Chapter 14
Automated Location Tracking in Clinical Environments: A Review of Systems and Impact on Workflow Analysis

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14.1 Background and Motivation

The impact of workflow on clinical error and consequently on patient safety has been widely known for some time (Frisby et al. 2017). While it may be convenient to blame human error for the findings presented in the report "To Err is Human," this is not a view shared by a majority of patient safety researchers (Henriksen et al. 2008). A more accepted view is to consider the complexity of a medical environment, where errors are typically caused by failure of one or more aspects of the system, leading to a sequence of further failures, which ultimately impact patient safety. Errors more often result from our lack of understanding of the environment and its bottlenecks than from a specific individual within the environment. To that end, thorough analysis of health care professionals' clinical workflow is essential to build a knowledge base of the areas of potential bottlenecks that may compromise patient safety.

Since the publication of the above report, research in clinical workflow has increased significantly. An important approach to studying complex environments is ethnography (Malhotra et al. 2007; Patel et al. 2008; Vankipuram et al. 2011). Ethnography pertains to the study of the individuals that make up the environments and how their biases and interactions affect the outcome of that setting. Ethnographic observations combined with surveys, interviews, and questionnaires are all techniques that help piece the puzzle of an environment together. However, each data

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collection method has its own limitations. Specifically, these methods rely heavily on single or multiple human observers processing multiple, and at times parallel, streams of information (Vankipuram et al. 2009). Increasing the number of observers can help in such a situation, but this can also quickly lead to logistical issues as accounts are combined.

Our goal in writing this chapter is to summarize an important modern technological advancement that can potentially help enhance our understanding of the intricacies within clinical environments and processes. We will present an overview of automated location tracking technologies followed by related research on the efficacy of the technologies. We then look at case-studies from our own work to elucidate the potential impact of location tracking in the medical domain. We break down the case-studies into analytics derived from location tracking data and data visualization techniques that can help present this information to relevant target users (i.e., clinicians and researchers).

14.2 Automated Location Tracking Technologies

Automated tracking of entities in a clinical environment has gained popularity over the past decade, with uses ranging from equipment tracking in clinical environments to research. Automated tracking refers to the use of technological advancements to continuously track clinical personnel, patients, and equipment with minimal human supervision. The methods associated with automated tracking were inspired by those in the field of aviation. Specifically, by considering tracking of processes in a complex medical environment to be comparable to a black box in aircrafts (Vankipuram et al. 2011). In this analogy, the black box continuously monitors various aspects of flight, such as pilot communication, altitude, cabin pressure, and relays this information to the ground or recorded for post-flight analysis and in case of emergencies. Clinical environments can be similarly monitored to reveal underlying process bottlenecks or sources of error.

One of the most popular techniques to achieve automated tracking is the use of sensors. Several examples of such technologies exist, including Radio Frequency Identification (RFID), Bluetooth, ZigBee, and Wi-Fi (Vankipuram et al. 2018). The efficacy of these various methods depends greatly on the nature of the environment itself and the constraints (safety protocols, lead-lined walls, inference from other medical devices) placed on signal transmission in medical environments. As a result of these constraints, RFID and Bluetooth have become the most popular technologies for automated tracking (Vankipuram et al. 2018). Lee and colleagues (Lee et al. 2007) compared the various safety protocols discussed above, and while they determined that the suitability of a protocol was most dependent on its use-case, Bluetooth and ZigBee were the most suited protocols for low data, low battery use applications. Near-Field communication was effective for much shorter distances than would be convenient for tracking. Wi-Fi, while a popular method, was found to interfere with existing hospital networks.

14.2.1 Radio-Frequency Identification (RFID)

RFID tags are typically carried by the subjects being monitored and they relay their information at regular intervals to a central receiver. Typically, multiple receivers are needed in larger areas. Information, such as proximity of tags to the receiver, is used to determine interactions between subjects. This helps build a model of interaction that can be used to analyze the impact of interventions or general workflow. Figure 14.1 shows an early version of RFID tags provided for clinical tracking purposes. These earlier technologies suffered from a significant amount of interference leading to a loss of data quality. Data collection over wireless networks also posed a challenge and often the data collected was stored at a central location by the vendor and had to be specifically requested as a data file when needed. Obviously, this was a significant barrier to adoption due to the circuitous and time-consuming collection process, but, more importantly, resulting from an inability to restrict ownership of potentially sensitive data, especially when dealing with patient tracking. Therefore, these technologies were rarely, if ever, used on patients. Additionally, the receiver stations shown in the figure were meant to be placed, manually, at the most appropriate locations and since they were ground stations it meant that they had a higher probability of interfering with the normal clinical workflow and could be distracting or concerning for patients and physicians.

Fig. 14.1 SNiF® RFID tag (Vankipuram et al. 2011)

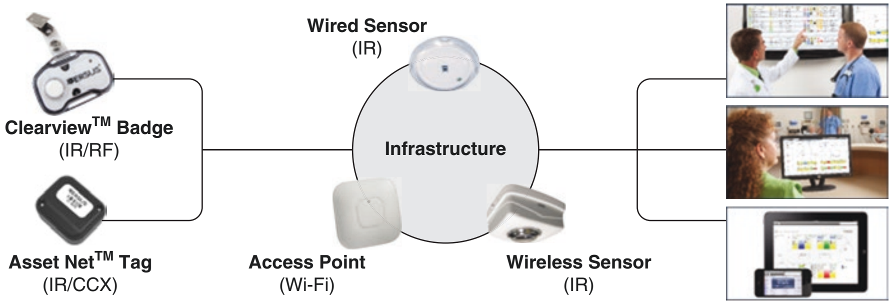


Fig. 14.2 Versus RFID-RTLS system

A modern version of an RFID system is shown in Fig. 14.2 (Versus Technology, RTLS Technology | Accurate, Reliable IR-RFID RTLS | Versus RTLS n.d.). The technologies have been updated to conform with the standards required of medical data including security. In the case of the Versus system, a reduction in the size of the receivers along with an improved tag detection mechanism has allowed the system to improve the efficacy of collected data. While the Versus system is used as an example here, there are several vendors who use variations of similar techniques and achieve similar effectiveness. Additionally, medical organizations have also begun to implement their own solutions because RFID tags and receivers tend to cheap and easily available.

There are two broad classes of RFID technologies that are available:

1. Passive RFID: The tags have no power source and only transmit a signal when they are within range of a receiver. This typically leads to a longer lifespan and passive tags can last up to 10 years. However, due to a lack of onboard power their detection range is within 40 ft. The receivers are often more expensive than active RFID owing to a need to transmit radio frequency energy.
2. Active RFID: These tags are battery powered and continuously transmit a signal. They have a detection range of over 300 ft but have reduced battery lives (3–8 years depending on the range). Receivers are cheaper than their passive counterparts.

Choosing between these technologies is largely based on the characteristics of the medical environment in which they are implemented as well as organizational concerns, such as safety and cost.

14.2.2 Bluetooth

Bluetooth based tracking solutions are a more modern approach to clinical tracking. The technique was originally introduced, and is most often used, in non-medical settings (e.g., keyless entry for houses) (Andersson 2014). Bluetooth offers certain advantages over RFID, especially in terms of cost and battery life (Frisby et al. 2017).

The Bluetooth tracking setup is similar to RFID and relies on receivers and tags on tracked entities/personnel. An additional advantage of this technology is its increased compatibility (compared to RFID) with mobile devices and PCs (i.e., most devices can receive and process Bluetooth signals without purchase of a specialized receiver). Bluetooth tracking setups can therefore be more cost effective than the equivalent RFID systems. However, to maximize the efficiency of data collection and minimize the cost, a higher level of technical knowledge is required for setup and maintenance of ad-hoc solutions. Bluetooth technologies are classified by their versions. The latest version of Bluetooth, released in 2016, was Bluetooth 5.0. Each subsequent revision of the Bluetooth standard has led to an increase in communication range and a reduction of power/cost. In version 4.0, an associated technology called Bluetooth Low Energy (BLE) was released. This version greatly reduced power consumption of Bluetooth devices while having a comparable communication range. Figure 14.3 shows an example of the Bluetooth tag (beacon) by Estimote (n.d.), which is an example of a BLE device. The Estimote tags and similar BLE sensors were estimated to have an increased battery life, making them more efficacious for automated tracking solutions.

As mentioned earlier, Bluetooth signals can be received by a range of commonly found devices, such as mobile phones and laptops. Raspberry Pi (low cost processors used in mobile devices and computers) have also been used as receivers (Frisby et al. 2017).

14.3 Efficacy of RFID: A Research Perspective

Clinical workflow analyses are especially important when attempting to assess the impact of an intervention or other modifications to everyday processes. An example of such an intervention, and potentially the most relevant to modern medicine, is the introduction of technology into typical clinical workflows. Zheng and colleagues (Zheng et al. 2010) assessed the impact of health information technology implementations (specifically for Computerized Physician Entry (CPOE) forms) on clinical workflows. They introduced a set of new analytics for assessment of impact and demonstrated a means to use data visualization to make complex data more decipherable and useful for quicker assessments. Drawing from this work, Vankipuram and colleagues (Vankipuram et al. 2009) introduced a Hidden Markov Model based approach to capture and analyze interactions using RFID tag based data.

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 RFID tags in combination with receivers set around the hospital to track the various resources in real-time at times of emergency. There are two different kinds of RFID tags,

Fig. 14.3 Estimote® Bluetooth Beacons

active and passive. Active tags constantly broadcast a signal and passive tags wait until they are near a receiver. Ohashi et al. (2008) compared different RFID systems typically employed by hospitals and found that in general both passive and active were affected by the environment. Active tags are battery powered and therefore have a set lifespan whereas passive tags need to have a local receiver to be used.

A study by Elnahrawy and colleagues (Elnahrawy and Martin 2004) compared localization algorithms for tracking precision and found that the uncertainty associated with tracking was likely fundamental and any approach (i.e., Wi-Fi, RFID, Bluetooth, etc.) would suffer from the same issues. Frisby and colleagues (Frisby et al. 2017) implemented a similar system using a beacon to track physicians in the emergency room at the Mayo Clinic hospital, using Raspberry Pi as a receiver. In this study, six receivers and fourteen beacons were used in the hospital.

14.3.1 Case Studies: Emergency Room (ER)

In this section we present our work using location tracking data, specifically, RFID data, in deriving workflow-related analytics in an ER.

14.3.1.1 Automated Location Tracking for Clinical Performance Analysis

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 and 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 (Welch et al. 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.

14.3.1.2 Location Tracking Data Collection

To understand the implementation of techniques to analyze clinical workflow and processes using location tracking, we need to understand the structure of tracking data. Most commonly, tracking data is stored in a tabular format. When tracking tags are within the range of a receiver, a single data point is written into the table which may be a locally stored or network relational database. An additional concept to understand is that most effective tracking systems require a high level of coverage (i.e., receivers placed in the environment to achieve a reasonable level of granularity of location data). The data table, therefore, typically has low dimensionality (i.e., few columns, but is usually large since data is recorded per instance of tag detection and this can happen several times a minute per tag that is within the receiver range). It is not uncommon to collect several gigabytes worth of data in a year for a sufficiently large system, such as the one we are describing in this case study. It is therefore incumbent on organizations attempting to implement similar systems to understand their baseline technical requirements and to plan for the growing needs with each year of the system's operation.

Table 14.1 shows two rows of the RFID data collection for a single tracked clinician in the ED. The columns of the recorded data are as follows:

- 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 14.1). The ID could be, therefore, used to

Table 14.1 Structure of location tracking data from the ED (Vankipuram et al. 2018)

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

identify each tracked clinician. It is worth noting that while this case study deals with RFID data, Bluetooth data will likely need to be similarly structured.

14.4 Data Analytics

Having understood the type of data being collected we can now consider the types of analytics that can be performed on the data. The value of automated techniques over manual observations can best be described by considering methods that require large and higher fidelity datasets, such as the ones we can create using an automated system with good coverage.

14.4.1 Entropy (Degree of Randomness)

A valuable goal of tracking tasks and movement in a fast-paced, concurrent environment like the ED is to be able to map the inherent structure or lack thereof of the various processes that make up clinical workflow. To that end, we can use the location data to compute the entropy or degree of predictability of processes. Structured processes should have a lower level of entropy or unpredictability since they are, by nature, a series of repeating patterns of movement or behavior. Computing entropy can allow researchers and clinicians a birds-eye view of workflow in an environment like the ED. The entropy of a sequence of movements that underlie a process can be compared to a baseline of truly random movement to get a relative degree of predictability. The associated methods are described in detail in our previous work in the Mayo clinic ED (Vankipuram et al. 2018).

14.4.2 Discrete Event Simulations (DES)

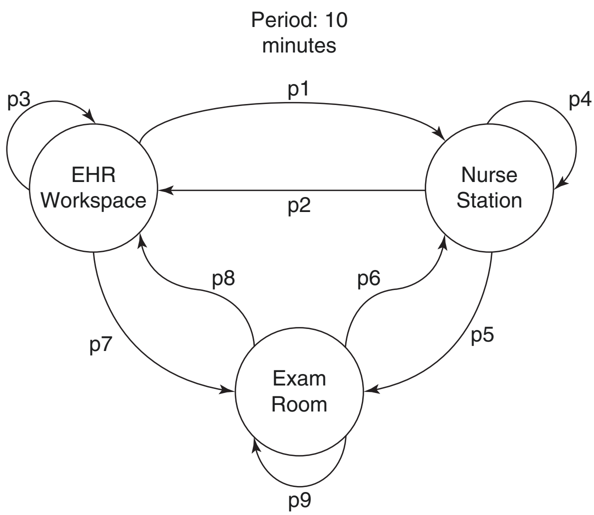
Demonstrating clinical utility of location tracking data is incumbent on deriving meaningful metrics and relevant ways to present those metrics to the relevant target clinical users. Location tracking data has been used in the creation of new workflow metrics for the ED from RFID data (Vankipuram et al. 2018). 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 (Rutberg et al. 2013; Asamoah et al. 2018). 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 (Vankipuram et al. 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 (Patel et al. 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).

The task of estimating the underlying distributions associated with parameters of interest in a medical environment has been researched (Asamoah et al. 2018). With automated tracking, we can enhance our understanding of the underlying structure of the uncertainty.

Figure 14.4 represents a simplified view of a clinical movement probability model. Such a model can be utilized to simulate outcomes of interest. Figure 14.5 shows the results of DES for three behaviors in ED (providers tracking). The time computed represents predicted time to exam for a physician over 1000 simulated runs. The transition probabilities were used to pick the next location to

Fig. 14.4 Simplified probability model of the ED (actual model contains all 59 locations)



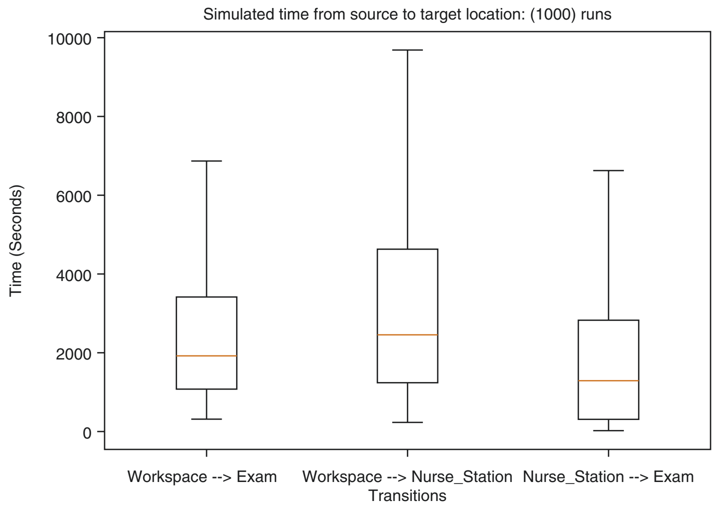


Fig. 14.5 Result of DES for three cases of interest in ED

move in the simulation. To pick the duration at each location, we compute the skew for each duration and generate a random number from a distribution with the same mean, std, and skew. Figure 14.6 shows the time distributions generated using tracking data that form the underlying models used in this sample simulation.

14.5 Data Visualization

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 and 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. In this section, we present some example of visualizations created using the ED location tracking data to illustrate the value further. At the end of the section, we provide a sample workflow dashboard which is used as an example of an idealized outcome of an integrated location tracking analytics system in an ED or similar clinical environment.

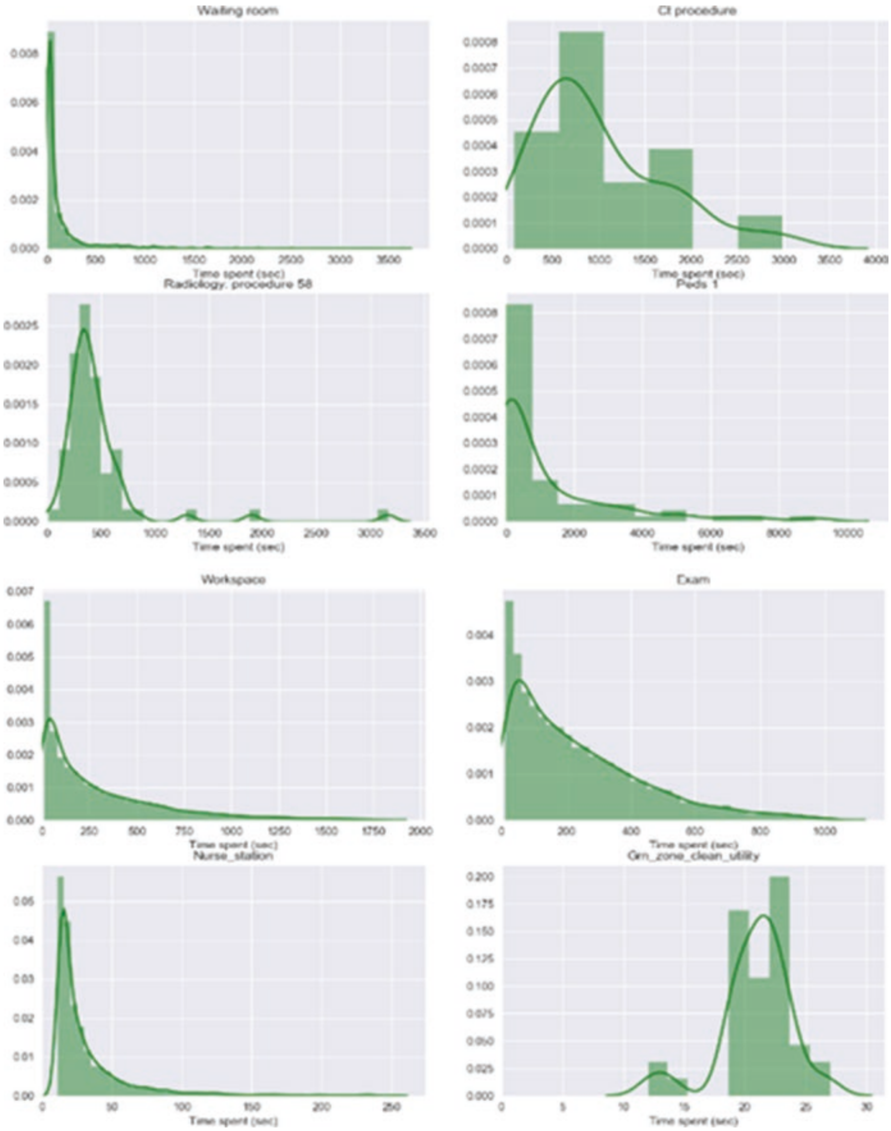


Fig. 14.6 Time distributions for four sample locations in two EDs

14.5.1 Chord Diagram

Figure 14.7 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 practical value of this is its use in process management to provide

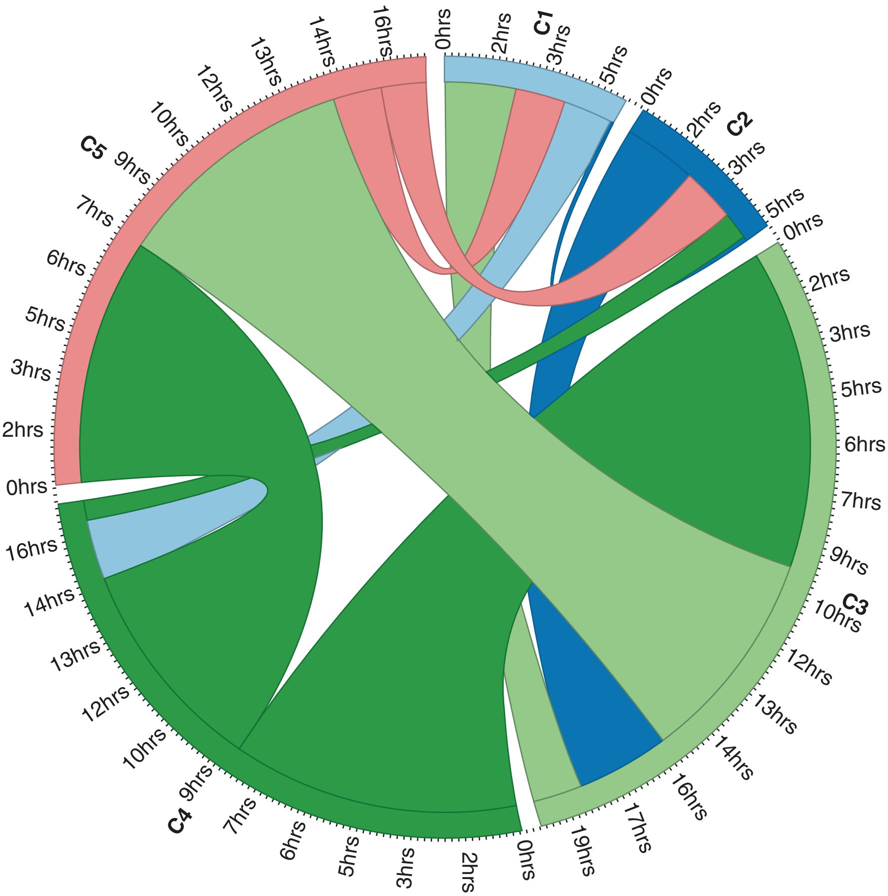


Fig. 14.7 Net duration of interactions between tracked clinicians at Mayo Clinic

circumstances that maximize interactions and to find pairs of clinicians who are more likely to interact and study them further.

The chord diagram (Fig. 14.7) shows duration of interactions between clinicians. Each colored segment on the boundary represents a different clinician (C1–C5, respectfully). 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).

14.5.2 Longest Common Subsequence

The longest common subsequence (LCS) is a computational problem that deals with finding the longest common set of sub patterns within two series. An example of this is to find the longest common sequence of nucleotides in two gene sequences. By treating movement data as a series of location sequences, we can compare two sequences of movement, either by time or by tracking personnel, to derive additional insight into behavior.

LCS can be computed for each tracked clinician and visualized as seen for one clinician in Fig. 14.8. This can also be used for process management, but additionally may be used to compare clinicians with varying expertise. The figure shows a movement graph of the most common movements a single tracked clinician makes during a shift. This can be potentially used to compare novices and experts and see if the experts' movement allows them to manage time better or mitigate certain types of error.

The blocks on each axis represent a move within the location (e.g., 'Workspace' to 'Workspace,' with the arrows representing direction of movement). This chart can be compared over lengths of time or between a specific pair of clinicians (e.g., novice vs. expert). It is also possible to use the chart in Fig. 14.8 to view arbitrary length sequences for any clinician, but in this case, we use it to view the LCS of movement across all shifts of a clinician.

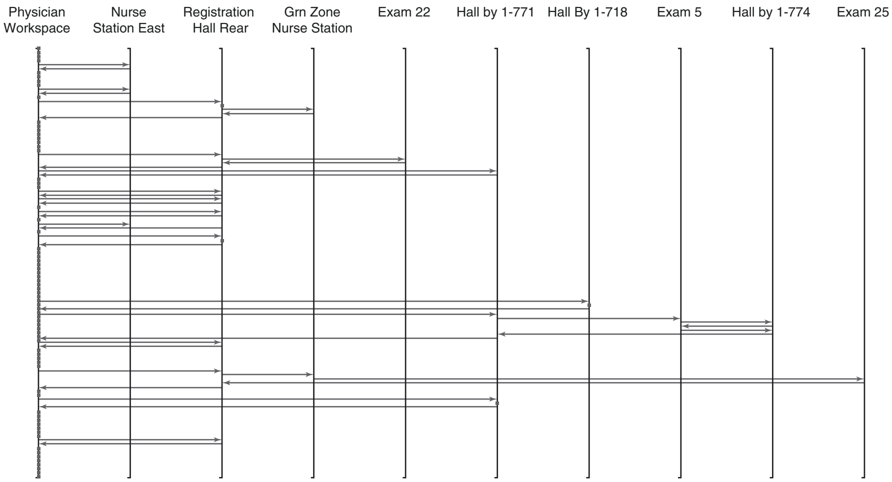


Fig. 14.8 Longest common subsequence for a single clinician over 7 months at Mayo Clinic

14.5.3 Network Graph-Based Visualization

Relationships and probabilities can be represented as a network graph, as seen in Fig. 14.9, which gives the probability of a clinician's next location. The radius of each colored circle represents the time spent in that location. The strength of the relationship is represented by the number of the links between locations (i.e., more links indicate stronger relationships). These links also show the probability of the physician's next locations from any origin point. This type of graph eliminates any overlapping edges to provide a clearer interpretation of the relationships between locations. Network graphs work well in a dynamic setting, such as an interactive dashboard.

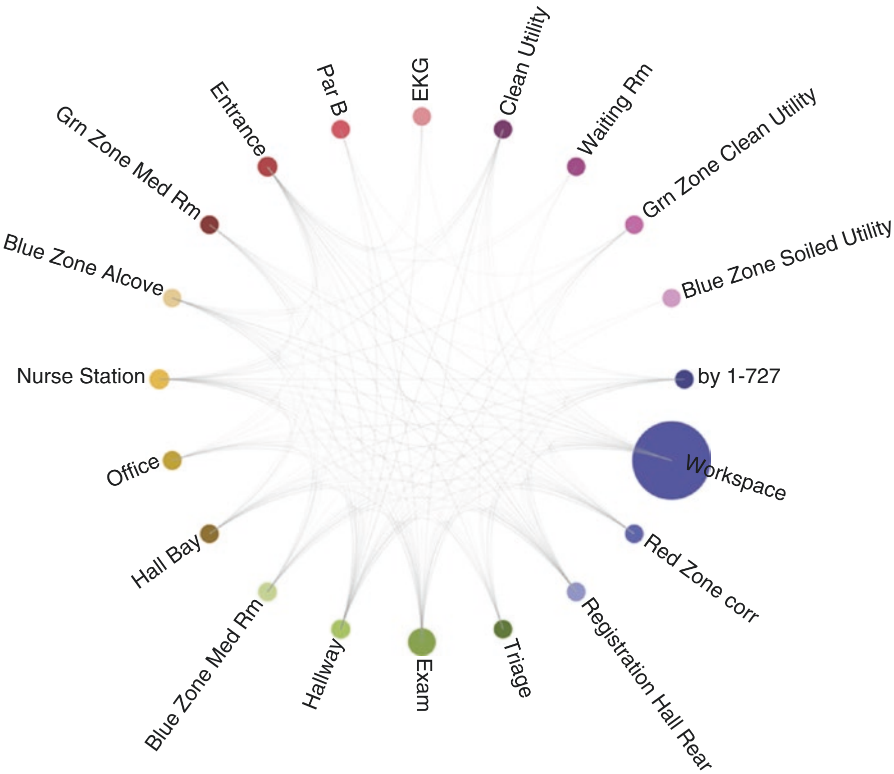


Fig. 14.9 Probability of clinician's next location at Mayo Clinic

14.5.4 Radar Chart

A radar plot/chart is a form of visualization that is a good way to represent a single discrete axis. It is a popularly used plot in gamification research, which is the introduction of video-game elements into visualization dashboards to enhance clarity and intuitiveness. Below (Fig. 14.10) we look at an example of a radar plot generated to display the probability of the physician's next location from any origin point.

The radar chart is a useful representation of clinical movement as a Markov process (i.e., when we model the system as a Markov chain where the probability of the clinician being in the current location is only dependent on the immediate previous location). Markov process are usually a good approximation of complex processes and can be further used in methods like the discrete event and Monte Carlo simulations described earlier. Radar charts are an effective way to convey Markov systems.

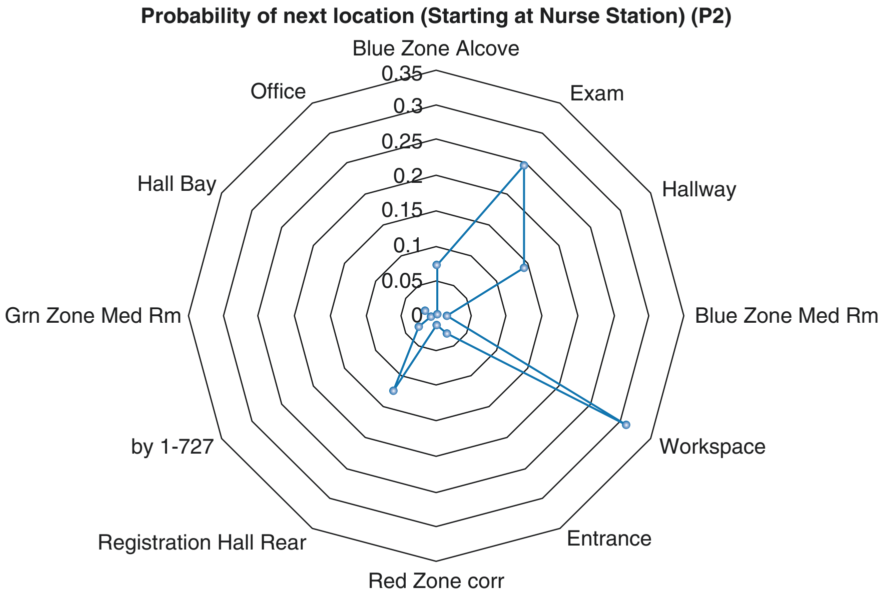


Fig. 14.10 Probability of next physician location, with nurse's station origin. The axis of a radar plot is categorical giving a discrete representation

14.5.5 Clinical Workflow Dashboard

As mentioned previously, an ideal goal of visual analytics work is to provide a platform for clinicians and researchers to receive feedback on the results of data analysis. Below we present a proof-of-concept dashboard developed using ED location tracking data. Figure 14.11 shows a sample dashboard for a single physician based on measures derided from location tracking. The top row shows instances of direct patient care (movement from workspace to exam room), multiple patient

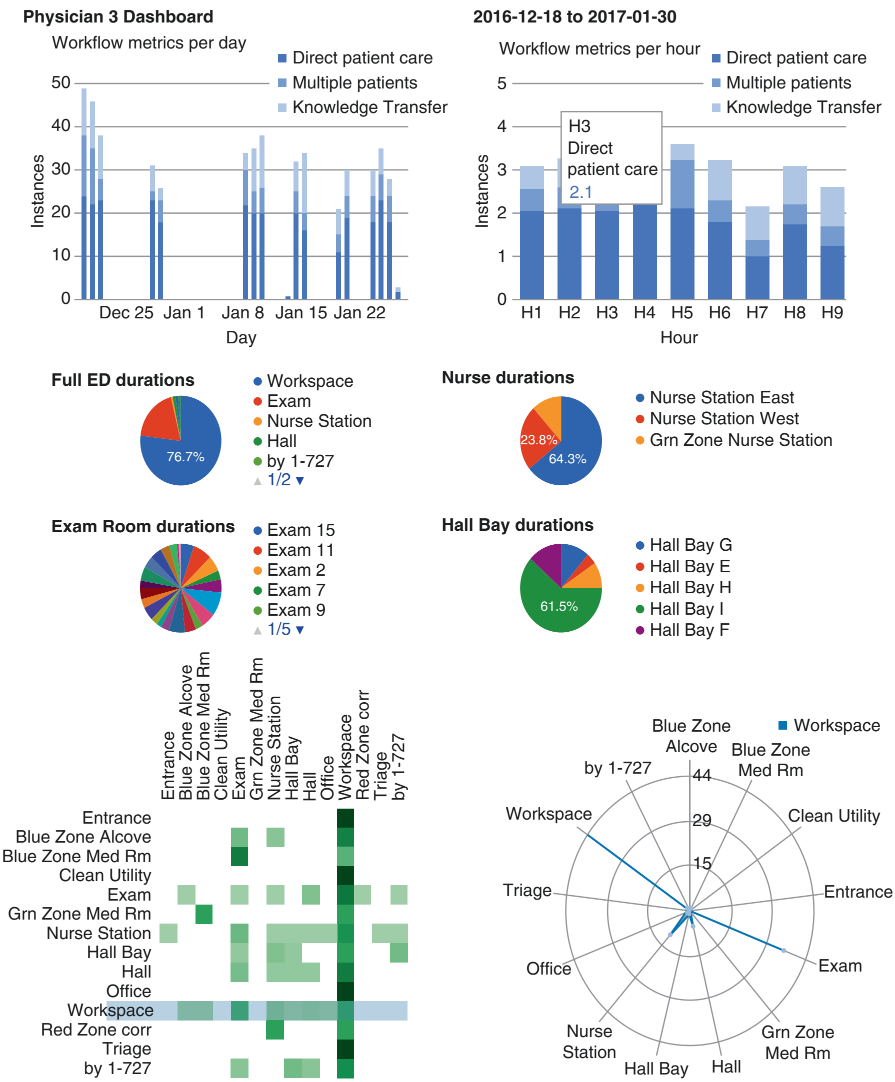


Fig. 14.11 Location tracking analytics visualization dashboard

exam room visits, and knowledge transfer (movement from workspace to nurse stations). The plot of the left shows the net count of each of the above metrics per day. The plot on the right shows a single day as selected on the stacked plot (left). This plot is shown per hour of the shift.

The second row shows a set of pie charts representing time spent in various locations within the ED. EHRs have been a disruptive influence on clinical workflow and clinicians are often concerned with time spent with patients compared to other areas and activities. These plots can convey the proportion of time spent in exam rooms compared to other areas in the ED.

Finally, the transition probabilities described in the radar chart section is represented in the final row. Transition probabilities for a single physician represented as a heatmap (left). The darker squares represent a higher likelihood of movement from location on the column to the location on the row. Useful for presenting net behavior. The radar plot on the right is populated by selecting one of the location in the heatmap and presents probability values for movement from that location.
Figure 14.11 is an example of an interactive dashboard and can be updated to display measures for any arbitrary length of time. A possible use for such a dashboard could be to observe trends in these measures across time to assess the impact of technological or process interventions.

14.6 Conclusion

In this chapter, we described automated location tracking technologies and associated analytical methods in medical environments. Clinical workflow is inherently complex, and the techniques described above were developed to complement other quantitative methods typically used in the analysis of clinical workflow. Derived measures can assist researchers and clinical stakeholders as they identify bottlenecks which can be further investigated in greater detail using ethnographic techniques. We believe that the most effective way to study workflow is to use a combination of available methods. Our goal in this chapter is to present the utility of, what we believe is, an efficacious modern method to supplement workflow study.

There are also additional sources of data that can be leveraged to create a more holistic picture of clinical processes which we have not included here, but are equally important. Location tracking provides just one dimension of qualitative data. Another example of a valuable data source is EHR trace/usage log files. EHR logs are collected by most mainstream vendors, which includes the use of the system by various authorized personnel. Including this data in clinical workflow analysis can increase the granularity of our view into the medical environment to provide more context to movements and related activities, and thus improve the depth of our automated monitoring capabilities.

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