ("RFID and Interference - The Risks of Interference," 2015). Another issue with RFID technologies is that the cost of proprietary systems can be high.

**Bluetooth**

Figure 3: Bluetooth Beacons (Estimote)

Bluetooth is a wireless standard for communication over short distances. Most desktop and mobile devices are natively capable of reading Bluetooth and therefore it is more easily integrated into an existing technological ecosystem. Traditionally power required to transmit Bluetooth was prohibitively high and therefore was not used in continuous tracking solutions. However, Bluetooth has gained popularity as an RTLS technology due to release of the low energy Bluetooth standard (BLE) introduced as part of Bluetooth 4.0. BLE devices, have a lower mean power consumption than similar low energy technologies such as, ZigBee (Dementyev, Hodges, Taylor, & Smith, n.d.) leading to an improved lifetimes of Bluetooth slave devices i.e. tags (Gomez, Oller, & Paradells, 2012). Andersson (2014) demonstrated the use of a Bluetooth low energy beacon in the implementation of proximity-based door locks. Frisby, Smith and colleagues (2017), capitalizing on this technology, implemented a Bluetooth RTLS solution in a ED.

One of the key limitations of Bluetooth, like RFID technologies, is the potential for interference. Bluetooth performance has been shown to degrade in the presence of Wi-Fi (Punnoose, Tseng, & Stancil, 2001). However, recent advancements and properly configuring the Wi-Fi network has been shown to mitigate the issue (Frisby et al., 2017).

**Automated location tracking data**

The data collected from any tracking technology has two distinct features which are important when considering the implementation of such a system within a clinical environment. These are:

1. High density: data is collected continuously and is logged at frequencies as high as several times a second. The logging infrastructure i.e. servers, databases etc. must be able to deal with high volume of data being added from concurrent sources continually. Most mainstream databases should be able to accommodate this type of data without concern.
2. Simplicity: The most effective utilization of tracking data can be achieved by logging the following attributes: Location of receiver, Tag identification number, Timestamp. These three unique identifiers are enough for effective utilization.

However, when Bluetooth tracking technologies are implemented in an ad-hoc manner, it becomes necessary to deal with data as a signal i.e. a sequence of bits representing the strength of the signal and tag information. The distance of the tag (location) to the receiver can be then computed. An additional stage is the reduction of noise in the signal and there are several techniques to achieve this, one involving Kalman filtering is discussed in work by Frisby et al (2017). Proprietary Bluetooth systems often perform the noise reduction and location computation tasks behind the scenes and provide the data structured as described.

This research deals with data collection from ALT which is structured in the way described above. The conversion of signal to location and distance or noise reductions techniques are not discussed in this document as they are beyond the scope of this research. Most medical organizations are more likely to have proprietary installations and therefore the concern of this research to demonstrate utilization of data and not of system development.

These technologies can be used in the continuous mining and mapping of clinical processes (Pasupathy & Clark, 2014). Given the inherent complexity of clinical environments, an essential part of analyzing workflow is to study processes and activities from multiple perspectives and dimensions. By leveraging and mapping quantitative tracking data with qualitative ethnographic data, we can better understand the impact of EHRs on clinical behavior of clinicians and the clinical activities of interest.

However, one of the key limitations of tracking systems in general is the need to compensate for the loss of contextual information. In an ideal state, a tracking system is best implemented in such a way as to maximize coverage. Coverage is the area of the environment that is "seen" by the system of receivers where the presence of a tag can be detected. While there are computational techniques to maximize the range of detection, often the most efficient case is to ensure the presence of a receiver at each location of interest. In large environments, this can be an expensive and complicated task. Additionally, in medical environments sources of interference discussed previously, are more likely owing to a variety of equipment emitting wireless signals. The second limitation of tracking systems is that certain types of contextual information cannot be collected at all. An example of this is interactions between tracked entities. Tracking systems can at most yield information about co-located entities, but we cannot use the data alone to ascertain if the event constituted an interaction or the type and form of the interaction.

For these reasons, this research is primarily aimed at complementing existing workflow analytics techniques, both quantitative and qualitative. The developed methods are aimed at supplementing findings or in an exploratory capacity to find areas of concern or bottlenecks that can be studied in more detail using a combination of methods.

**Electronic Health Record Data**

A second important form of automated data collection in the in clinical environments is from EHRs. We have already discussed the broad-ranging impact of EHRs on clinical workflows. In modern EHRs data is collected in a variety of formats and stored either locally or on the cloud. Many medical organizations actively create data warehouses from clinical data. EHR data consist of several types of data: image, textual, numerical, event, video etc., the processing of each requiring a varied set of considerations.

One important type form of EHR data is usage (trace) logs which are a log of events (actions) performed in the system. Trace logs can be used to mine relevant processes. Kannampallil et al. (Kannampallil, Denton, Shapiro, & Patel, 2018) studied the use of EHR trace logs in the automated creation of “meaningful use” performance measures for the ED, namely: door-to-doc, door-to-disposition, admit-decision etc. These measures were then correlated with the use of EHR modules categorized by their general purpose (Documentation, ordering, notes, review etc.). They found that patient chart review was positively associated with door-to-disposition time. The goal of their study was to show the value of EHR activity logs even as a standalone data source in performance analysis within a clinical environment. Hribar et al. (2018) conducted a study to validate the use of EHR timestamp data in the prediction of clinical workflow related timings in four outpatient ophthalmology clinics. They found that the EHR timestamps were within 3 minutes of observed times for >80% of appointments. They were able to conclude the EHR timestamp data provides a reasonable approximation of clinical activity/workflow. To understand the potential of secondary EHR data in assessing elements of clinical workflow, Goldstein et al. (Goldstein, Hribar, Sarah, & Chiang, 2017) conducted a study to assess the impact of trainees on workflow in an academic outpatient clinic. They found that secondary EHR data could be used to comment on trainee behavior and specifically that presence of trainees was associated with an increase in session length. Wu et al. (2017) similarly compared known workflow changes from their previous study using EHR audit logs and were able to quantitatively demonstrate those changes suggesting that the logs could be as valid source for workflow analysis when used as an objective measure.

Process mining is a family of automated techniques that utilize trace logs to yield additional insight into the underlying process of a sequence of activities. Grando and colleagues (2017) utilized EHR trace logs to study provider and patient-based workflows in pre-operative setting. They were able study workflows associated with handoffs, time spent using reviewing information, and time spent documenting using trace log mining. Process mining using EHR trace logs has also been used in conjunction with cognitive analysis to study workflow (Furniss, Burton, Grando, Larson, & Kaufman, 2016; Kai Zheng et al., 2015).

The other form of EHR data is in the form of aggregate or summary information usually categorized based on time, location, personnel etc. This form of data is utilized in the EHRs vendors own analytics platforms. The data available is not in the form of raw event data but has been aggregated into meaningful types based on specific EHR modules (notes, documentation, orders) or types of activities performed (clicks, tab hops). This form of data is easy to visualize or present in other ways to target users. One of the goals of this research is to utilize this form of EHR data in conjunction with automated location tracking data to analyze workflow using a different perspective to yield new insight.

**Visual and Temporal Analytics**

Utility of analytic techniques are the greatest when derived information can be presented to target users in meaningful ways. In the medical domain, users may include clinicians, administrators, or clinical researchers. The theoretical foundations for this space are provided by the science of visual analytics. Visual analytics is the "science of analytical reasoning facilitated by interactive visual interfaces" (Thomas & Cook, 2006). Visual analytics can aid in the deeper exploration and insights derived from data and the presentation of this information to specific types of end-users.

It is essential for any data collection that tracks entities to preserve the temporal relationship between observed activities. Consequently, the value of temporal information extraction is the ability to then infer higher-level concepts. Aigner and colleagues (Aigner, Miksch, Müller, Schumann, & Tominski, 2007) provide a generalizable framework for the visualization of temporal data. They categorize visual methods into three high level categories: time, data, and representation. Each are sub-categorized based on the structure of data (number of variables, frame of reference), structure of time (linear, branching, cyclic), and time-dependent and dimensionality of representation. They also define the types of interactions that should be expected from any temporal visualization i.e. the ability to change time intervals or the ability to further explore any one data variable. Their work provides a foundational view of visualizations in ED like environments. Loorak et al. (Loorak, Perin, Kamal, Hill, & Carpendale, 2016) developed a system called TimeSpan demonstrating the visualization of temporal patient data with multiple dimensions.

Visualizations can also be used to develop modeling paradigms that can be used to creating and representing the structural specifications of systems to standardize varied representations and for shared development. A popular example of this is UML (Unified Modeling Language) (Group, 2010) which is used in extensively in software system architecting and development. An advantage of these type of modeling languages is the ability to execute or simulate the model as a state machine to test the performance, utility, logic flow of the system against specific inputs. In the clinical domain, GLIF (Guidelines Interchange Format) (Boxwala et al., 2004) was developed to model clinical guidelines. The goal of this work was to allow clinical guidelines to be represented, shared, and executed using conceptual flowcharts and computable specifications. Encoded GLIF models were tested with actual patient data.

Deeper insight from data can also be achieved using knowledge mining and representation. Yuval Shahar (1997) presented a domain-independent framework for knowledge-based inference using a temporal abstraction framework. The crux of this work was the formalization of the Knowledge-based temporal abstraction (KBTA) method. The KBTA method decomposes to five independent temporal abstraction mechanisms. The model itself could be utilized within a variety of contexts within the clinical domain by acquiring the knowledge through domain experts or automated techniques. More recently, the KBTA model was utilized in the development of a system (VISITOR) for patient records that allowed users to intelligently retrieve, visualize, explore raw time-series data from electronic patient records (Klimov, Shahar, & Taieb-Maimon, 2010). The system additionally allowed for the retrieval of abstracted concepts (temporal abstractions) from the records data. Their research serves as a guide for the process of converting knowledge representation modules to actionable systems for providers and patients. It also demonstrates the utility of visual analytics in converting abstractions to meaningful insight.

Adlassnig, Combi, Das, Keravnou, & Pozzi (2006) discuss the areas of research that are potentially valuable in the development of meaningful temporal reasoning techniques in medicine. The first set of methods presented was in the space of fuzzy logic and medicine with respect to time. They claim that the ability to deal with potentially ambiguous terms and events ("in the last few days", "increased glucose level") is a vital step towards richer temporal analytics. The next relevant concept is the use of probabilities to model temporal events owing to the inherent uncertainty of medicine and related events and reasoning. Finally, they tout the use of specialized databases that support rapid querying and retrieval of temporal data unlike standard relational databases.

Visual data exploration can generally be thought of as a hypothesis-generation process. The three key features of a useful visual exploration tool per Keim (2001) are:

ability to deal with noisy data, intuitiveness,  and requires no understanding of complex mathematics. He further categorized data visualization based on the data type being visualized: 1-dimensional, 2-dimensional, multi-dimensional, textual, and hierarchical.

One of the primary considerations of visualizations are that there is no universal technique for evaluating visualizations (Keim, 2001). It is often the case that each visualization can be evaluated only with respect to the task at hand. This adds a level of complexity to research in this space, and to implementations of visual exploration tools. The second consideration is that a visualization interface is that with an increase in complexity the level of understanding and intuitiveness is likely to reduce for the average user. Often relying on fundamental plots may be required over a more complex alternative. This scenario also needs to be evaluated on a per case/task basis.

### Hypothesis and Objectives

As mentioned earlier, medical organizations have increasingly begun to collect a variety of automated information but there is no coherent framework in place to translate ALT data to actionable insight or to be able to explore data to generate new hypotheses. In this case, we define actionable insights as:

1. Creation of quantitative quality measures, and
2. Redesigning/Refactoring workflow by merging ALT and other data sources

Furthermore, clinicians often don’t see any immediate benefits from the data collected in the environment. While some measures are collected for the purposes of reporting (ex. formerly meaningful use), they yield no information that could facilitate self-guided behavior change. Often these measures tend to be high-level summaries that don’t allow for the analysis of the different pieces that constitute the overall workflow.

The target users of the workflow analysis are typically: medical providers, staff, administrators, and researchers. Each of these types of users have a set of disparate perspectives. To that end, any data analytics effort must be able to present its results in a manner that is relevant to each user i.e. the visualization or presentation of this data must adapt to the type of the target user. There are only a few studies that deal with this aspect. Based on the discussion above, the major hypothesis for this research is as follow: *Automated Location Tracking data can be, independently or in conjunction with alternative qualitative and quantitative data sources, used for deeper analysis of clinical workflow, new hypotheses generation, and to present relevant findings by way of visualizations.*

The testing of this hypothesis was achieved through two primary aims/objectives with the sub-objectives listed below:

1. Use ALT data to develop a novel methodological/exploratory framework for clinical workflow analysis that can aid in the tracking of efficiency and quality measures and in the generation of new hypotheses.
    a. Develop quantitative metrics to facilitate in workflow analysis
    b. Develop visualizations to present metrics to target users.
2. Overlay ALT data on EHR aggregate/summary usage data and data from qualitative observation and shadowing studies (mixed methods) to facilitate workflow refactoring/redesign to improve efficiency.
    a. Develop measures from ALT data that can be overlaid on EHR usage data.
    b. Develop a mixed-method approach to workflow analysis.
    c. Discover inefficiencies and barriers from the findings and suggest ways to

refine/improve workflow.

### Scientific and Practical Contributions

The primary contributions of this research are to develop methodologies associated with workflow modeling and analysis with the use of naturalistic data collected from the clinical environment.. Additionally, we aim to introduce novel data modeling methods that can be used with tracking data to create meaningful performance and error analytics. This research can also be used to complement existing qualitative methodologies to create mixed-method studies that can provider broader insight into clinical processes, and this is generalizable.  Finally, visual analytics can have a great impact on the feedback provided to clinicians and researchers and facilitate a continuous monitoring of care quality. In the future, the creation of visualization dashboards can help organizations institute a platform of quality management and self-driven behavior change related to clinical workflow.

### Structure of the document

The manuscript is structured as follows: Chapters 2 and 3 deal with the two primary aims. Chapter 4 presents a series of case-studies of utilization of tracking and EHR data in the creation of workflow-related visualizations using. The goal of this chapter is to present on-going and future work in this domain. Chapter 5 place these studies associated with the aims of this research into the broader context of clinical workflow analyses and discuss its future goals and direction.

# CHAPTER 2

## AIM 1: DEVELOPMENT OF METHODOLOGICAL/EXPLORATORY FRAMEWORK FOR CLINICAL WORKFLOW ANALYTICS

The analysis of clinical workflow offers many challenges, especially in settings characterized by rapid dynamic change. Typically, some combination of approaches drawn from ethnography and grounded theory-based qualitative methods are used to develop quantitative metrics. Medical institutions have recently attempted to introduce technological interventions to develop quantifiable quality metrics to supplement existing purely qualitative analyses. These interventions range from automated location tracking to repositories of clinical data (e.g., electronics health record (EHR) data, medical equipment logs). The goal of this study is to present a cohesive framework that combines a set of analytic techniques that can potentially complement traditional human observations to derive a deeper understanding of clinical workflow and thereby to potentially enhance the quality, safety, and efficiency of care offered in that environment. We present a series of theoretically-guided techniques to perform analysis and visualization of data developed using location tracking, with illustrations using the Emergency Department (ED) as an example. Our framework is divided into three modules: (i) transformation, (ii) analysis, and (iii) visualization. We describe the methods used in each of these modules and provide a series of visualizations developed using location-tracking data collected at the Mayo Clinic ED (Phoenix, AZ). Our analytics go beyond qualitative study and includes user data collected from a relatively modern but increasingly ubiquitous technique of location tracking, with the goal of creating quantitative workflow metrics. Although we believe that the methods we have developed will generalize well to other settings, additional work will be required to demonstrate their broad utility beyond our single study environment.

This study was published in the Journal of Biomedical Informatics in 2018 (Akshay Vankipuram, Traub, & Patel, 2018a). The sections associated with this aim below are adapted from the paper in question to better preserve the structure of the peer-reviewed work.

**Study Setting**

The study to test our concept and methods, was conducted at the Mayo Clinic emergency department in Phoenix, Arizona. The ED serves an average of 26,000 patients, with an admission rate of approximately 30% (Traub et al., 2016). The layout consists of 24 patient rooms with an additional 9 hallway beds to board extra patients. There are also additional medication rooms (2), and cleaning utility rooms (2), and the triage area. The ED is staffed 24hrs/day with board-certified physicians. Assignment of patients to match with the physicians, is algorithmically determined using a 'rotational patient assignment' process, whereby patients are automatically assigned to the incoming physicians, who are all attending staff with a few or non- resident staff (Traub et al., 2016).

**Real-time location sensing (RTLS) setup**

For the purposes of this study, we leveraged the data collected by a proprietary RFID system installed at the Mayo clinic. The RFID system was installed as part of large-scale quality initiative at the Mayo clinic and was vetted by the relevant stakeholders prior to deployment. The system consists of ceiling-mounted receivers and an RFID tags carried by tracked clinician. Figure 4 gives a schematic map of the ED, along with areas of interest (highlighted areas in Figure 4), tracked by the system. There are 59 unique tracked locations including each patient room, hallway bed, workstation areas, nurse stations, medical supply rooms etc. We inspected a few of the recorded samples of the RFID data with mapped these against the observation timestamps based on the notes from shadowing the clinicians. Please note that the terms used in the legend in figure 4 do not correspond exactly with those in the data, since there are used for simplicity. Furthermore, the terms EHR Workspace, Workspace, and Physician Workspace are all used interchangeably.


Figure 4: RFID tracked location in the ED

Figure 5 illustrates the setup. The receivers are mounted in each location of interest. The transmitter (tag or badge) continually transmits information in the form of RF waves. It typically transmits information used by the receiver to identify each unique tag. This is explained further in the data collection section below.

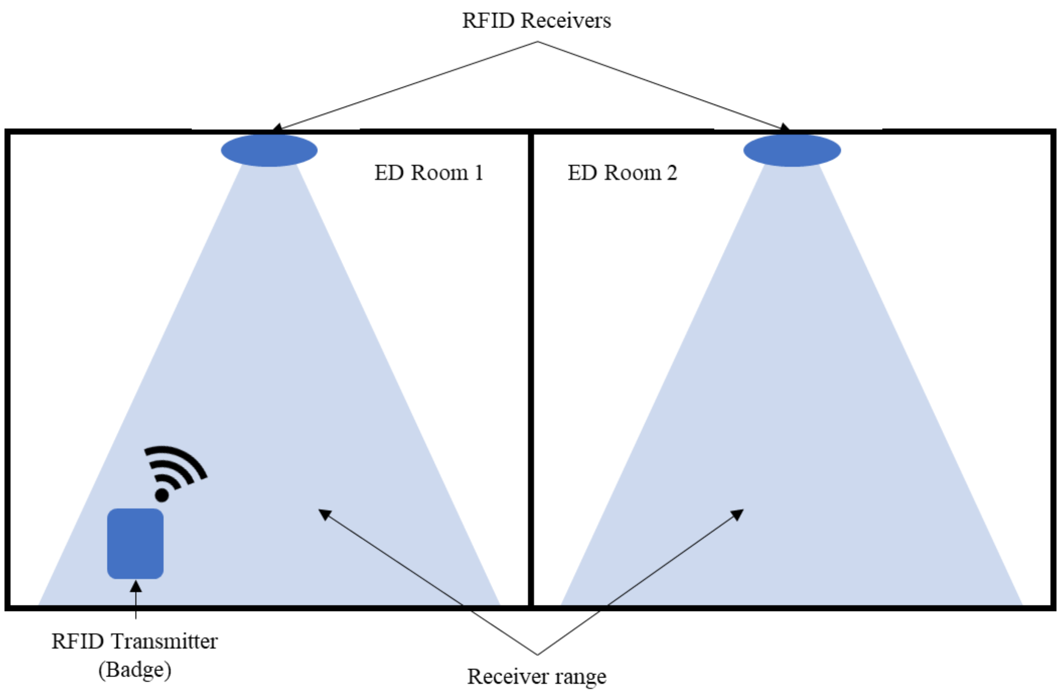



Figure 4: Illustration of RFID transmitter (badge) and receiver setup in the ED

**Participants**

Eighteen physicians were consented as volunteers to take part in this study, as a part of a broader research on workflow including RTLS, observation/shadowing, and interviews. Five physicians were shadowed and interviewed. We decided, therefore, to use the RTLS data for these five physicians collected over a longer period of seven months (August 2016 to January 2017) to ensure that we had shadowing and interview notes on the tracked clinicians for comparisons and to address any discrepancies in the data for subsequent analyses. Each clinician was given a unique RFID tag, which was fastened to their badge. Nurses were not tracked by the RFID system and thus they were not included in this study. This was entirely due to the logistical issues associated with the introduction of a new intervention into the ED environment. We believe that the nurse tracking data are important to supplement physician data, and we hope to extend this study in the future to create deeper analytics for clinical workflow.

## Data Collection

Table 1: Structure of RTLS data collection snippet from the ED

| Location | Start | End | Duration |
|---|---|---|---|
| Office | 11/20/2016 12:04:09AM | 11/20/2016 12:06:44AM | 0:02:35 |
| Physician Workspace | 11/20/2016 12:06:47AM | 11/20/2016 12:12:11AM | 0:05:24 |

Table 1 shows two instances (rows) of the RFID data collection for a single clinician. We extracted 7 months of data for 5 clinicians. Each row is recorded when a RFID tag on a clinician is within range of any ceiling mounted receiver. The attributes of the recorded data are:

- Location: The location of the ceiling mounted receiver.
- Start: First instant of time when the tag is within range of the receiver
- End: Instant of time when the tag moves outside the range of the receiver
- Duration: time spent within range of the receiver

Additionally, each RFID tag was associated with a unique ID which was stored by the receiver, once per row (Table 1). The ID could be, therefore, used to identify each tracked clinician.

### Data preprocessing

The location names were shortened for simplicity e.g. "ED Physician Workspace" was modified to "EHR workspace" since in the Mayo ED the EHR systems were placed in the general workspace area show in Figure 1. We also removed the "ED" prefix from all locations, since all locations are within the ED. We combined the data for the five clinicians and added the unique tag ID for each of them under a new attribute *Name*. So, our final collated dataset contained 64226 rows with 5 attributes: *Name, Location, Start, End, Duration*.

### Data Analysis

### Analytic Framework

In this section, we describe the analytics framework we've developed using the data. The framework (figure 6) was developed to generalize the processes associated with data manipulation (transformation), analysis, and plotting (visualization), as it pertains to exploratory analysis of workflow in the ED.

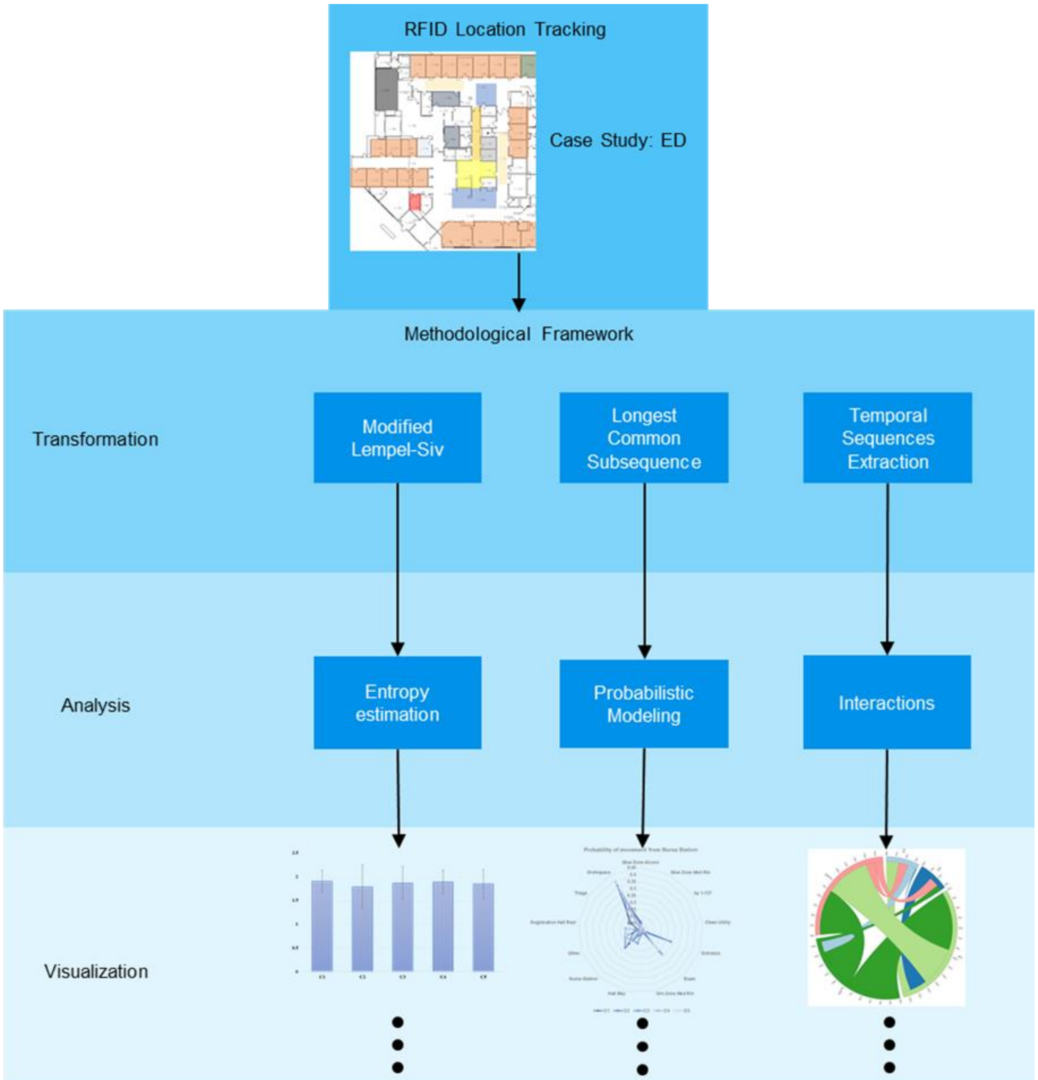



Figure 5: Analysis framework divided into three modules:(i) Transformation, (ii) Analysis, and (iii) Visualization

The conceptual foundations for this framework were inspired by multiple sources. The framework developed by Aigner and colleagues (Aigner et al., 2007) served as a basis for developing time based exploration of clinical activities and movement. Additionally, Kannampallil et al. (Kannampallil et al., 2011) introduced the idea of computing entropy (degree of randomness of movement) as a way of studying complex clinical environments. Their methodology served as an introduction into probabilistic modelling using RFID data. Finally, the visualizations were inspired by other research in process management and clinical workflow explained in the background section. The three phases of the framework are:

1. Transformation: Computational techniques that convert tracking data structured as described in chapter 2 to alternate representations and structures that facilitate the analysis phase.
    a. Modified Lempel-Ziv converts the data into sequences (location1 -> location2 -> location3 -> … locationN) of movements per tracked entity and then extracts repeated sub-sequences within the broader sequence.
    b. Temporal sequence extraction converts sequence of movements and timestamps to intervallic data i.e. (location1, start1, end1) -> (location2, start2, end2) -> … -> (locationN, startN, endN); where startX, endX represent the start and end times at a locationX and start2 ≥ start1.
    c. Longest-common-subsequence is a computational technique that compares two sequences by comparing the longest progression of non-contiguous elements that are common. In this case, locations that are common between the movement sequences of two physicians. This requires a specific type of transformation and utilizes a computing concept called dynamic programming (Paterson & Dančík, 1994).
2. Analysis: The utilization of the transformed data in the transformation phase

to generate quantifiable measures of workflow used in an assessment or exploratory capacity. Each of the methods in this phase are described in detail in the succeeding sections.

3. Visualization: Deals with the presentation of results of the analysis phase. Once again these can be used for reporting or to explore elements of workflow.

**Entropy or "Degree of Randomness"**

The first step toward meaningful analysis of data in a complex environment requires the establishment of inherent predictability i.e. the tasks tracked have some repeating pattern. In a truly random environment, analysis of underlying patterns is obviously not achievable. We use entropy as a measure to quantify the inherent randomness of the clinical environment. Zhang et al, 2010 (Zhang, Li, Kong, Zhang, & Patel, 2010) demonstrated the use of entropy as a measure of randomness in clinical environments and their work elucidates the methodology. This was later used to quantify randomness in the ED by Kannampallil and his colleagues (Kannampallil et al., 2011). The crux of the concept lies in the use of a modified version of the Lempel-Ziv (Ziv & Lempel, 1977) data compression algorithm. The Lempel-Ziv encoding algorithm is used to reduce the size of input data by replacing repeated sub-sequences in a stream of data with the same output code. The algorithm keeps track of each sub-sequence encountered and the more times a sub-sequence is repeated the smaller the output will be. In the case of entropy determination, a higher number of repeated sub-sequences suggests a greater amount of predictability. Formalizing this concept, we compute $S_{estimate}$, the entropy for a fixed-length time series (N), as:

$$S_{estimate} = \frac{\ln N}{\frac{1}{N}\sum_i \Lambda_i}$$

Where, $\Lambda_i$ is the length of the shortest substring starting at position *i* such that the substring does not previously appear in positions *i* to *i-1*. The baseline entropy, which is defined as the entropy of the system if all observations are uniformly random, is defined as (for N distinct behaviors):

$$S_{baseline} = \log_2 N$$

The difference between the estimated and baseline entropies is used to assess the randomness of the system. A larger difference (i.e. greater baseline) implies greater predictability. The closer the estimated measurement is to the baseline the more random the system is likely to be. Besides analyzing the nature of the system, an additional use of estimated entropy is to assess differences in the randomness of the behavior of clinical personnel or their behavior during various times in a shift or across several shifts, since we can compute entropy for a sequence of actions for any given time-period.

**Temporal Sequence Extraction**

Temporal sequence extraction is the ability to extract relevant pieces of information (directly in data or computed) for any arbitrary time-period within the time range of the dataset. For e.g. the ability to compute entropy for different lengths of time (which would also yield differing lengths of sequence). The conceptual aspect of temporal manipulation is discussed in Aigner et al. (Aigner et al., 2007) and offers a set of basic operations that must be performable on time instances and intervals. To do this, the software used in processing of data must have a *datetime* type that allows for basic operations on date and time formatted data (such as the ones described in (Aigner et al., 2007)). Most modern programming languages that are typically used for data processing and analysis have either inherent functionality or external packages that support the datetime format (we have used R and Python with the *Pandas* package).

**Probabilistic Modeling**

Uncertainty is inherent to medical environments and processes, and this is as true today as it has ever been (Hunter, 2016; Logan & Scott, 1996). Modeling probabilities therefore remains a vital part of workflow analysis. We separate the probabilistic modeling into two methods:(i) next-location probabilities and (ii) longest-common subsequences. The methods are elucidated below. It is important to note that for each of these methods, as described above for entropy computation, we can perform summary analysis over a pre-defined period or represent the variation of the outcomes in a real-time framework.

**Next-location probabilities**

Assessing the impact of the introduction of a technology or process on the probability of movement involves assessing sequences of clinician movement of some pre-determined length. This is usually computationally inefficient, and without a clearly defined threshold for length of sequence, may not yield meaningful statistics. One method for sequence analysis is using the longest common subsequence algorithm, which we describe in the next section. The other is to consider clinical movement to be a discrete Markov process. Clinical activity has been represented and modeled as Markov chains in the past (Bouarfa & Dankelman, 2012; M. Vankipuram et al., 2011). In our work, we compute probabilities of the next location of movement from each of the clinical locations in the ED.

**Longest common subsequence (LCS)**

The LCS problem involves finding the maximum length of subsequence shared between two sequences. For any two sequences *X* and *Y*, LCS of prefixes $X_i$ and $Y_i$ is given as follows:

$$LCS(X_i, Y_i) = \begin{cases} \emptyset \text{ if i} = 0 \text{ or j} = 0 \\ LCS(X_{i-1}, Y_{j-1})\ if\ x_i = y_i \\ longest\left(LCS(X_i, Y_{j-1}), LCS(X_{i-1}, Y_j)\right) if\ x_i \neq y_i \end{cases}$$

A matrix of values created with each element of the sequence (of movements) forming the rows and columns. When the two sequences are traversed, we then backtrack to find the actual longest sequence.  In our case, we first encode the locations tracked (assign each unique location a number between 0 and N; where N is the number of unique locations tracked). Then we can compute the LCS for each clinician across all their shifts or across multiple clinicians. LCS may be used in clinical workflow assessment as way to contrast behavior, for e.g. based on expertise or to analyze the most likely sequences of movement per clinician. Like the calculation of entropy, here too we can restrict the computation to any length of time.

**Interactions**

Lack of ‘interprofessional’ communication can be responsible for an increase in errors committed, increasing the hospital costs (Zwarenstein, Rice, Gotlib-Conn, Kenaszchuk, & Reeves, 2013). Therefore, it is meaningful to track interactions more precisely from the tracking data. We define an *interaction* as a period where the receiver at each location recorded multiple tags. Kannampallil et al, 2011 (Kannampallil et al., 2011) define clinical interactions from RFID data using three attributes: *location, duration of interaction, and size of team*. Our data does not contain tag-tag pings, and so our ability to track interactions is limited to instances of interaction potential i.e. moments where clinicians share a space for a period. Dean and his colleagues in 2016 (Dean, Gill, & Barbour, 2016) suggest that instances of professional or casual conversation can be identified by tracking the shared spaces where the communication or interactions occurs. We, therefore, focus on identifying instances of time spent by clinicians in shared locations. In the future, this data could be used to identify the types of conversations expected to occur based on information procured through more traditional qualitative techniques.

The general procedure to find interactions used is as follows:

```
For each location l
     Create a list L of ((clinician, start-time, end-time)); for
all clinicians at l
     Order L by increasing start-time
     Iterate over L
     Interaction If (L[next][start-time] <= L[current][end-time]
     or  L[current][start-time] <= L[next][end-time]) and
     L[current][end-time] – L[next][start-time] >= 15sec and
     L[next][clinician] ≠ L[current][clinician]
```

Note that we use a 15sec threshold as the minimum time overlap required to consider the instance an interaction. This was selected to avoid instances of physicians passing each other being recorded as an interaction.

## Results

### Estimated Entropy

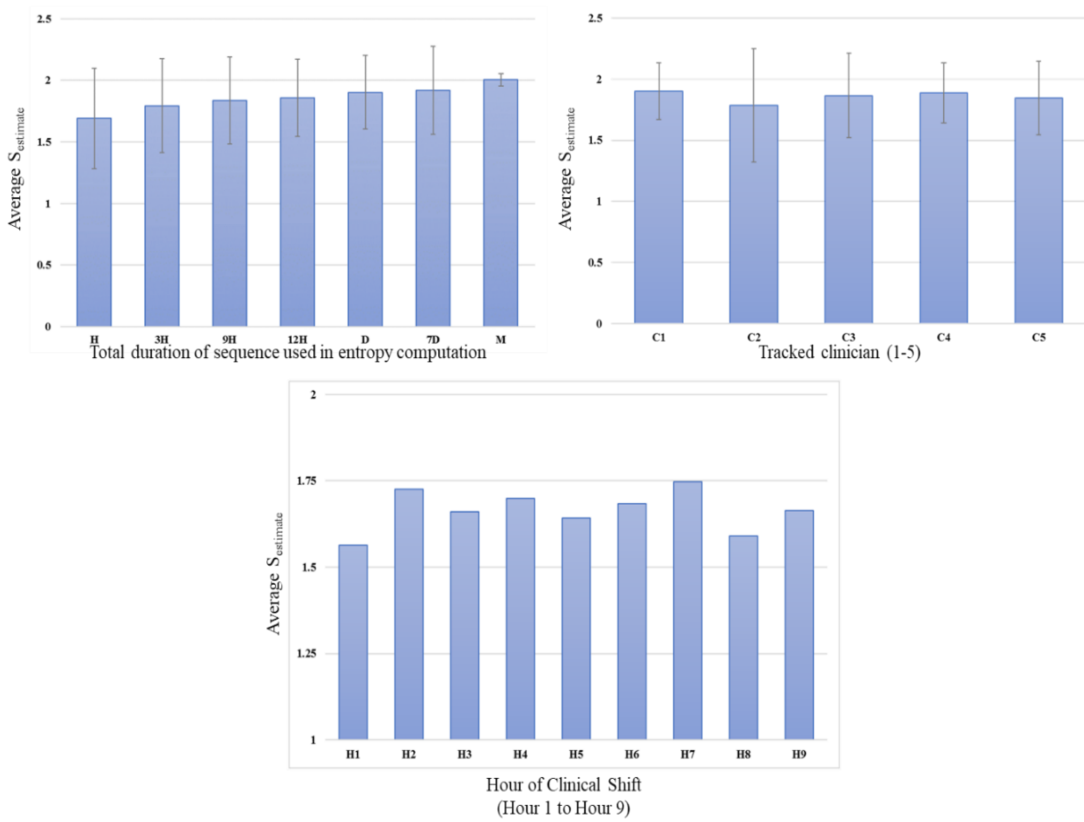


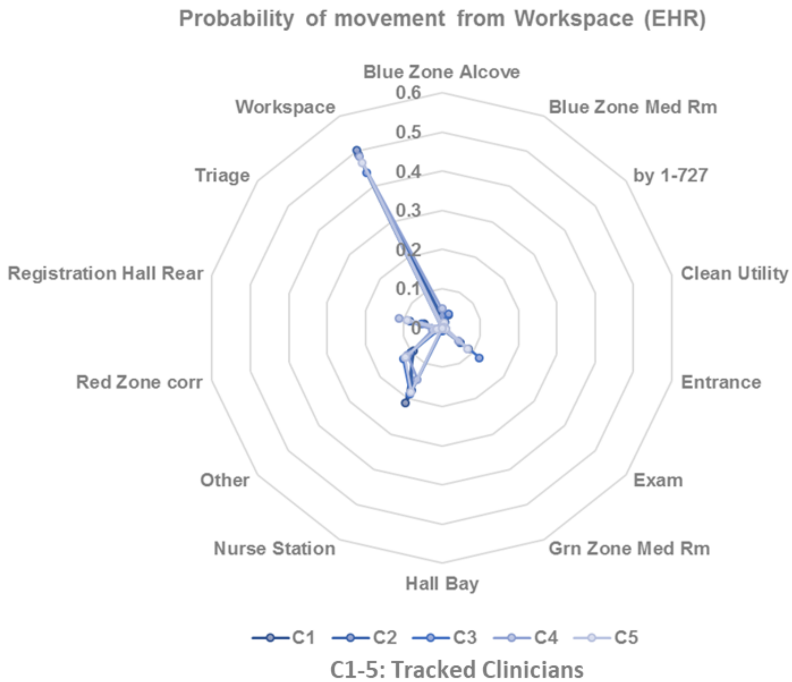

Figure 7: Average entropy computed(i) (Upper left) for varying sequence durations, (ii) (Upper right) for each tracked clinician, and (iii) (Bottom) for each hour of a shift

Figure 7 shows the average estimated entropies ($S_{estimate}$) computed for a set of relevant groupings. $S_{baseline}$ was computed to be *5.88*. Figure 7i) shows the average estimated entropy computed for a set of sequence lengths. '9H' represents the length of a shift at the Mayo clinic. The purpose of using this measure is to find a length of sequence where the greatest predictability of movement exists. It is clear from Figure 7i) that while the entropy is higher when larger periods of time are considered but they are still well below the $S_{baseline}$. In Figure 7ii) the variance between clinicians is 0.002 suggesting a similar level of predictability in movement. This is in keeping with the notion that the differences between individual clinicians is lower than between all clinicians across processes or systems. This suggest a further need to explore cross-site data using similar measures. Figure 7iii) shows the average entropy per hour of a shift for all clinicians. The variation across all hours in a shift are minimal as well.

Assessing the clinical relevance of the finding above, we can see a couple of trends that can be explored further. A few hours during the shift show more randomness (i.e. estimated entropy closer to the baseline) than others. Notably, hours 2, 7, and 9 are higher than the other hours. Hour 9 represents the end of a shift and may be associated with cognitive fatigue leading to less structured activities. Hour 7 is more difficult to explain but it may correspond to the busiest time in the ED. If this is the case, then the support (by way of resources) given to physicians could be reviewed and improved. Additionally, if a new process was put in place to target these kinds of inefficiencies then this data could reflect the results (positive or negative) of that change.

**Next Location Probabilities**

We chart the probability of immediate movement i.e. without a duration threshold, which is given in Figure 8. The ‘Workspace’ and ‘Nurse station’ notations were chosen to demonstrate the charting of next location probabilities since they are the two locations where the most amount of time is spent. Several of the ancillary locations were combined into a single location ‘Other’ for simplicity of plotting. Also combined were the exam rooms (25) into one location ‘Exam’ and the two ‘Nurse stations’. One of the key findings given in Figure 8 is the similarity of movement among the clinicians.



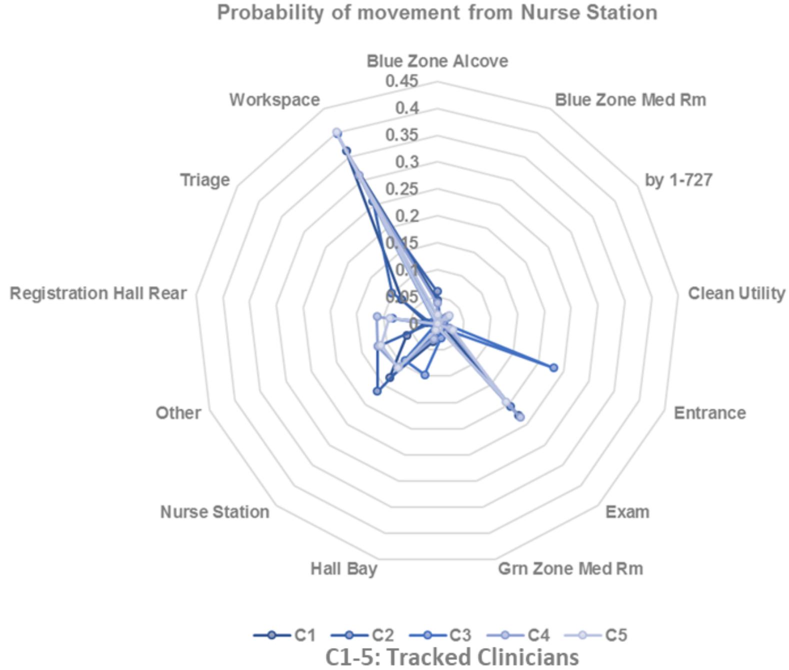




Figure 8: (Top) Probability of physician movement from workspace to locations in the ED (this includes movement within the location which is only true for the Workspace since it is the only location with two receivers); (Bottom) Probability of physician movement from Nurse station to other locations in the ED.

As in the case of entropy computation, the variation in movement between clinicians is limited. Another takeaway from the data is that the workstation area and nurse stations form a tight coupling, i.e. most likely movement for clinicians seems to be back and forth between these two locations. Depending on the relative positions of these locations, this may or may not be an efficient use of time. It would be worth identifying the types of information needs for the clinician that are not satisfied by EHR based communication requiring that coupling to exist.

**Longest Common Subsequences**

We computed the LCS for each tracked clinician and visualized one clinician's data as an illustrated example in Figure 9. It is also possible to use the chart in Figure 9 to view arbitrary length sequences for any clinician, but in this case, we use it to view the LCS of movement across 1 full shift of a *single* clinician. This visualization was developed using d3.js (Bostock, Ogievetsky, & Heer, 2011) and is called a sequence diagram. The X axis of the diagram represents a single instance of physician movement i.e. arrows and the Y axis (top to bottom) represents the sequence. The blocks on each axis represent a move within the location i.e. for e.g. 'Workspace' to 'Workspace'. The sequence diagram does not represent the absolute or relative duration of the movements, only the sequence. As an example of the type of analysis that can be conducted here, looking at the highlighted section of Figure 9, the clinician moves from the workstations to the nurse station east and then return and moves to the nurse station west. In this case, it might have been that the clinician was looking for information that was not to be found at

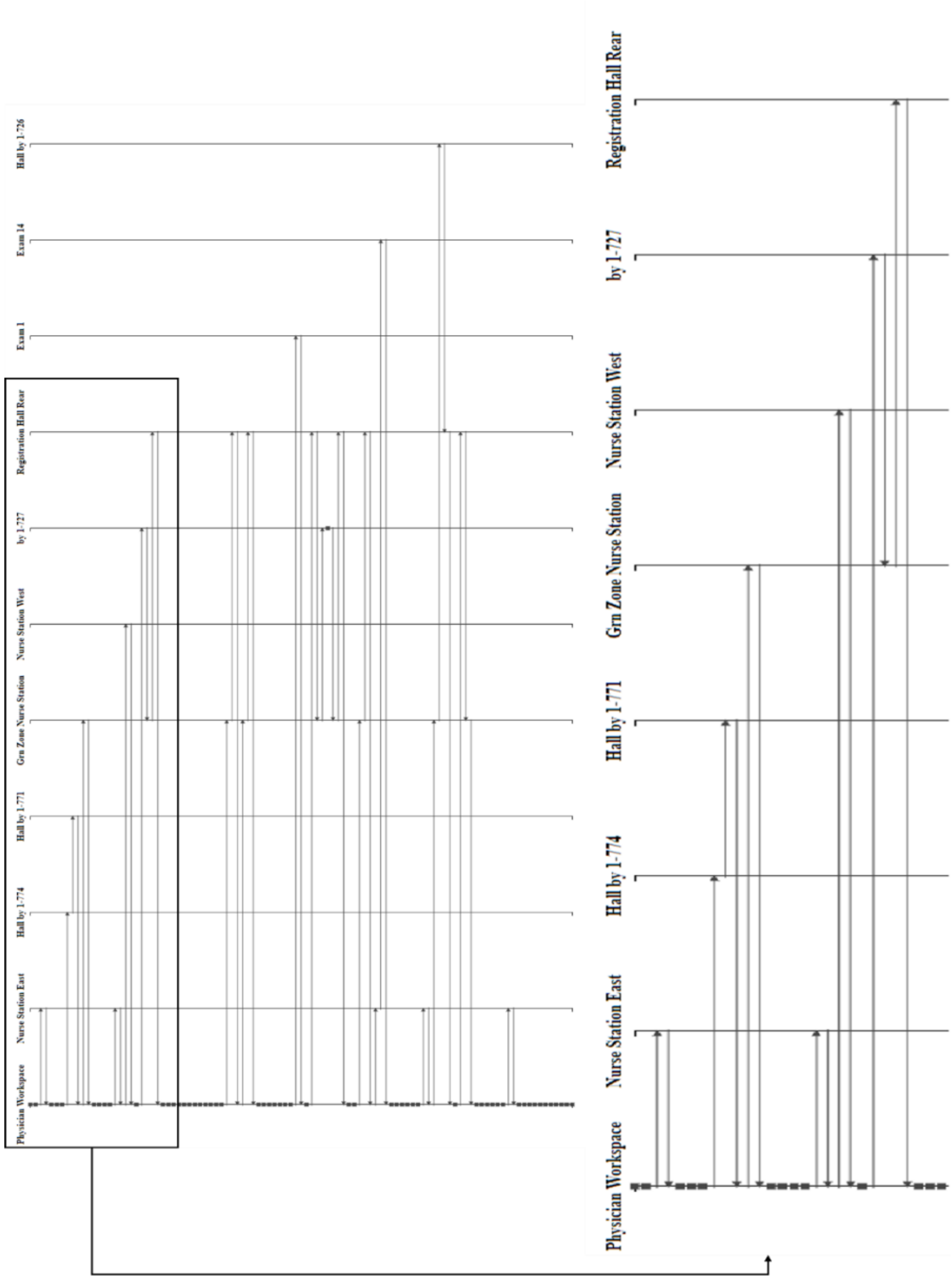



Figure 9: (Above) Sequence diagram showing the longest common subsequence of movement of two clinicians; (Below) Zoomed in section highlighting a specific sequence of movements

the first nurse station and had to check the other. Typically, a clinician would combine a patient exam with visiting the nurse station and would rarely visit two nurse stations in succession. Since this chart was created using the most common sequences, this pattern is relatively common for this clinician and therefore could be explored further.

The sequence diagram can be used to plot and analyze any length of sequence but when trying to identify patterns of behavior it is more useful to consider common sequences. The data shown here was created from a full shift's worth of sequences i.e. 9-hour long sequences of movement. If paired with other analytics for example, the entropy calculation, we can create this plot for a single hour of interest (interest as described in the entropy calculation section).

**Interactions**

The first method developed to find interactions involves the use of Gantt chart. Gantt chart have long been a popular type of chart used in scheduling and process management. Figure 10 shows a sample Gantt chart created to represent clinical activities using d3.js. The different colors correspond to the various locations. Gantt charts allow for a quick assessment of interaction trends. In Figure 10, Clinicians 3 and 4 were co-located in the workspace multiple times during the shift. The chart could also, be used to vary the time intervals being assessed. The default shown here is a shift length of 9 hours. The zoomed section is used here for clarity and shows three instances where the physicians were co-located for a duration greater than 15sec in the workspace.

We also created a list of potential interactions using the procedure described earlier. Our aim was to extract information about the three attributes: location, duration of

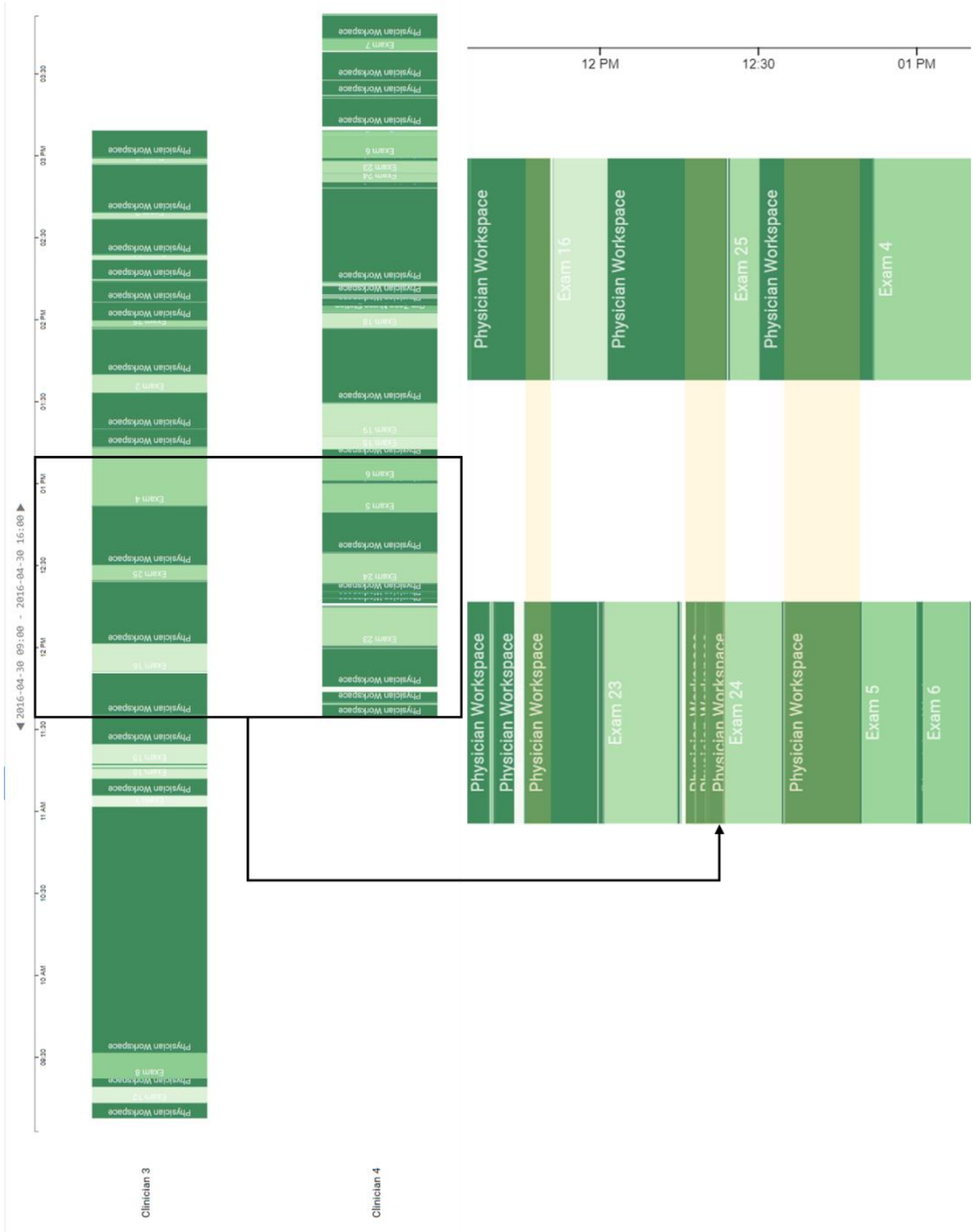



Figure 10: Gantt chart showing activity of three clinicians with interactions with a zoomed section showing three instances of potential interactions in the workspace

interaction, and size of team. As expected, most of the interactions occurred in the clinical workspace area. Figure 11 shows the median and maximum duration of interactions per hour of the shift. Specifically, every provider interaction was computed by the methods described previously and were grouped by hour of the shift. The shift times were all relative to the start of the shift to account for varying shifts. Then the median and maximum per hour of the shift was considered. The goal of this was to assess interaction behavior over the hours of the shift and compare them to patient load in the future. The median interaction duration of seems to be higher during the initial hours of the shift with a noticeable dip at hour four.

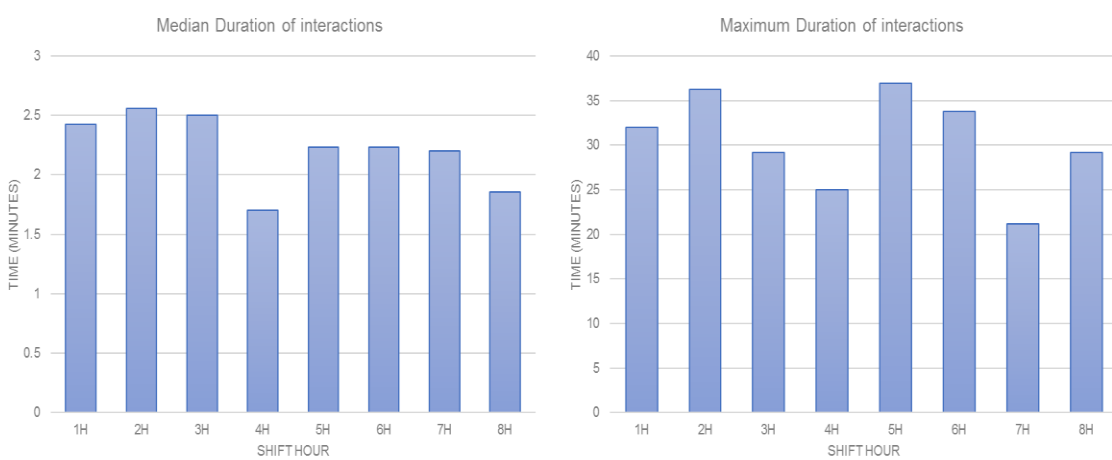



Figure 11: Per hour of shift statistics for duration of interactions for ED clinicians at Mayo Clinic ED

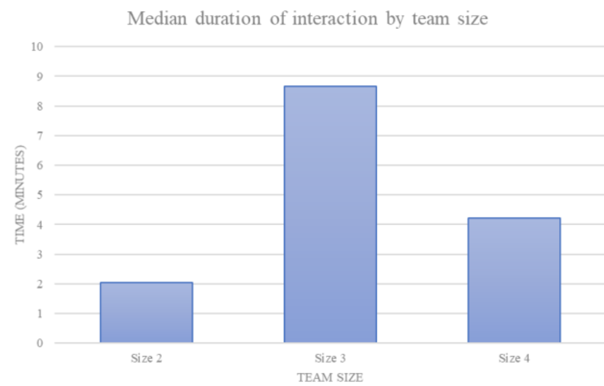



Figure 12: Duration of interactions by team size

Figure 12 shows the size of the team (i.e. number of clinicians' interactions) by median duration. When computing the interactions between providers, the number of providers in an interacting group was extracted and the median time of interaction given the group size was calculated. No interacting group larger than 4 was found. Figure 12 shows that groups of size 3 were spent the longest amount of time interacting i.e. when three providers were collocated they spent the most time together (potentially collaborating). While it is difficult to arrive at any conclusions based on this data alone, it's worth exploring further how the team size may impact collaboration. From the perspective of the hospital, this type of analysis may help scheduling shifts in such a way as to maximize potential collaboration.

**Discussion**

In this study, we show the development of analytics using RFID data in an Emergency Department setting. We also present a generalizable and extendible framework underlying our methodology. While traditional qualitative techniques are required to capture the nuances of a complex environment such as the ED, the analytics methods we present, serve to complement these techniques, the benefits of which as an exploratory tool and as a technique to supplement human observation are given below:

1. Monitoring activities in the ED in real time

The Gantt chart is a convenient way to monitor clinical activities in real-time. We only report physicians tracking activities, but tracking additional personnel is a relatively straightforward process. The sequence diagram can be used to view a subset of the physician's movement patterns over a period of interest, for example, at a shift change or at patient arrival. Administrates could use this information to deploy additional resources (personnel and equipment) as needed.

2. Assessing impact of interventions and process changes

An example of an intervention that has had a significant impact on clinical workflow is the introduction of the EHR, as mentioned earlier. Additionally, there are often changes in the medical and clinical processes, either caused by changes in regulations or quality initiatives or simply business processes. An example of the latter is the transitioning between various EHR systems, which can disrupt workflow. For administrators, being able to view the impact of process changes or interventions over a period is vital to remaining proactive towards inefficiencies and barriers to clinical performance. Probabilistic models viewed continuously over a period beginning at the introduction of a process change or interventions will reflect changes in behavior. Sequence diagrams can also be used to track behavior trends around periods of interest. An example of this might be, when a change in the hand-off process would reflect a change in behavior around shift changes.

i. Error analyses

The ability to study the origin and propagation of errors can lead to a reduction in similar errors in the future and enhance patient safety. Kannampallil and colleagues (Kannampallil et al., 2011), demonstrate a scenario where clinical data combined with sensor data were used for the analysis of error propagation. While more research is required to create a framework specifically for error analyses, our analytics can serve to provide a deeper perspective on the events leading up to or surrounding an error.

One of the challenges associated with the process described here was the lack of access to raw RFID data. This meant that we had to rely on the algorithms used in the proprietary software for noise reduction and localization. This was not a concern at the Mayo Clinic owing to extensive validation undergone by the RTLS system. However, the same may not be true in a smaller organization. In a fully generalizable framework, we would have a pre-processing stage that includes noise reduction and localization algorithms. Such a framework would produce consistent results in the case of a less efficacious RTLS system. Another limitation was the lack of availability of tracking data for other roles (nurses, technicians etc.). In the future, we hope to collect RFID data for all roles, such that our analytics can capture the diversity of an ED care team.

**Limitations**

**Generalizability**

One of the major challenges with analytic frameworks such as the one described here, is their use in other organizations. We have already mentioned how the inability to collect raw data impacts our generalizability. However, there are a few considerations that were made during the development of the methods discussed that may help us to speculate on the generalizability of the methods presented. These are as follows:

- There were four data attributes considered for all the analyses: Physician ID, Location ID, Start Time at Location, and End Time at location. This was, in our opinion, a good simple yet generalized structure for location tracking data. Real-Time Location Sensing (RTLS) solutions in other medical environments may not store data precisely in this format. However, transforming the data to a format usable by these methods should be achievable without much difficulty. Languages like Python have built-in libraries that can convert most relational database schemas to textual representations like CSV and JSON (called serialization). We can add a data conversion layer to the transformation phase in the case of proprietary data formats.
- Each technique in the data analysis phase can also be structured as a method in a Representational state transfer (REST) service. REST services treat data transfer stateless operations i.e. each send or receive operation is treated in isolation with no "memory" of previous operations. This allows us to have a simplified yet extendible interface. The advantage of this is that we can dissociate the presentation i.e. visualization stage from the transformation/analysis stages. This abstraction can allow the presenting of information to be unique to the needs of the environment or the target clinical users (administrators, physicians, nurses etc.). We illustrate this with an example:
    - URL: *<some_server>/get_probabilities/?from=01-2016&to=05-2016&name=Physician1*
    - The above URL could return the transition probabilities computed for

physician 1 from RTLS data over a 5-month period. Any frontend (i.e. visual user interface) can request data using this exact URL or by modifying any of the parameters (from, to, and name) and present them in a variety of ways depending on the target audience (plots or text). However, the technique used to generate probabilities does not change between requesting frontends.

  - Given a set of URL endpoints like the one above, frontends can request data from a subset of URL or all of them. This decouples the presentation from the analysis algorithms improving generalizability.
  - Another advantage of REST service is that the underlying algorithms in the methods themselves may be updated without affecting the presentation of information if the data is returned in the same specified format.

- In the context of interoperability, modern EHR vendors have begun to introduce plugin capabilities to their systems that allow custom web applications to be created and deployed based on the needs of the site, and the methods presented in this manuscript can be used for just such a purpose. Plugin technology is relatively new, and this idea needs to be explored further. In the future one could envisage leveraging a paradigm like SMART on FHIR.
- Finally, privacy concerns are a potential barrier to adoption of these types of tracking technologies and the analytics that leverage them. We had initially encountered some questions about clinicians being tracked in their downtime, as we did in our earlier such studies in Banner Health System in Phoenix in 2010. However, we were able to show the benefits of such technologies and were careful to monitor privacy and security issues. More recently, acceptance of these technologies has risen based on

several scientific publications showing how these technologies can be used to our benefit, when carefully monitored. We have not felt much pushback from the clinicians who have been well informed about its use during the time of requesting consent, when a team of researchers, including the clinical site PI, the study PI, and the senior nurse practitioner, as well as the person requesting consent, are all present to answer any questions.

However, as mentioned earlier, the biggest barrier to true generalizability at this moment, is the need for the input data to be consistent i.e. a relatively high tracking accuracy, which is often not the case with smaller, ad-hoc RTLS systems.

**Validation**

To validate the methods discussed, we compared Gantt chart representation of the data discussed in the results and compared it to a similar representation of results used by Yen and colleagues(Yen et al., 2016). The authors conducted a time and motion study and represented the activities in three dimensions. In our case, with location tracking data, we can only represent one of these dimensions. However, in the critical care environment it is easier to derive the underlying activities from the location of the physicians. We can also model underlying activities given the relative abundance of data using probabilistic models (for e.g. Hidden Markov Models). This is something we are exploring in our ongoing work.

It will ultimately be desirable to demonstrate the utility and validity for our framework in multiple settings. However, the work we have done to date has been carried out in one environment, the Emergency Department (ED), and in one hospital (Mayo Clinic). The work took almost two years and is itself a substantial demonstration of the utility of the framework, which is theoretically based. Each new site would require months of work to get IRB approvals and the like. It was not realistic for us to do more than a single site for this initial formative work and the proof of concept for this manuscript.

As we have stressed, the goal in this work is to present a series of theoretically-motivated methods to perform analysis and visualization of data developed using location tracking. Our analytics complement our earlier qualitative studies and include user data collected from a relatively modern but increasingly ubiquitous technique of location tracking (RFID). Our goal has been to create quantitative workflow metrics. A combination of approaches drawn from ethnography and grounded theory-based qualitative methods has been used to develop the relevant metrics we develop and demonstrate in this work.

The methods have content and face validity, where the metrics measure clinical workflow in the ED, which is quantifiable and can be correlated with what is observed using a more labor-intensive method, shadowing. These quantitative workflow metrics measure the concept of interest (movement and team communication) in the emergency department at one institution. As we've discussed, the validity of what we have measured is evident, since we have other ways of observing the same variables. This is what our manuscript aims to show, and there is no reason to suspect that the framework or techniques would be discordant in other environments. Further validity of these methods can be tested in other EDs and other team-based clinical environments, but this aspect of the work was not funded and accordingly not within the scope of this work.

The next step to understanding the utilization of tracking data in clinical workflow analysis is to attempt to combine measures derived from the data with other qualitative and quantitative measures. As mentioned previously, the goal of a robust approach to clinical workflow analysis must combine those multiple perspectives to be successful in affecting process modifications. To that end, the next chapter details a study in which we create a mixed-method approach to clinical workflow analysis utilizing multiple qualitative and quantitative data streams.

# CHAPTER 3

## AIM 2: MIXED-METHOD APPROACH FOR WORKFLOW REDESIGN

The pursuit of increased efficiency and quality of clinical care based on the analysis of workflow has seen the introduction of several modern technologies into medical environments. Electronic health records (EHRs) remain central to analysis of workflow, owing to their wide-ranging impact on clinical processes. The two most common interventions to facilitate EHR-related workflow analysis are automated location tracking using sensor-based technologies and EHR usage data logs. However, to maximize the potential of these technologies, and especially to facilitate workflow redesign, it is necessary to overlay these quantitative findings on the contextual data from qualitative methods such as ethnography. Such a complementary approach promises to yield more precise measures of clinical workflow that provide insights into how redesign could address inefficiencies. In this work, we categorize clinical workflow in the Emergency Department (ED) into three types (perceived, real and ideal) to create a structured approach to workflow redesign using the available data. We use diverse data sources: sensor-based location tracking through Radio-Frequency Identification (RFID), summary EHR usage data logs, and data from physician interviews augmented by direct observations (through clinician shadowing). Our goal is to discover inefficiencies and bottlenecks that can be addressed to achieve a more ideal workflow state relative to its real and perceived state. We thereby seek to demonstrate a novel data-driven approach toward iterative workflow redesign that generalizes for use in a variety of settings. We also propose types of targeted support or adjustments to offset some of the inefficiencies we noted.

A paper based on this aim was submitted to the Journal of Biomedical Informatics titled: "*Vankipuram A, Traub S, Patel, VL, and Shortliffe EH. Overlaying Multiple Sources of Data to Identify Bottlenecks in Clinical Workflow.". * The sections below are adapted from the manuscript to preserve its structure.

**Clinical setting and location tracking setup**

The Mayo ED serves between 26 and 30 thousand patients a year with an admission rate of approximately 30% (Traub et al., 2016). There are 24 patient rooms and an additional nine hallway beds within the ED. There are also additional medical rooms, nurse stations, cleaning utilities etc. The ED is staffed round the clock by board-certified physicians, and it is equipped with a Cerner EHR (Cerner, n.d.-b) for which hands-on system training is provided to all users.

We tracked the movements of clinical personnel using a proprietary RFID system that allows tracking of individuals throughout the entire ED. The system consists of ceiling-mounted RFID readers and passive RFID tags given to each tracked clinician. Fig.13 shows a simplified schematic map of the ED with the RFID tracking locations highlighted. There are 59 uniquely tracked locations in the ED, with only a subset shown in the figure for illustrative purposes. Greater detail about the RFID setup can be found in our earlier article on workflow analytics (Akshay Vankipuram et al., 2018a).

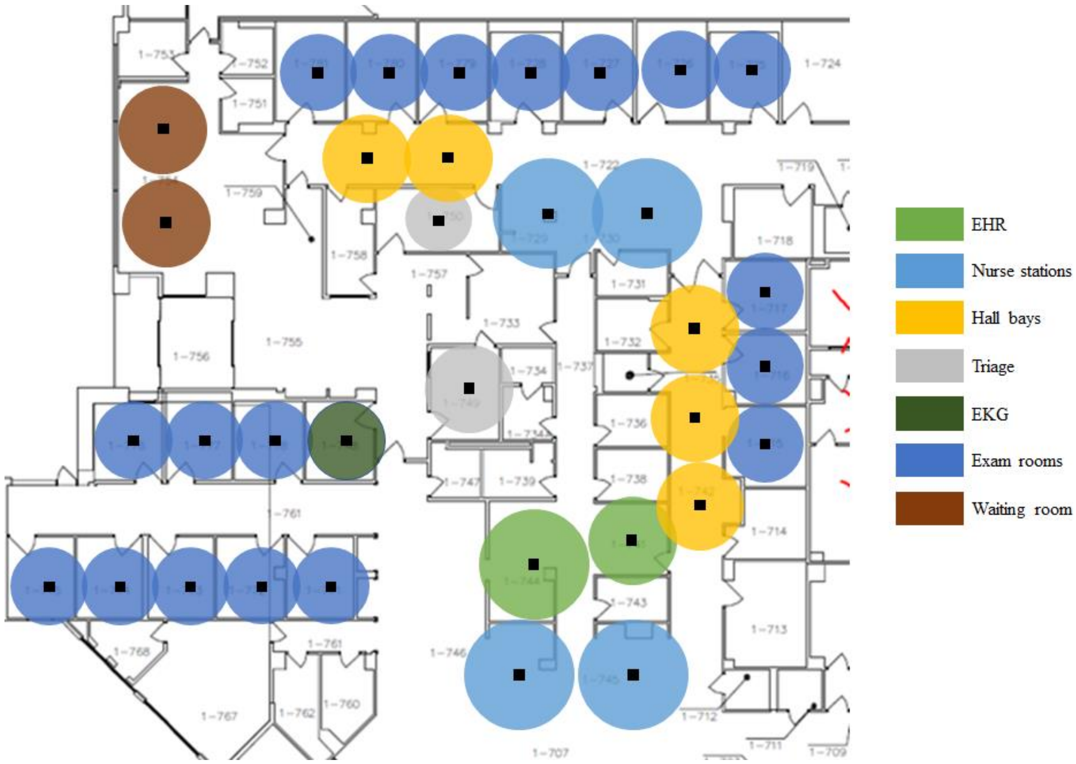



Figure 63: RFID tracked locations (non-exhaustive) in the Mayo-Phoenix ED overlaid on an ED blueprint. The RFID receiver locations are represented as black squares with the colored circles representing the approximate tracking range of each receiver. The circles are colored to denote the type of their location as shown in the legend on the right. The RFID system combines the receivers of the same type together when storing some of the location data (e.g., multiple nursing-station receivers were stored as a single entity). When an RFID tag is detected within the receiver range, a single time-stamped data point is added to the database, including the location and RFID tag id.

## Participants

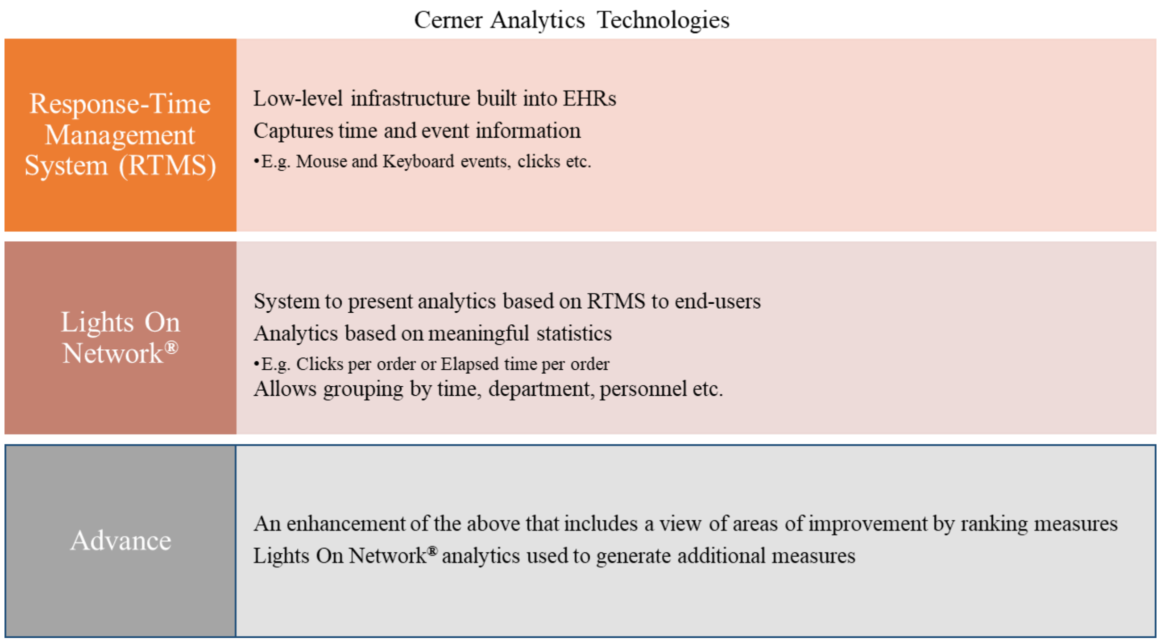
The participating physicians were recruited as part of our study on the influence of EHR on various performance metrics related to workflow. The study was approved by the Institutional Review Board (IRB), and written consents were obtained from all participants in the study (n=20). For the research described here, we used a subset of these physicians (n=5) for whom we were able to conduct an overlay analysis by matching their interviews, the shadowing results, and the associated RFID tracking data. Even though the physician sample was small, our methods were able to combine data to provide a representative and precise match between perceived and real processes in the ED.

**Data Collection**

As we have indicated above, three sources of data were used: Cerner EHR usage measures, RFID movement-tracking data (with context from shadowing observations), as well as the coded data from the physician interviews.

**Cerner Advance Data**

We collected EHR usage data for a period of 1 year and 4 months (Jan. 2016 – April. 2016) from the Cerner Advance (Cerner, n.d.-a) analytics platform to obtain quantifiable measures for EHR usage (Figure 14 details the Cerner analytics technology stack). The dataset consisted of monthly summaries of time spent using EHR modules such as charting, documentation, and ordering as well as usability measures such as number of "tab hops" per clinical note. We consider the latter to be a usability measure since it is a commonly used metric for usability along with number of clicks. We then eliminated non-numeric measures and other invalid or erroneous data, and for each tracked physician, we computed the mean value of the attribute for the entire dataset. For example, mean "time spent in the orders" and mean "time spent on clinical notes" for each physician. The monthly datasets were designed to provide the mean measures over that period, so we simply extended the time to the




duration of the entire dataset. The final dataset consisted of 77 EHR usage related attributes. A sample of the attributes are shown in table

Table 2: EHR usage data snippet

| **Chart review time per patient** | **MPages chart review time per patient** | **Flowsheet chart review time per patient** | **Clinical notes chart review time per patient** | **Doc viewer chart review time per patient** |
|---|---|---|---|---|
| 0:00:36 | 0:00:08 | 0:00:16 | 0:00:07 | 0:00:04 |
| 0:00:33 | 0:00:03 | 0:00:07 | 0:00:04 | 0:00:19 |
| 0:01:05 | 0:00:22 | 0:00:15 | 0:00:17 | 0:00:08 |
| 0:00:35 | 0:00:08 | 0:00:17 | 0:00:07 | 0:00:01 |

**RFID data**

The RFID data, which are a record of the movement of the physicians tracked for the entire duration of their shift every day, were collected over a period of 7 months (Aug. 2016 – Jan. 2017) for five physicians. The attributes of the recorded data were as follows:

- Unique identifier of RFID tag corresponding to the tracked participant
- Location of the RFID reader
- Time stamp recorded when an RFID tag is within the reader's range
- Time stamp recorded when RFID tag leaves the reader's range

The data were then preprocessed by shortening location names and grouping certain locations (i.e., renaming them to the same prefix) for simplicity as shown in Figure 1.

**Interviews**

Face-to-face semi-structured interviews were conducted over an 8-month period (Feb. 2016 – Oct. 2016) as part of a related study conducted by Denton et al (Denton et al., 2018). The interviews were designed to include four categories lasting about 45min each. The categories of physician-specific data were: (i) demographics and experience, (ii) perceptions regarding the implementation and use of the current EHR and of any previous systems they may have used, (iii) awareness of ED-specific meaningful-use measures and their perceived impact on workflow, and (iv) EHR's impact on workflow, quality of care, and patient safety. The physicians rated each factor on a 10-point Likert scale. Upon completion they were asked for any additional topics relevant to them, not covered during the interview.  Interviews were additionally audio-recorded for further analysis and transcription.

Emerging themes were identified from the interviews using a grounded-theory approach (Saldana, 2013). Here, we consider the recurrent themes identified by the authors (including perceptions of the EHR, usability concerns, and the EHR's influence on workflow and quality of care) to be the physician's perceived state of current clinical workflow.

**Data Analysis**

The RFID data were used to map two measures (multi-patient visits and information transfer) that are potentially affected by EHR usage (or perceptions of EHR usage). RFID data captured movements of physicians and were contextualized with observational data. We found two aspects of physician movements to have the greatest potential impact on their perception of EHR use: (i) multi-patient visits and (ii) information transfer during clinical workflow.

**Multi-Patient Visits**

Physicians in the qualitative aspect of the study reported concerns associated with EHR usability, including the number of clicks and screen navigation problems. This is a common issue found in other EHR usability studies as well (Guo, Chen, & Mehta, 2017; Mosaly, Mazur, Hoyle, & Marks, 2015). Additional findings also highlighted the burden placed by EHR usability concerns on working memory (Mosaly et al., 2015). Based on our clinical observations, physicians at times would read several patient charts at a single session in the EHR prior to visiting the patient rooms. While it is unclear whether this was always in response to EHR usability concerns or a general workflow pattern, this behavior could potentially lead to increasing the cognitive burden on the physicians, as they would have to remember patient-specific details both when evaluating each of the reviewed patients and when returning to the workstation to chart the results of the patient encounters.

For our analyses, an instance of a multi-patient visit is defined as occurring when a physician is noted to have visited more than one exam room between sessions interacting with the EHR, as tracked by the RFID system. To analyze this behavior, we computed the number of instances of patient visits between EHR sessions per physician per day. It must be noted that in the ED in question, EHR workstations are used by physicians only at a central location (titled 'Workspace' in the RFID data) and therefore separating patient visits from EHR use was a straightforward task in our analysis. We consider each visit to an exam room as being an instance of a patient-evaluation session.

The results of multi-patient visit analysis of the physicians from observation and RFID data were compared with the reported EHR perceptions from the interview data. Finally, we correlated the multi-patient visits with each of the attributes in the EHR usage dataset to find the measures that were most highly correlated with multi-patient visit behavior.

**Information transfer**

Information transfer during care coordination is an important element in clinical workflow and can be used to assess clinical workflow (Malhotra et al., 2007). In the context of EHR use, an increase in information searching or transfer needs may be associated with additional physical or cognitive burden for physicians. To investigate patterns associated with information transfer, we analyzed the sensor tracking data to determine instances of potential interaction between nurses and physicians. We did not include physician-physician interactions because the Mayo ED is relatively small. Since we used tracking data for only five physicians, the likelihood of interactions beyond hand-offs is small. In addition, co-location data do not allow us to ascertain the direction of information movement. We accordingly are concerned only with instances of potential communication.

In the Mayo ED, a majority of nurse and physician communication occurs at the nursing stations. We identified the instances of physicians visiting the nursing station (to communicate with nurses) after using the EHR and correlated these data with timing provided by the EHR usage data. While nurse stations contain EHR workstations for their use, these are not used by physicians and therefore the group of workstations that is being considered is at a separate central location used by physicians.

## Results

### Multi-patient Visits

Figure 14 shows the distribution of the number of instances of multi-patient visits per day for each physician. The median number of multi-patient visits per day for all physicians was zero. We chose not to disregard the zero values as that is representative of how many days physicians engaged in said behavior. The colored section of the boxplot for the two physicians represents the third quartile of the data for that individual. As we see in Figure 15, all physicians show varying instances of the behavior, but the distribution is affected by the number of days with no instances of multi-patient visits and accordingly reflects the true distribution of this behavior per physician.

From Figures 14 and 15 we can see that two physicians engage in this behavior more often than the others. Figure 14 shows that two of the physicians more often selected the physical vs the cognitive trade-off compared to the other two in the group. In their interviews, physicians 3 and 4 both had a negative perception of the EHR and its impact on their workflow. Physicians 1 and 5 held a more neutral to positive view of the EHR and physician 2 held an overall negative view.

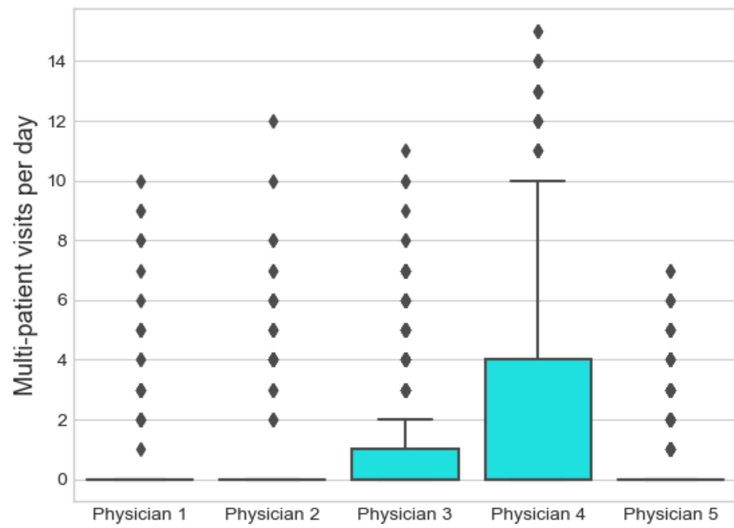



Figure 14: Probability distribution of number of multi-patient visits (defined as visiting multiple patients between each EHR session) per day for each physician. The diamonds represent the total number of multi-patient visits on outlier days for each physician.

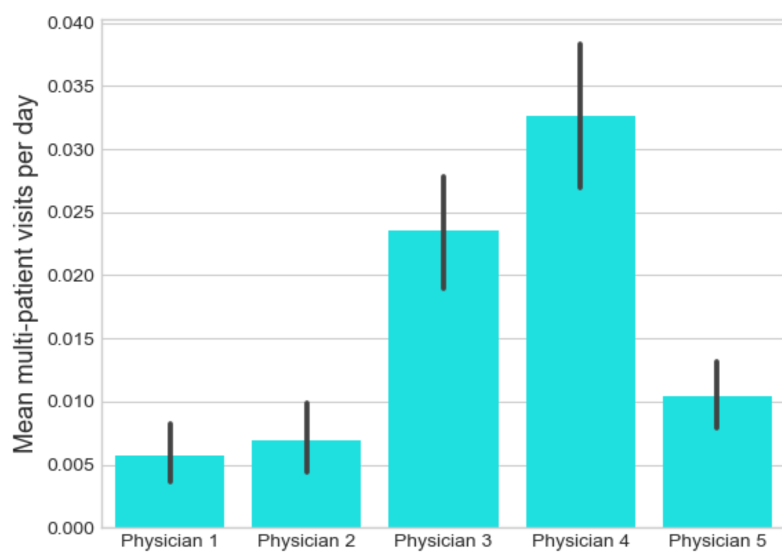



Figure 15: Mean multi-patient visits per day. Lines represent confidence interval (95%).

### Associating multi-patient visits with EHR use

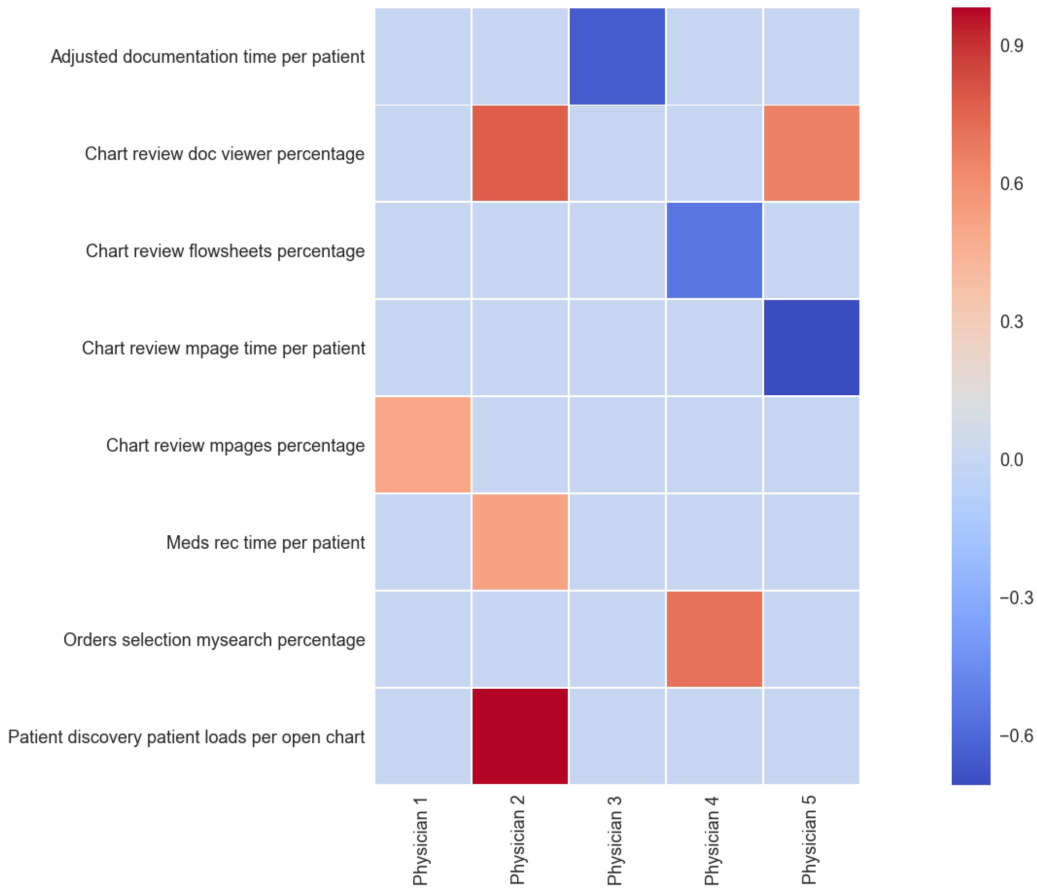



Figure 16: Multi-patient visits correlated with EHR module usage (95% confidence level). The deeper reds signify a stronger positive correlation i.e. higher instances of multiple patient visits per day and the deeper blues signify stronger negative correlations.

We computed the correlation coefficient (Pearson) and p-value for each attribute in the EHR usage data (from the data logs) and the multi-patient visits per day for each physician and all physicians (by computing the mean of all their EHR usage values). Figure 16 shows a heatmap of the highest positive and negative correlations at the 95% confidence level ($p \leq 0.05$) and Table 3 shows the correlations across all physicians. The goal of this analysis was to derive an understanding of the impact of EHRs on the tracked behavior both as individuals and groups.

Table 3: Correlation between multi-patient visits and EHR use

| **EHR usage attribute** | **R** |
|---|---|
| Chart review tab hops per patient | 0.96 |
| Doc viewer chart review time per patient | 0.97 |
| Documentation time per patient | 0.89 |
| Electronic documentation percentage | 0.9 |
| Electronic documentation percentage authored | 0.9 |
| Patient discovery open chart per patient | 0.97 |
| Power note percentage | 0.9 |
| PowerNote (Cerner UK, 2017) documentation time per patient | 0.9 |
| Transcription percentage | -0.9 |

**Information transfer**

As with multi-patient visits, we plotted the distribution of information transfer visits per day for each of the physicians (Figure 17) and the mean of the information transfer visits per physician per day (Figure 18). Here too, physicians show varying levels of the behavior but, accounting for the days where this behavior was absent, show two physicians for whom the information-transfer behavior was more prevalent.

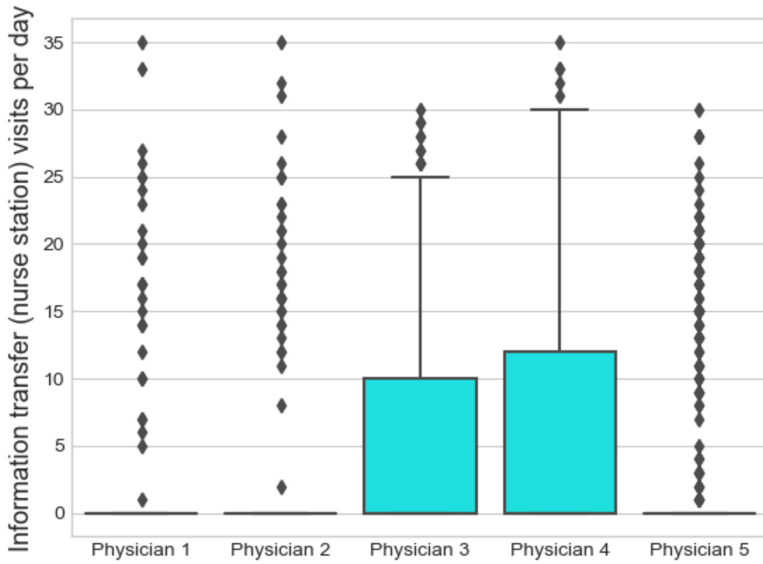



Figure 17: Probability distribution of number of information-transfer visits (defined as visiting multiple patients between each EHR session) per day for each physician. The diamonds represent the total number of multi-patient visits on outlier days for each physician.

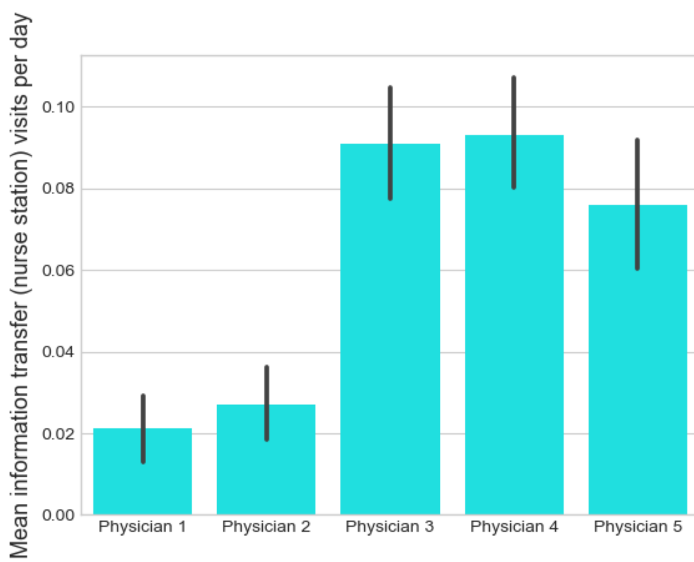



Figure 18: Mean information transfer (nurse station visits) per day. Lines represent confidence intervals (95%).

Unlike what was measured in the case of multi-patient visits, the elements of workflow being assessed here are the information needs of the physician and the EHR's ability to support transfer of that information either to the physician or from the physician to nurses. Physician frustration due to a lack of information in EHRs based on need has been documented in research (Koopman et al., 2015). However, it is also known that physicians and nurses prefer to receive information from colleagues (Clarke et al., 2013). In our interview data, two of the physicians revealed specific frustrations with information access in the EHRs. Physician 3 who held a strongly negative view of information access in the EHR also showed a higher number of nurse station visits than the others in the group.

**Associating information-transfer visits with EHR use**

We computed correlations to EHR module use individually and as a group. The individual correlations are shown in Figure 19. The group correlations revealed no associations of interest. In the case of both multi-patient visits and information transfer, chart review and documentation time per patient were correlated with the behaviors. In this case, most of the positive correlators for nurse station visits (i.e., those associated with an increase) were orders and documentation modules.

The use of PowerNote (Cerner UK, 2017) and order-selection features (specifically, favorite items which offers a type of selection shortcut) was correlated to a reduction in nurse station visits for some physicians, suggesting the need for additional training on these features as well.

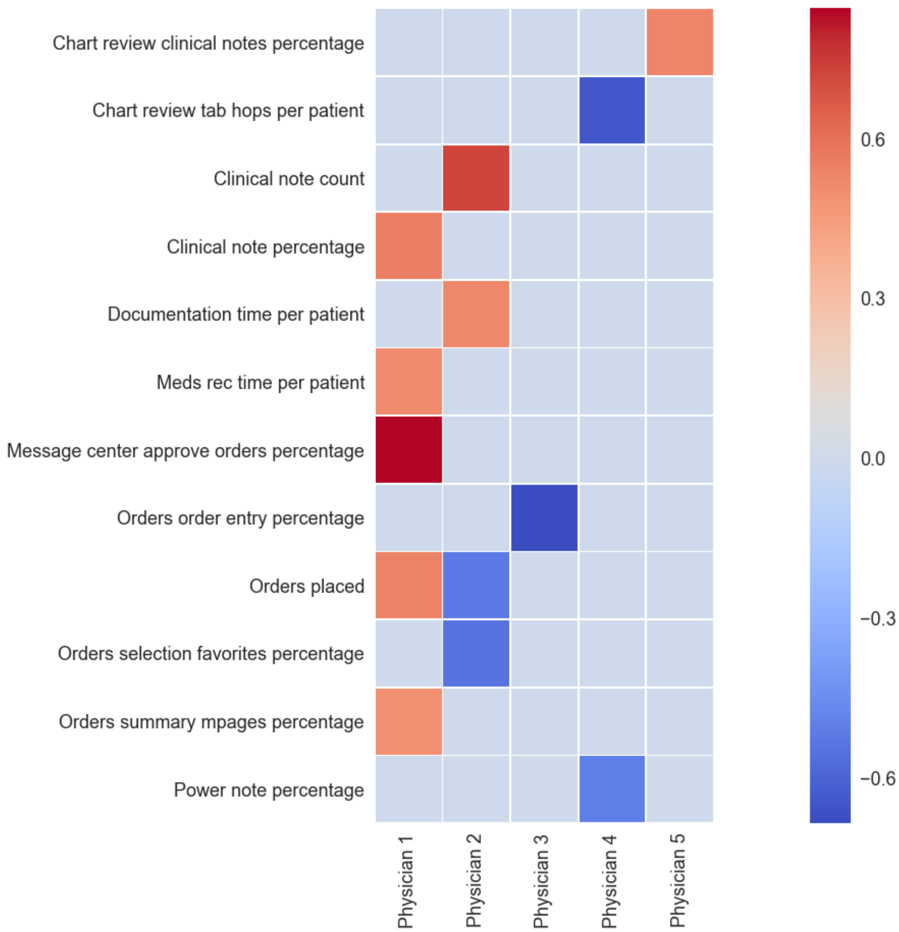



Figure 19: Information transfer visits correlated with EHR module usage (95% confidence level). The deeper reds signify a stronger positive correlation i.e. higher instances of multiple patient visits per day and the deeper blues signify stronger negative correlation

## Discussion and Limitations

The goal of this research was to develop and implement novel methods that would leverage a set of qualitative and quantitative data sources to analyze, identify, and facilitate data-driven iterative workflow redesign. Assessing inefficiencies in workflow is best achieved through a combination of targeted and group-wide analysis. In this study, we detail and demonstrate the methods for achieving workflow insights by overlaying the results of clinical interviews with time-stamped RFID tracking data and EHR usage data.

We categorized clinical workflow into perceived, real, and ideal states, and our studies show how the collection and analysis of information about the former two states (from interviews and RFID data, including observations), inform the movement towards the latter. It is also important to specify that in the case of workflow, 'real' can be defined only contextually, i.e., in relation to the specific topic area being studied. The goal of this work was not to discover a global real state because, in a complex environment, that is not realistically achievable. We focused, rather, on non-EHR behaviors that are influenced by EHR use. To that end, we chose two measures we consider to be most relevant to mapping the real state and that are extractable from RFID data: multi-patient visits and information transfer. Discrepancies between the real and perceived state of workflow, as captured by interviews, served both to narrow down the elements of workflow that bore further analysis and to help explain the findings. The value of quantifiable data is not only that inferences may be easier to draw but, in the context of incremental workflow redesign, they can be used to assess impact either long-term or before and after the introduction of interventions into clinical practice.

There are several findings that could be potentially vital to effecting change in the physicians' workflows. The physicians' individual EHR usage correlations (Figure 4) suggest a different set of EHR modules being associated with this observation. Four out of the five physicians held a generally negative view of the usability of and time taken for documentation tasks in the EHR (Denton et al., 2018). The pursuit of an idealized state requires an improvement in their perceptions of tasks (including documentation) performed within the EHR. However, it's clear that targeted interventions are likely to yield better results.

Additionally, we were interested in capturing the potential impact of EHR use on these behaviors and leveraged EHR usage data to facilitate that analysis. The usage data capture the real-state of EHR utilization by the group of physicians. By overlaying those measures with RFID data, we can infer the two dimensions of the real-state of workflow. Correlating the measures per physician yields information on specific elements of EHR use, the targeting of which could individually yield changes to the workflow.

We have speculated that multi-patient visits are related to an increase in cognitive burden in environments (such as the one being considered) where there is no EHR use within patient rooms. So, in this case, the physicians had to place the information of the patient in working memory. The alternative to this would be to visit a single patient each time, but this represents an inefficiency of a different kind since there would need to be repeat trips to the EHR workstations. This element of workflow, therefore, represents a trade-off between physical and cognitive inefficiencies. However, we believe the physical inefficiency of the latter is less significant than the cognitive inefficiency associated of the former. We could speculate that the multi-patient visit behavior is related to a less positive perception. To achieve a more ideal state from perceived and real state of workflow, moving physicians 3 and 4 towards the less physically efficient (more cognitively efficient) approach may help increase their overall satisfaction with the EHR. Alternatively, the ability to record patient interactions or taking notes in the exam room may help offset the cognitive burden of multi-patient visits. Tablets or handheld recorders may be an appropriate intervention. This needs to be implemented and studied in-situ, but we can see how this combination of data sources would allow us to target and facilitate those behavior modifications and assess its impact.

In our data, two physicians showed an elevated number of multi-patient visits, and they had different EHR usage elements that correlated with it. The reason for computing correlations individually and as a group was that the former could be used to target specific areas of the EHR that could impact broader workflow and the latter could be used to find common themes in the group that may require different types of support/interventions. An interesting finding in Figure 4 is that use of chart review MPages (which is specific chart review feature of the EHR) was correlated with a reduction in multi-patient visit behavior for physician 5. However, MPages are not used by all physicians. If utilization of this feature could help reduce instances of multi-patient visit behavior, then specific training could be enacted on this feature for the group.

The findings in Table 1 (group) suggest  that an increase in chart review time per patient (time spent by the physicians in the EHR chart review module) is associated with an increase in multi-patient visits. There is also a difference in this behavior based on the physicians' use of either transcription services or the EHR documentation module. Transcription services are provided to allow physicians to dictate their notes and to have them transcribed for electronic documentation using either a human scribe, handheld recorder, automated speech-to-text services (i.e. software that converts speech to unstructured text that can be structured subsequently). Alternatively, EHRs provide a documentation module that ostensibly simplifies the process of entering data into the system, thereby negating the need for a transcriber. Increasing satisfaction with the electronic documentation services may be a case of performing usability studies and determining types of support needed in that manner.

Individually, for physician 3 an increase in documentation time per patient was associated with a reduction in multi-patient visits. This may seem obvious but data from the other physician (4), with higher instances of multi-patient visits, did not show this correlation. In their interviews both these physicians highlighted documentation as being a specific source of frustration, but reduction of documentation time for physician 3 might lead to an increase in multi-patient visits and thereby to a related elevation of cognitive load on memory. So, for this physician, a more adequate adjustment may be to improve the quality of the time spent on the EHR by providing tools or training that would facilitate those elements of the interaction and, for physician 4, a more appropriate adjustment might to target their use of the ordering module, which was associated with an increase in multi-patient visits. Similar judgements can be made about the other physicians as well. It is important to note, as previously mentioned, that visiting a single patient per EHR session is not the most physically efficient behavior, but likely represents a positive trade-off by reducing the cognitive burden of remembering data for several patients at one time.

In the case of information transfer, our methods and analysis yield a different set of insights, related to information seeking and behaviors to offset workload. Further studies are required in this case to capture the content of conversation (i.e., conversational analysis) to make more detailed judgements, but information transfer can be tracked over a long period to view trends based on interventions. The EHR usage correlations revealed a set of ordering and documentation features that are negatively associated with information transfer (nurse station visits). This was consistent with the interview data, where physicians specifically singled out the steps required to place on order as being a source of frustration. In this case, rather than information needs, physicians may look to offload to the nurses, certain tasks that take a long time (per their perception) to improve their perceived workflow. We also found that the use of specific ordering features was associated with a reduction in information transfer visits by other physicians. Accordingly, the best approach to incremental change may be to train the other physicians on features of the EHR ordering module with which they may be unfamiliar and to assess the impact on the nursing-station visits over time. In this case, instead of individual support, we can use the findings from other physicians to influence the whole group positively. Another intervention could be to determine the types of information resources required to satisfy those needs and provide them on a per-physician basis. Topic-specific infobuttons have been shown to have potential (Clarke et al., 2013). This must be balanced with information that providers may prefer to receive directly from colleagues.

The primary limitation of this work is that the generalizability of these measures needs to be further demonstrated and tested under other conditions or in another setting. Although this work is targeted toward the emergency department, the overlay methodology is intended to be a generalizable approach that can be employed in other medical or non-medical domains. In the future, we intend to collect data in a non-ED clinical environment and to conduct a similar analysis to demonstrate the generalizability of the overlay technique.

Another limitation of this study is that we have yet to validate the specific findings. To do this, we intend to review the results with domain experts and to categorize findings based on importance. We also intend to use their feedback to explore alternate measures from tracking data. Multi-patient visits are a trade-off between cognitive and physical inefficiencies, so we intend to interview physicians to learn more about their perceptions of this trade-off. In the case of information transfer, we have limited contextual information. We hope to resolve this in the future with modern tracking technologies such as the GPS tracking and audio monitoring tags (LOGISTIMATICS, 2018). Finally, we used aggregate EHR usage data based on availability. To supplement our tracking data, we also intend to use trace logs (i.e., time-stamped per-event data, based on detailed EHR use, that provide insights unavailable with the aggregate data gathered over a week or month that were provided to us by the EHR system). Trace logs capture every instance of actions performed on the EHR. This can potentially add greater depth and accuracy to our analyses of workflow. Such techniques could offer greater contextual information associated with specific events in the environments, and we could potentially determine what type of data a specific nurse was looking at during communication with the physician. This may give us more contextual clues than we are able to obtain with tracking and summary EHR data. We did not have access to such data at the time of conducting this study, but we intend to do so in the future. A limitation of the aggregate data collected from Cerner was that it had redundant attributes. In addition, some of these were named in ways that made it difficult to resolve ambiguities with other attributes. In this study, we dropped any attributes that were ambiguous but in the future we would like to resolve those discrepancies so that we avoid losing potentially relevant attributes.

This study details a way to overlay a set of disparate data sources to enable workflow assessment and to suggest areas for modification. The time-merged combination method described in this aim is novel and may serve as a guide for future studies utilizing similar data sources. The targeted nature of this type of analysis means that the smaller sample size is not necessarily a limitation. One consideration may be the utility of these techniques for larger groups. Tracking measures can be computed in parallel for the group. To generate individual correlations, we can use subsets of a larger group to simplify interpretation of results. The group-wide correlations can be generated for groups of any size because the results are of a manageable size (Table 2). For tracking, it is essential to have an RFID (or similar) system with good coverage (i.e., the entire area within the environment that is tracked), which was the case in this study. In the future, we hope to increase the pool of physicians and to add nurses so that we can analyze their workflow using similar methods. Similarly, one could also increase the RFID tracking measurements by expanding the system to include nurses and patients, given that full assessment of clinical processes requires information on other team members as well as those receiving the care. The real-state of workflow being measured and reported in those cases will be dependent on the specific set of processes that involve the individuals being traced, which will both supplement the findings and potentially yield new measures.

# CHAPTER 4

# ALT DATA ANALYTICS AND VISUALIZATION: CASE STUDIES

This document has covered the two primary aims this research thus far. Detailed first was the use of tracking data to develop quantitative clinical workflow related measures and visualizations. The second aim attempt to expand the depth of possible analysis by proposing a mixed-method approach to clinical workflow assessment by combining multiple qualitative and quantitative data streams. This chapter aims to speculate on the direction and potential destinations of this research by discussing a series of case-studies based on on-going and future work. The chapter is divided based different types of utilization of location-tracking and EHR data in analytics and visualization. Discussed are the kinds of tools and technologies that can leverage these forms of data to create a fully quality-aware clinical system. A fully quality-aware clinical system can be defined as a continuously tracked system with automated collection of contextual workflow information, which are used to generate and provide means to self-driven behavior change for clinicians through analytics and visualizations.

## Case Study: Patient-Provider Interactions

Patient-provider interaction is an important element of health-care delivery that has shown to impact patient/provider satisfaction and affect perceived quality of care. Studies have also suggested that providers perceive that they are spending less time with patients because of EHR proliferation and extent of use. However, patient-provider interactions are difficult to measure using observational techniques alone. Automated location tracking of actors in clinical environments has increasingly gained popularity, in recent times. Automated location tracking can potentially facilitate the capture of proximity information for patients and providers. In this study, we will analyze patient-provider interactions using Radio-Frequency Identification data collected over the period of one year at the Mayo Clinic Rochester emergency department. This study aims to find potentially clinically relevant findings from derived patient-provider interactions and to present methods that could be generalizable across clinical environments. It is important to note that the content of interaction is not extractable from tracking data alone. However, these findings can be supplemented by audio recordings or qualitative observations.

**System setup**

The Mayo Clinic ED located at Rochester, MN has installed a 750 sensor RFID system to track medical equipment, patients, and medical staff including physicians, nurses, pharmacists, and other medical staff. The locational data is structured similarly to the Mayo clinic Phoenix location described in chapter 2 i.e. containing tracking id, location names, time of tag's first detection by receivers.

**Participants and data collection**

A subset of data (year 2017) was stored on a SQL server database accessed securely through a Mayo clinic VPN. The database consisted of approx. 36million rows of data of which approx. 25 million rows are patients and staff tracking data. Owing to the size of the dataset for this proof-of-concept study we will use data for 1 month. The final dataset consists of 6127 patients and 339 providers information consisting of attending physicians, residents, interns, and nurses (21 types of personnel). No identifiable patient and provider information was be collected.  the RFID sensor, and time at which the tag left the range of the sensor.

### Finding patient-provider interactions

The underlying computing task associated with the capture of patient-provider interactions is to find overlapping intervals. Two intervals ($s_1$, $e_1$) and ($s_2$, $e_2$) are said to overlap if $s1 \leq e2$ *and* $s2 \leq e1$. An additional step in the case of location tracking data is to ensure that the two intervals are from users at the same location. Given two overlapping intervals ($s_1$, $e_1$) and ($s_2$, $e_2$), the duration of the interaction is *min(e1, e2) – max(s1, s2)*. On the Rochester database, we can find interactions simple based on the following join query:

```
Select patients table p and join staff table s on
     s.LocationName=p.LocationName and
     p.TimeEnter<=s.TimeExit and
     s.TimeEnter<=p.TimeExit
```

The duration of the interactions will be *min(s.TimeExit, p.TimeExit) – max(s.TimeEnter, p.TimeEnter)*. This query can be used to generate interactions between physicians, nurses, technicians, or across groups. For this purpose of this case-study, only patient-provider interactions were considered. This query generated a data table with approx. 800K rows for 1 month of data (from 01-01-2017 to 01-30-2017). Each row consisting of an instance of interaction between a patient and provider. The interaction dataset was then used to compare personnel of varying expertise and roles on their patient interactions patterns.

## Results

### Comparing patient interaction times for residents

We looked at the amount of time spent with the patient by interns, and pgy1-3 residents. Figure 20 shows the boxplot of the time distributions for each type of resident. While broadly similar it appears that PGY2 residents spend the most time while also having the highest variance in times of interaction i.e. interactions taking an unusually long time. Figures 20 and 21 show the breakdown of times spent by the resident in each exam room and other important locations within the ED, respectively.

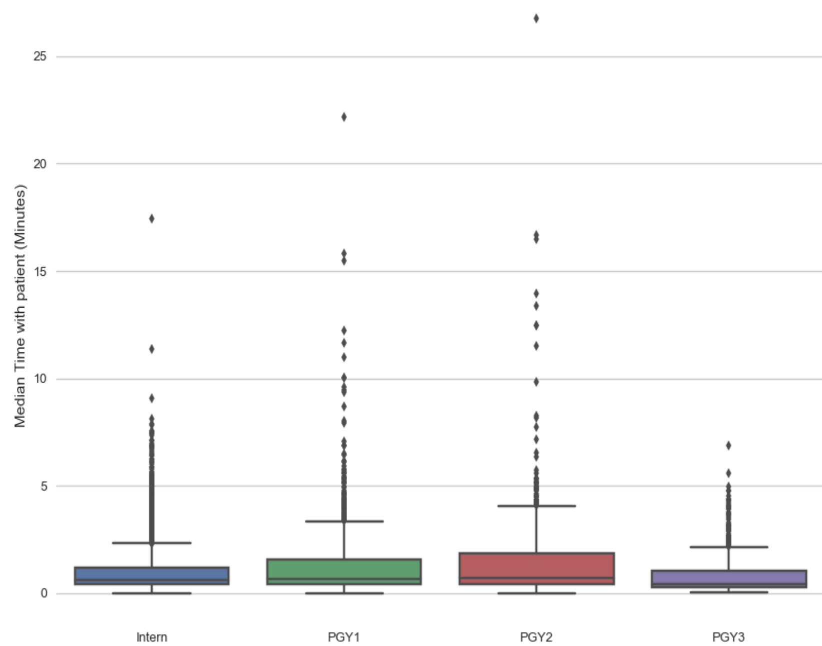



Figure 20. Comparison of patient interaction times in minutes for residents. Dots represent outliers.

The exam rooms were grouped by location with the ED i.e. central, north, south, east, west and each location consist of 5-8 exam rooms. We computed the median time per room group for Figure 21 which suggests that the times spent in exam rooms are not distinctly different for each type of resident except for south exam rooms. It is also important to note that at the Rochester ED, unlike the Phoenix ED, physicians use the EHR in patient rooms, so the times shows here are not necessarily time spent directly interacting with the patient.

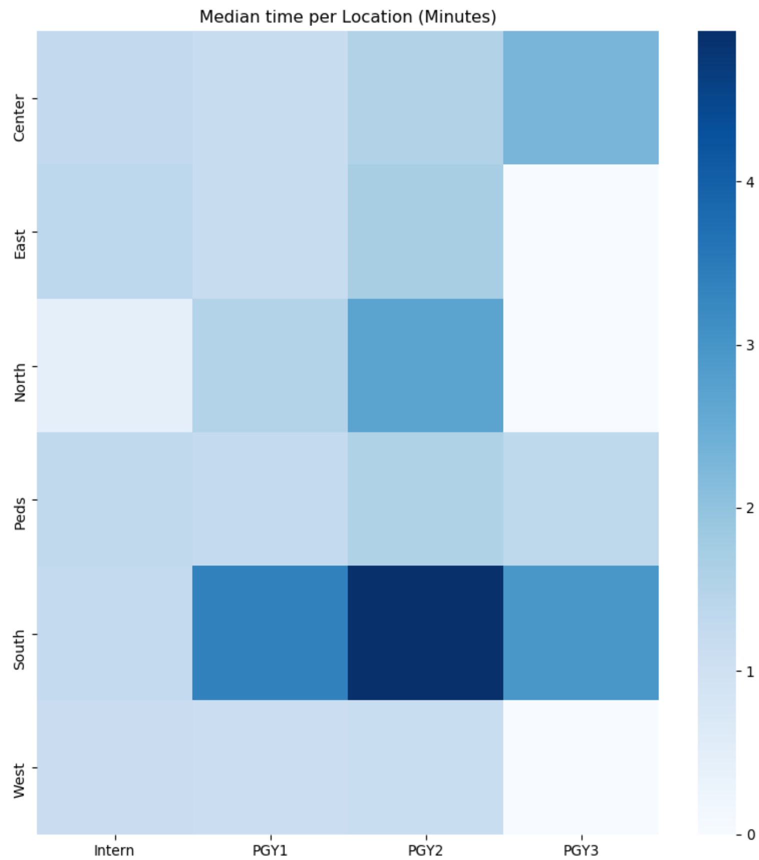



Figure 21. Patient interaction time per exam room by resident type

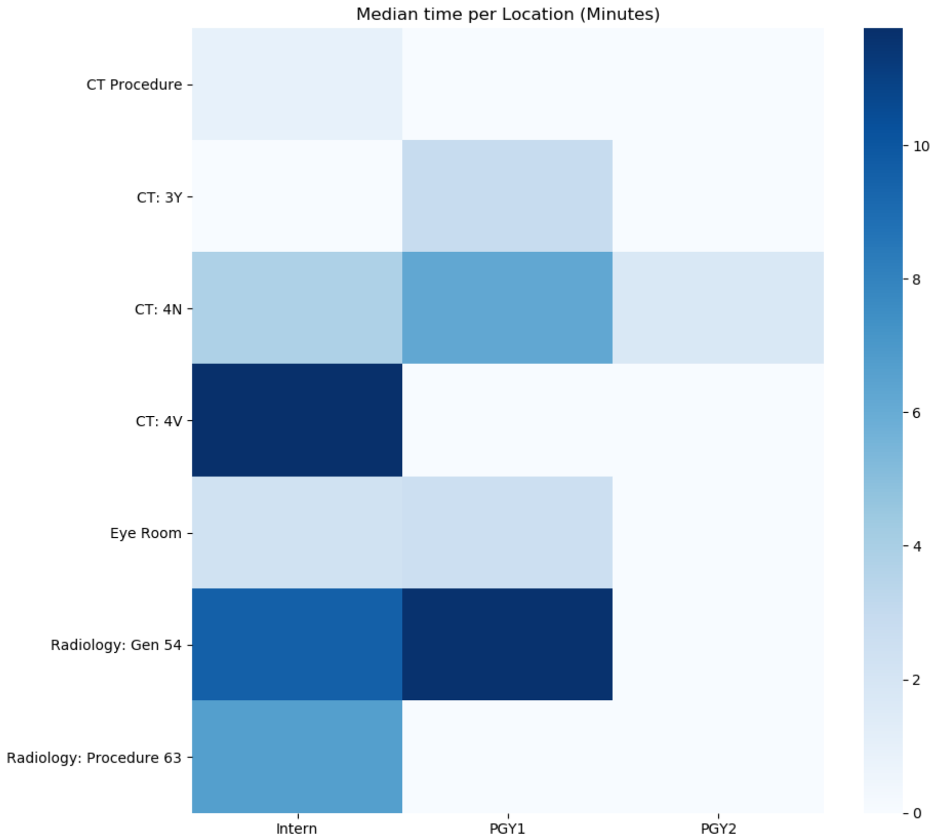



Figure 22. Patient interaction time by other locations by resident type

However, Figure 22 shows a more distinctive difference between the residents highlighting the varying responsibilities of each type of resident. Interns spent more time in Radiologic procedure and CT rooms with patients that PGY1 and 2 residents.

**Patient progress through the ED by interactions**

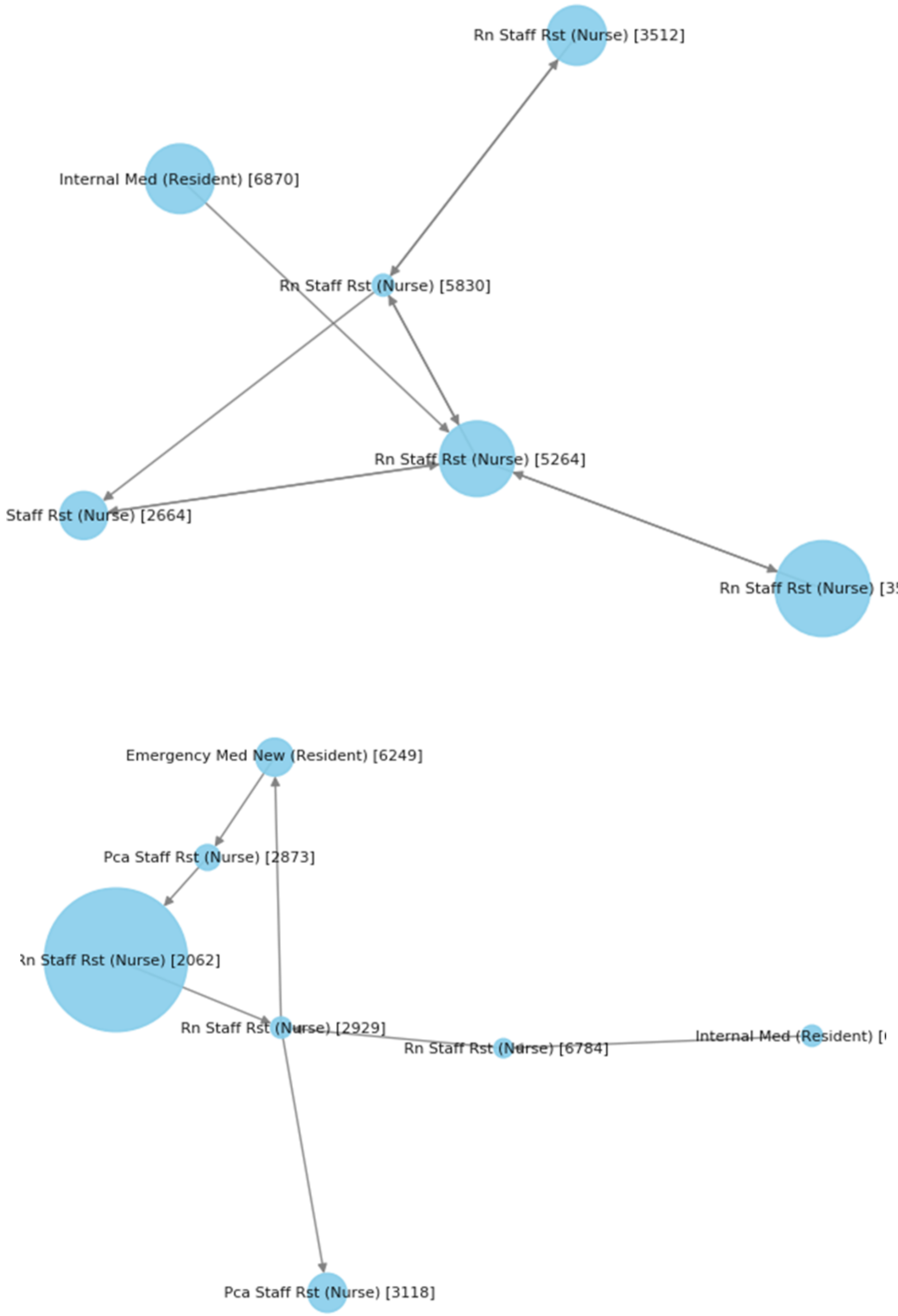



Figure 23. Patient progress (2 patients) through the ED. Radius of the circles represents time spent with the provider. Arrows represent the direction of movement.

The graphs in Figure 23 show the progress of two patients through the ED. A visualization of this type combined with knowledge of patient condition and stage of treatment can be used to assess the processes within the ED. The radius of circles represents the time spent with that provider and in figure 1(top) the times are relatively balanced where in figure 2 (bottom) there is larger amount of time spent with a single nurse than any other provider.

**Case study: Discrete event simulations**

Demonstrating clinical utility of location tracking data is incumbent on deriving meaningful metrics and relevant ways to present those metrics to the relevant target clinical users. Location tracking data has been used in the creation of new workflow metrics for the ED from RFID data (Akshay Vankipuram, Traub, & Patel, 2018b) . As part of this, the clinical environment was modeled using movement transition probabilities to capture its underlying uncertainty. This type of probabilistic model may be visualized to derive specific workflow-related insight, but it can also be used to simulate parameters of interest in the system (Asamoah, Sharda, Rude, & Doran, 2016; Rutberg, Wenczel, Devaney, Goldlust, & Day, 2013). These system simulations can be used to assess impact of specific processes or as a predictive model to assess trends.

DES is a technique used to model complex systems by simulating it in action to estimate or predict parameters and outcomes of interest (Rutberg et al., 2013). Systems are typically represented as a series of states, events, and transitions, each of which have a cost associated with them. The net cost of moving through the system in various scenarios is typically then used to estimate the value of the resource that one is looking to optimize. In the medical domain, examples of this could be queue length or wait times for patients (A. Vankipuram, Traub, & Patel, 2018). Traditionally, the costs associated within the system are set based on clinical expertise. Additionally, the movement through the system in the case of branching (concurrent) processes is determined randomly. While this is reasonable approximation of uncertainty, various medical environments may demonstrate varying levels of uncertainty. It is also possible that uncertainty levels may vary during a shift due to cognitive and physical stress (V. Patel, Zhang, Yosokowitz, Green, & Sayan, 2008). Using probabilistic models generated from RFID data, we can represent the uncertainty of the system in a way that better represents the actual workflow. One way to progress through a probabilistic system is to use the Monte-Carlo method which has been shown to work in DES (Rutberg et al., 2013).

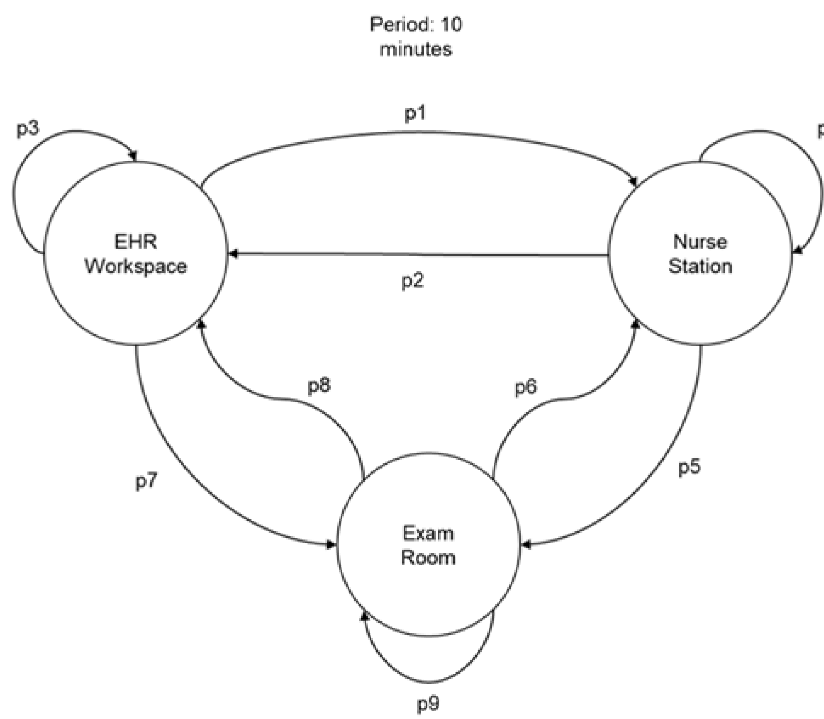



Figure 24: Simplified probability model of the ED

The task of estimating the underlying distributions associated with parameters of interest in a medical environment has been researched (Asamoah et al., 2016). With automated tracking, we can enhance our understanding of the underlying structure of the uncertainty.

Figure 24 represents a simplified view of a clinical movement probability model used to simplify the view for this document. As a proof-of-concept Monte-Carlo simulations were performed on tracking data. A model like Figure 22 was created for the all locations in the ED. The simulations allow us to use transition probabilities to model clinical behavior by simulating thousands of potential runs (i.e. movement from any ED starting location to an end location) and determine the average cost of each run. The cost in this case is the time taken to arrive at the end location from any starting location. The determination of appropriate starting and ending locations help us make valuable and varied judgments on behavior. As an example, we can consider the case of a physician looking up patient data in the EHR workspace and conducting the patient exam. Sometimes a physician may move directly to a patient room and others they may move to other locations such as the nurse station or other exam rooms first. Determination of the average time taken to move between these locations can help assess time to patient visit for physicians. To do this, we first modify our computation of probabilities by standardizing the time spent between transitions (i.e. only consider locations separated by at least 10 minutes).

To run the simulation, we begin at the EHR workspace. This is required for the specific case being discussed here but depending on the measure being analyzed any location can be picked. Then we select a uniformly random number (n) between 0.0 and 1.0 inclusive. Do the following:

```
Set P = 1.0
For each transition with probability (pt) from current node:
      If n >= P - pt and n <= P:
            Select transition
      Else
            P = P - pt
```

Update the time counter by 10 minutes. Then we repeat the above for the new location until the required end location (in this case exam room) is reached. We now repeat this entire process 1000 – 10000 times and average the time counter.

```
Number of steps
Q25: 2, Median: 5, Q75: 9
Time taken
Q25: 10.00 min, Median: 25.00 min, Q75: 45.00 min
```

The above is an example of running this simulation 10000 times. The above is an example of using transition probabilities to simulate measures of interest. In this example, we can determine that a median of 25 minutes is required before a patient exam is conducted, and it takes a median of 5 movements (these are movement to locations that are not the exam room) before a physician meets with the patient. From the perspective or workflow analysis, a deeper look at the data can help us determine time sinks i.e. locations or activities that are the most time consuming (for e.g. is a majority of the 25 minutes being spent using the EHR or moving to other locations). This can help with process analyses and modification. We can also compare these values pre and post a process change to determine its impact.

**Case study: Dashboards**

Performance reporting through static reports is inconsistent, time consuming, and hard to categorize and group (Ghazisaeidi et al., 2015). We've discussed, in the introduction chapter, the value of visual analytics. One of its main advantages is the ability to dynamically update, contrast, filter, and group data for exploration and reporting. Dashboards are a collection of visualizations grouped together thematically to summarize the state of the system. In the case of healthcare, dashboards are being increasingly utilized to track and present relevant information (Stadler, Donlon, Siewert, Franken, & Lewis, 2016). In aims 1 and 2 of the documents, visualizations were generated to translate tracking and EHR data to reportable insight. In this section, we cover the creation of workflow analytics dashboards and the types of visualizations that may be used within them. The goal of such a dashboard would be reporting and facilitating self-driven behavior modifications for clinicians.

**Representing relationships**

Within complex systems, an important task can be to present the relationships between entities of interest. Relationships can be represented either directly or through probabilities. Examples of the latter can be seen in aim 1 when next-location probabilities were computed and represented. In the case of the former, two options for presentation are: hierarchically or as a connected graph.

A hierarchical view is a top-down view of organizational structure of an underlying process. Figure 25 is an example of a hierarchical chart generated using movement data for two physicians. These charts can be generated over different time periods to assess the impact of process modifications or they can be used in an exploratory capacity to find areas of concern or interest.

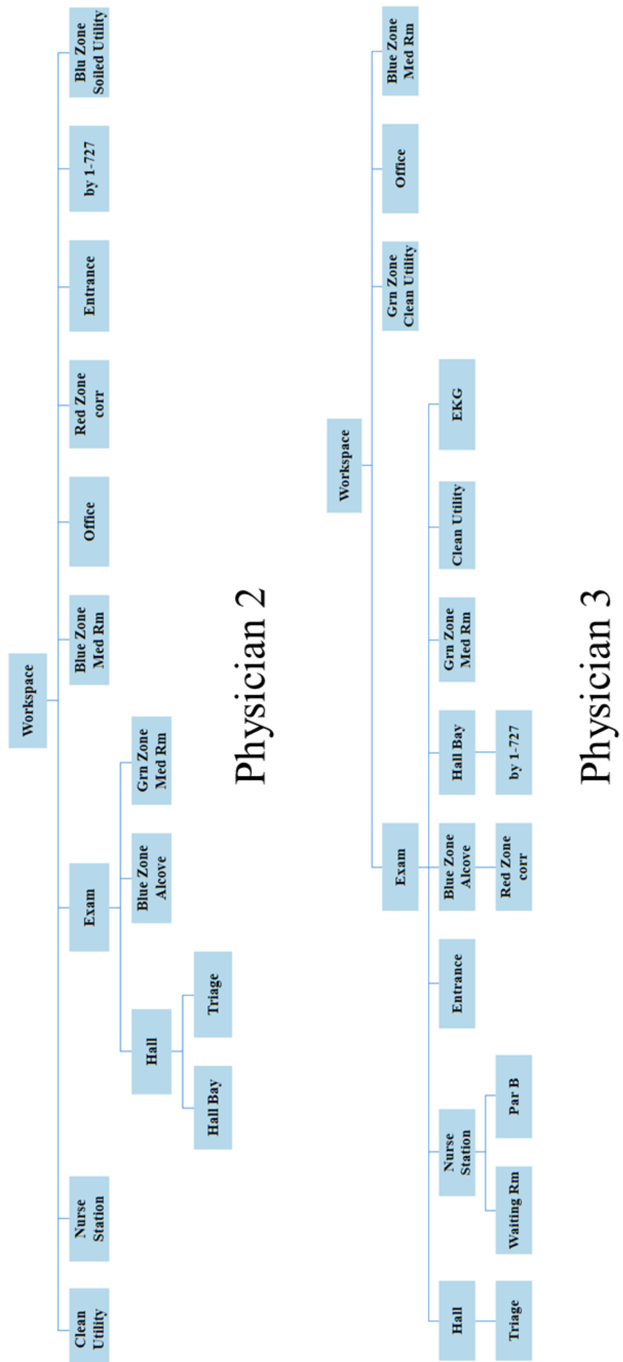



Figure 25. Hierarchical representation of two physician’s movement within the ED

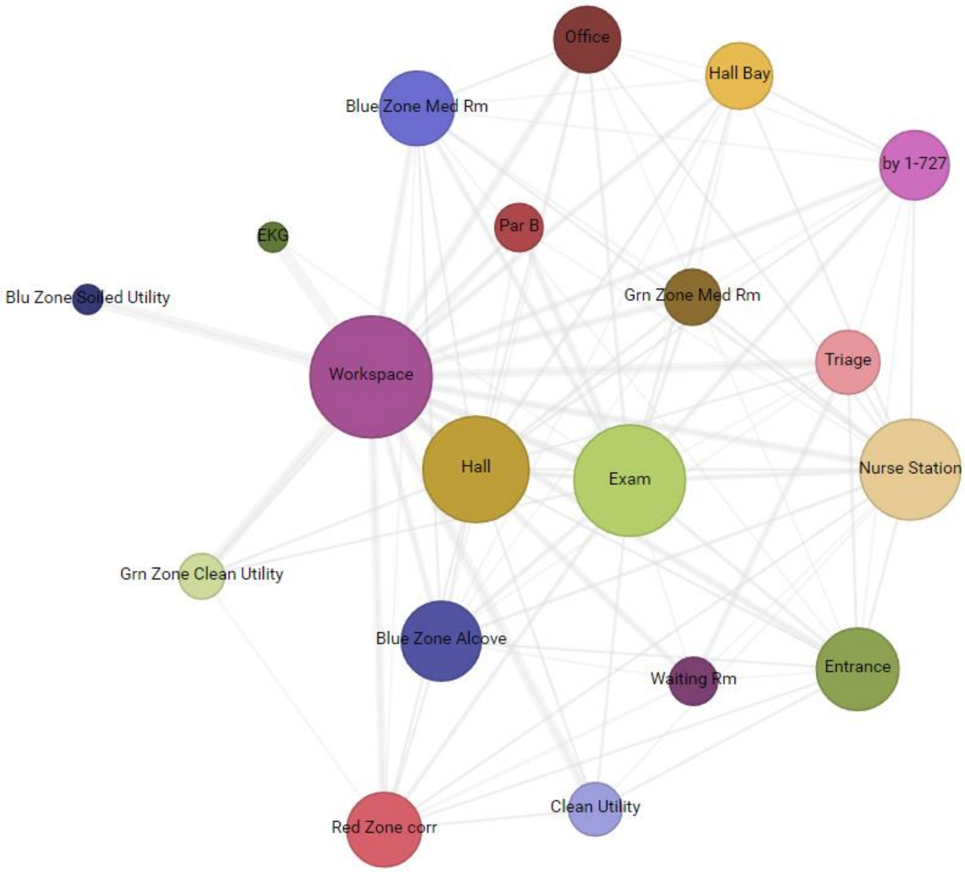



Figure 26: Probability of Clinician's Next Location at Mayo Clinic (Force-layout). Circle radius represents the time spent at location and edge thickness represents the probability of transition between those locations.

The second approach is the use of a connected graph. We've seen an example of this in figure 23 using the data from Mayo Clinic Rochester. Two more examples are shown in figures 26 and 27 from Mayo Clinic Phoenix. Connected graphs consist of nodes and edges between the nodes. The nodes represent the entities of interest (in the case of figures 26 and 27 the entity is location) and the edges represent their relationship. In the case of figures 26 and 27, the size of the nodes (circles) represents the time spent by physicians at that location and the edges represent the movement between the locations. Figure 27 is an alternative approach to graph generation that attempts to eliminate overlapping edges as in the case of Figure 26 (called circular-layout). However, figure 26 is a more common representation of a network using a force-directed graph generation algorithm (Fruchterman & Reingold, 1991). The utilization of each will depend on the target audience and the type of interaction allowed on the dashboard. Figure 26 is a better static representation of the system/environment, while figure 27 is better in a dynamic plot for exploration.

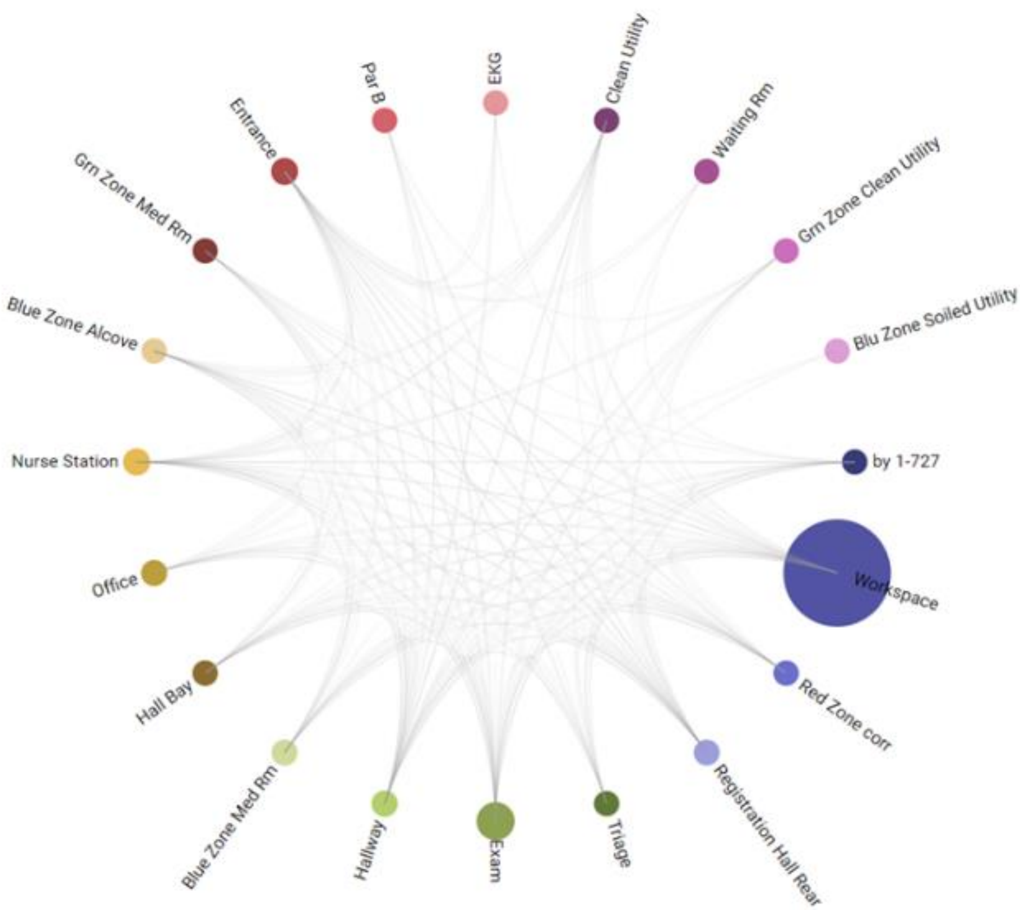



Figure 27: Probability of Clinician's Next Location at Mayo Clinic (Circular-layout). Circle radius represents the time spent at location.

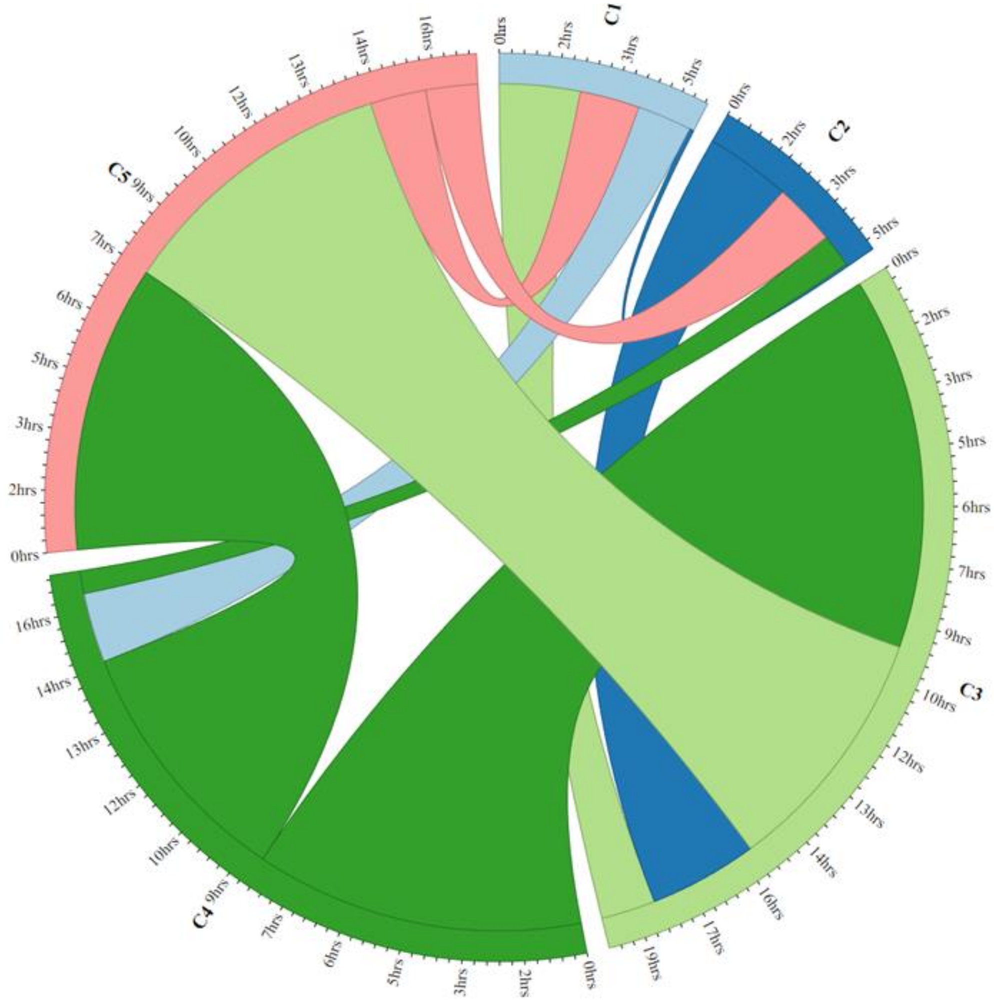



Figure 28: Net Duration of Interactions Between Tracked Clinicians at Mayo Clinic. C1-C5 are physician with their identities hidden. Chords (bands) represent the amount of time spent interacting. The values on the circumference are the absolute times.

Interactions between tracked entities (physicians in this case) may be another type of relationship that can be visualized and explored. Figure 28 is a representation of the net duration of interactions between clinicians. Interactions are defined as an event where the clinicians were co-located for a length of time. The chord diagram (Figure 27) shows duration of interactions between clinicians. Each colored segment on the boundary represents a different physician (C1-C5). The chords connecting the segments represent a pairwise link and the width of the chord represents the net duration of interaction (the axis of the boundary can be used to estimate the duration). The thickness of chords represents the absolute value of time spent interacting (potential interactions only since this is generated using tracking data) over the entire period of the dataset. As an example, in the figure, physicians C3 and C5 spent approx. 5hrs potentially interacting and C2 spent a net of 5hrs interacting with all other physicians. As mentioned we are unable to assess directly if these were only instances of co-location or interaction. However, since data for the 5 physicians was collected at the same location with the similar shifts and responsibilities, we can be more certain than these represent interactions since there would be no reason a subset of physicians would spend more time co-located than others.

The practical value of this is its use in process management to provide circumstances that maximize interactions and to find pairs of clinicians who are more likely to interact and study them further.

## Visualization of other measures in tracking data


Figure 29: Percentage of time spent at locations within the ED for a single physician.

One of the most common measures that can be extracted and visualized is the time spent at various locations within the environment. Figure 29 shows the percentage breakdown of time spent by a single physician over the duration of the dataset. Here we can see that this physician spent 76.7% of their time at the EHR workstations. We can also assess the time spent in exam rooms or nurse stations and compare them to other physicians or to other times based on the changing processes or technology.

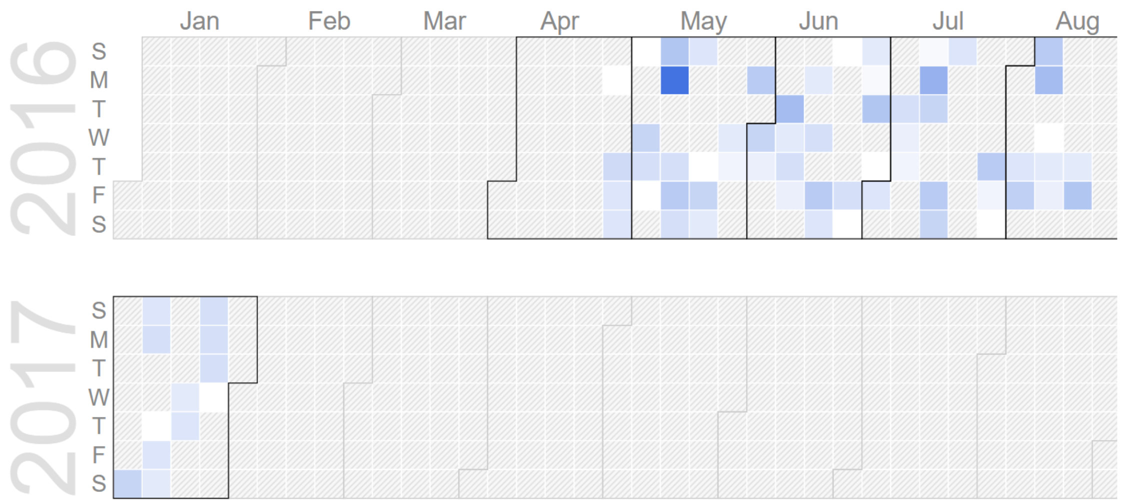



Figure 30: Trend/Timeline plot of multi-patient visit behaviors for a single physician.

In chapter 4 (Aim 2) the creation of two measures from RFID data was discussed (multi-patient visits, information transfer) which could be overlaid onto other data sources. We can also plot those generated measures to view trends over time. Figure 30 shows the trends of multi-patient visits over the period of the dataset for a single physician. Deeper blues represent higher number of instances. It's clear than this type of visualization can be used assess specific trends in tracked behaviors.

**Visualizing EHR usage data**

EHR aggregate usage data consists of several attributes each dealing with a specific module or subset of modules within the EHR. The attributes represent time spent within modules of the EHR and specific navigation-related usability metrics such as clicks and tab hops. Visualization of this type of data is most effective when representing trends or comparisons between users. Figures 31-33 show three different measures of interest from the EHR dataset. Figure 31 shows the distribution and trends of tab hops per patient chart per day for each physician. Tab hops are a measure of switching between module tabs in the EHR for each physician. The left side of the figure is the distribution of tab hops per patient for each physician and the right side shows the trends over the range of the dataset. The two relevant findings here are that physician 5 has a higher number of tab hops compared to the others which bears further study into their EHR-related workflow. The trends plot on the right is a repeating theme in figures 31 and 33 where there is clear change in trends on a period of the dataset. This most likely represents EHR usage down time due to the end-of-year holiday season. While, this doesn’t reveal anything significant in itself it is clear that we can derive very specific inferences from observing these plotted trends.

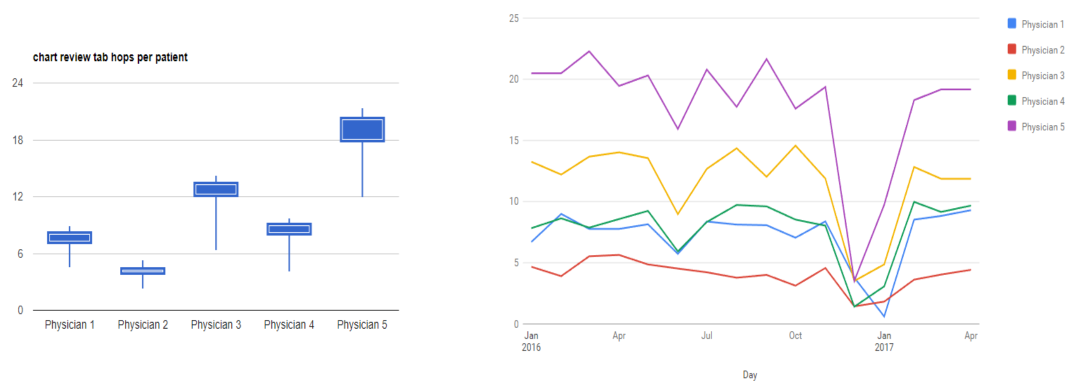



Figure 31: Tab hops per chart review in EHR per physician. The plot of the left represents the distribution of values and the plot on the right are the trends over period the dataset.

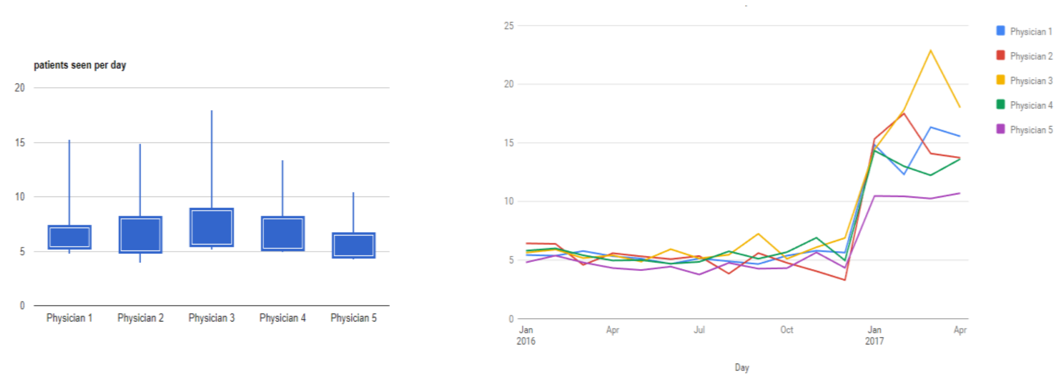



Figure 32: Patients seen per day by each physician. The plot of the left represents the distribution of values and the plot on the right are the trends over the period of dataset.

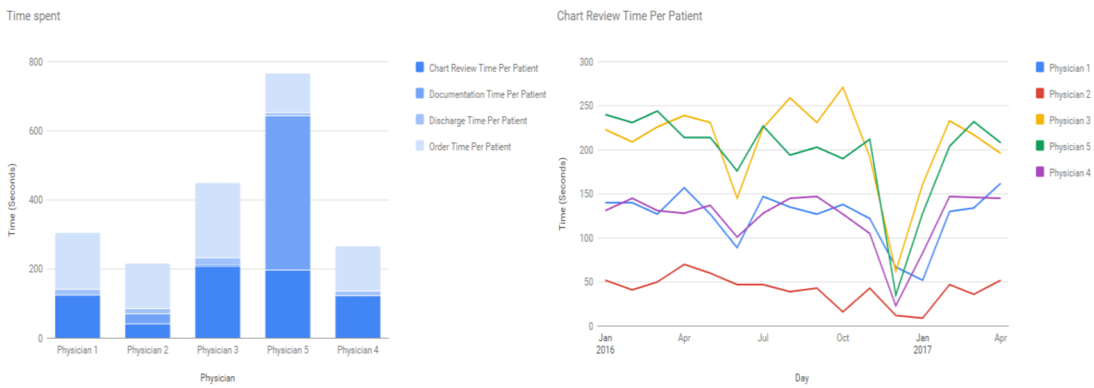



Figure 33: Time spent using EHR grouped by modules. The plot of the left represents the values per module (chart review, documentation, orders, and discharge) and the plot on the right are the trends over the period of dataset.

The added value of these visualizations is the ability to interactively plot these values over any span of time. Figure 32 shows the patient seen per day for each physician and this figure does not show any significant variability between physicians as expected but would be cause for further analysis if an anomaly were discovered. The trends plot on the other hand is significant since there is a significant climb in number of patients seen in around January. This can be explored further in the future to assess the cause. Figure 33 shows the net usage time of each EHR module per patient for all physicians. The bar plot on the right shows that for a single physician the documentation tasks are a significant time sink and leads to an overall increase in time spent compared to the other physicians. This type of insight can lead to hypothesis generation that seeds further research as demonstrated in Aim 2.

# CHAPTER 5

# CONCLUSION

In this document, research into creating an integrated framework and the use of automated location tracking in clinical workflow analysis was presented. The methods used are aimed at studying the efficacy of location tracking systems in workflow analysis either independently or when combined with other data sources and workflow analysis techniques. The goal of this research was not to study the ALT technologies themselves but the value of location data in workflow analytics. At the outset, the concept of computational ethnography used in this study was defined based on Zheng and his colleagues (Zheng, Hanauer, Weibel, & Agha, 2015). In our research presented here, ALTs role in computational ethnography are studied and detailed.

The two primary objectives of this research are: (i) to develop a methodological and  exploratory framework for clinical workflow analysis using automated location tracking data and (ii) to propose a mixed-method approach for workflow analysis by leveraging multiple data sources (qualitative and quantitative). Aim 1 provides a detail approach used in creating the methodological framework and for developing a specific workflow-related quantitative measures. It is shown that the measures can be used to (a) analyze patterns and behaviors in real-time through constant monitoring of the clinical environment, (b) assess the impact of interventions or process changes, and (c) to supplement or create error analysis mechanism in the future. One of key lessons learned during this process is that the key to development of methods for a thorough analysis of clinical workflow requires a combination of several quantitative and qualitative complementary data sources. This became the approach for aim 2 where the ALT data was combined with EHR log file usage data together with data from interviews and physician shadowing to derive two trackable measures based on location mapping. Next, these measures were correlated with EHR data to find patterns of interest that allow for the assessment of potential inefficiencies.

The maximization of the utility of workflow analytics is best achieved using visualizations and representations of the real-state of the environment. Chapter 4 details case-studies that deal with the modeling and representation of elements of workflow. We find that data from a modern clinical tracking system with continuous monitoring and a high volume can be used to generated and present new types of workflow measures or insights. Also presented are ways to simulate behaviors in environments using discrete event and Monte-Carlo simulations. These value of simulation techniques in the proactive assessment of workflow using predictive modeling is discussed. Finally, the role of visualization dashboards to facilitate the creation of a quality aware clinical system by utilizing location tracking and EHR data is discussed.

The primary limitations of these research methods are the need for further validation of the methods. This is a goal for the future research. The idea is to implement a visual representation of tracked clinical measures and obtain feedback from clinical domain experts. This feedback, combined with usability studies of the visualizations, will then allow for the demonstration of clinical relevance and to create new measures that are important to providers on the clinical floor. Additionally, to tackle generalizability, a similar process can be undertaken in other clinical environments, including other Emergency settings as well as other clinical departments.

The overarching goals of this work has been to present a set of methods that convey the value of automated location tracking either independently or combined with other sources of data in the analysis of clinical workflow. Both the methods themselves and the lessons learned in this research can serve as guides for future endeavors in this space. Location tracking is a relatively new technology in the clinical space and the work hopes to seed the interest in its utilization. The hope is that this work serves as a basis for healthcare systems adopting location tracking technologies into their environment to track processes in a pursuit of quality through workflow analysis.

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# APPENDIX A

# PUBLICATIONS

Paper based on Aim 1 was submitted to and published in the Journal of Biomedical Informatics in 2018. *Vankipuram, A., Traub, S., Patel, V.L., A method for the analysis and visualization of clinical workflow in dynamic environments, Journal of Biomedical Informatics Vol. 79, March 2018, Pages 20-31.*

Paper based on Aim 2 has been submitted for publication (under review) to the Journal of Biomedical Informatics. *Vankipuram A, Traub S, Patel, VL, and Shortliffe EH. Overlaying Multiple Sources of Data to Identify Bottlenecks in Clinical Workflow.*

A subset of the work in Chapter 5 was presented at the AMIA Annual Symposium 2018. *Vankipuram, A., Traub, S.J., & Patel, V.L. (2017). Clinical Workflow Visualization: Representation of clinician activity from location tracking data. AMIA Annual Symposium, Washington D.C, Nov 4-8. 2017*

**Posters**

*Vankipuram, A., Traub, S.J., & Patel, V.L. (2017). Clinical Workflow Visualization: Representation of clinician activity from location tracking and EHR log file data. Presented at ASU BMI-Mayo Clinic Poster & Employer Networking Event, April 21st, 2017, Mayo Clinic Campus, Scottsdale, AZ*

*Soni H, Vankipuram A, Denton CA, Shapiro JS, Traub SJ, Patel VL. Characterization of Clinical Workflow and Electronic Health Records in Emergency Medicine. Poster presented at the AMIA Clinical Informatics Conference 2018;May 9; Scottsdale, AZ*

**Panel**

*Patel, V.L., Kannampallil, T. G., & Vankipuram, A. (2016). Automated Monitoring of Clinical Workflows: Opportunities and Challenges. International Symposium on Human Factors and Ergonomics in Healthcare, San Diego, CA.*

APPENDIX B

IRB

Available upon request