METHODS TO ASSESS PROCESS FLOW

AND WAIT-TIMES AT STUDENT RUN FREE CLINICS

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by

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The undersigned, appointed by the dean of the Graduate School, have examined the thesis entitled:

METHODS TO ASSESS PROCESS FLOW AND WAIT-TIMES AT STUDENT RUN FREE CLINICS

presented by Riyad Haq,

a candidate for the degree of Master of Science,

and hereby certify that, in their opinion, it is worthy of acceptance.

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List of Abbreviations

ACA	Accountable Care Organization
API	Application Program Interface
BI	Business Intelligence
BI&A	Business Intelligence and Analytics
BPM	Business Process Management
DBMS	Database Management Systems
DDD	Data-Driven Decision Making
EMR	Electronic Medical Record
ETL	Extraction, Transformation and Load
HCI	Human Computer Interaction
IT	Information Technology
OLAP	Online Analytical Processing
PPACA	Patient Protection and Affordable Care Act
PHT	Preventive Health Therapy
QI	Quality Improvement
RDBMS	Relational Database Management Systems
RFID	Radio Frequency Identification
SRFC	Student Run Free Clinics
VSM	Value Stream Map(ping)

Chapter One
Introduction/Background

1.0 Statement of the Problem

The enactment of the Patient Protection and Affordable Care Act (PPACA) signaled a major milestone in the United States' healthcare history, allowing millions to receive affordable health insurance, some for the very first time (Kaiser Family Foundation, 2015). However, individuals are still left without health insurance and must rely on other means to obtain some degree of care; one reasonable option of which are Student Run Free Clinics (SRFC). SRFC serve a dual purpose of being a training ground for health professionals of different backgrounds and a source of health care for the underinsured. These clinics have shown success in imparting education to students through practical application and improving the health status of patients and their surrounding communities (Riddle et al., 2014; Ryskina, Meah, & Thomas, 2009; Shabbir & Santos, 2015). However, personal experience with a SRFC and a search through the literature shows that administrative and informatics efforts related to improving operational efficiency has been lacking or nonexistent. Thus, a concern arises that SRFC are not operating at their highest level of efficiency due to a lack of understanding about process and having the tools necessary to improve on it.

MedZou Community Health Clinic is one such SRFC clinic. MedZou was established in Columbia, MO in October of 2008 and moved to a new location in 2014.Health professionals from spectrum of backgrounds, including medical, nursing, social work and health administration students together to treat the underserved and uninsured residents of Mid-Missouri. The clinic operates twice a week with a specialty clinic on Mondays and a general clinic on Thursdays each seeing between 10 and 20 patients a night. To date, the clinic has served over 1,200 patients, providing basic primary care, social services, pharmaceuticals, referrals and preventive health screenings. However, because the clinic is still relatively new, has recently moved, and has a high volunteer turnover rate the workflow that is not completely understood and controlled. As a result, of these problems that there are highly variable durations for services and long wait-times for patients, which resulted in clinic finishing late into the night and has caused patients to leave without being seen. Additionally, there have been concerns with stations such as social work and preventative health treatments being underutilized. These concerns can have some profound implications on the health of the patient and also the effectiveness and efficiency of the organization. A proven strategy for empirically verifying if these concerns are real is to be employed. Additionally, if concerns are verified actionable measures to mitigate the concerns can be suggested.

1.1 Purpose of the Study

One of the current trends in healthcare is that of improving quality of care for the patient through evidence based practices; this entails not only clinical quality improvement in the realm of evidence based healthcare but also nonclinical and administrative efforts as well, which have been termed evidence based management (Burgers, Grol, Klazinga, Mäkelä, & Zaat, 2003; Rousseau, 2006; Walshe & Rundall, 2001). The two areas are dependent on one other and both need to be realized for an organization to produce its highest yield. Evidence based medicine such as clinical guidelines have been widely used but only recently have quality improvement principles such as Lean Six Sigma been implemented in healthcare from the manufacturing sector in an effort to produce data driven action and policy (Ng, Vail, Thomas, & Schmidt, 2010). Regardless of being a small clinic predominately run by students, the effect of the clinic on individual lives is great, and the concerns and problems it faces are the same as larger healthcare organizations, albeit on a smaller scale. The same principles being implemented in healthcare to improve quality on the clinical and nonclinical fronts should still be effective at improving care and operations within MedZou Community Health Clinic and all other SRFC. Therefore, the purpose of this study is to see if we can use prevailing business process management (BPM) tools, such as Process Mining and Dashboards, and quality improvement methodologies, such as Lean Six Sigma, to provide SRFC with an informatics foundation to generate the data necessary to suggest measurable recommendations to improve quality within the clinic. Thus we seek to answer the following questions:

> Question 1. Can we use Business Process Management(BPM) and Quality Improvement (QI) tools to generate data to understand the current processes used to deliver services at MedZou Community Health Clinic?
>
> Question 2. Can the data produced lead us to suggest measurable recommendations that can benefit the clinic either by 1) Allowing us to give better care to the patient and/or 2) Improving clinic operations?

Chapter Two
Related Literature

2.0 Search Strategy

Our search strategy was divided into two parts which were conducted through Google Scholar and PubMed searches. We first broadly searched if anything had been written on the topic of assessing or improving operations efficiency at SRFC which yielded no results. Our second set of searches was to provide background knowledge on what we were aiming to study and how to go about it. We therefore conducted a series of searches again through, Google Scholar and PubMed, for free full text articles written post-2000 in the areas of uninsured patients, process mining, dashboards, and wait times. Searched keywords include, uninsured, ACA, student run free clinics, process mining, efficiency, workflow, dashboards, wait times and clinical decision making. Articles that were applicable to the topic were then saved in the standalone version of Zotero.

2.1 The Still Uninsured

The enactment of the ACA in 2010 was the first major piece of legislation to impact healthcare in decades, allowing for nearly 17 million Americans to receive health coverage, some for the first times in their lives. However, despite this momentous feat many Americans are still left without coverage. According to research from Kaiser Family Foundation, in 2014 around 32 million Americans went uninsured, predominantly from low to moderate income families (Kaiser Family Foundation, 2015)[1]. Figure 1 provides insight into the various reasons individuals remain uninsured. 'Too expensive'

[1] Low-moderate is defined as below 400% of the poverty level, which was $19,055 in 2014.

Figure 1: Reasons Being Uninsured Among Uninsured Adults, Fall 2014

[redacted]

made up close to half the responses followed by 'Unemployed/Work doesn't offer/Not eligible at work'. Additionally, reasons related to perceived ineligibility and lack of knowledge on how to acquire insurance were also mentioned. In 2014, 63% of uninsured adults reported they did not even attempt to gain ACA coverage, almost half of which were deemed likely eligible by KFF for Medicaid or Marketplace credit (Kaiser Family Foundation, 2015). On a smaller scale, the University of Michigan Student-Run Free Clinic found a similar trend with their patients failing to acquire insurance due to "Perceived expense of plans and belief of ineligibility for Medicaid (Desmond, Laux, Levin, Huang, & Williams, 2015)". In summary, there still remains a large segment of the population without coverage; reasons for why individuals remain uninsured could be grouped into 1) those who cannot receive coverage, 2) those who do not want coverage, 3) those who are eligible but face barriers to obtain it (mainly price) and finally 4) those who can obtain coverage but are unaware due to lack of knowledge or preconceived notions.

2.2 The Importance of Student Run Free Clinics

SRFC are organizations generally affiliated with medical schools that have a dual function of serving as a prime training area for medical students and helping to fill gaps within healthcare by providing free treatment for the uninsured. The specific services vary from clinic to clinic but they all provide general treatment for primary care ailments with some clinics equipped to treat more specialized conditions. SRFC, have heavy involvement with medical students but they are also largely interdisciplinary, incorporating social work, public health, pharmacy, nutrition, nursing and other areas disciplines (Holmqvist, Courtney, Meili, & Dick, 2012). These interdisciplinary teams are capable of making a substantive impact within healthcare and training the next generation of health professionals, key points of which are highlighted in Appendix A, *"Summary of Literature Related to the Impact of SRFC"*. However, the prevalence of administrative and operational practices within SRFC remains largely unknown as there is little indication of research toward efforts to improve efficiency, quality and financial sustainability within these clinics in order to improve their long term viability.

2.3 Data Driven Decision Making

Table 1: BI&A Evolution: Key Characteristics and Capabilities (Chen, Chaiang, & Storey, 2012)

[redacted]

The ability to generate large amounts of data has increased considerably over the past few years due to cheaper data storage systems and the wide spread use and integration of data systems. Now the challenge has become how to leverage the copious amount of data being produced so that it can be transformed into value (LaValle, Lesser, Shockley, Hopkins, &

Kruschwitz, 2011). To meet this challenge, entire fields have developed such as informatics, Business Intelligence (BI) and Big Data Analytics to manipulate and analyze this data through tools and methods such as databases, machine learning, visualization, data mining, statistics and so on (Chen, Chiang, & Storey, 2012). Over the years this capacity has grown and evolved going from being able to analyze structured content (BI&A1.0) to structured content (BI&A2.0) to mobile and sensory based content (BI&A3.0) allowing for more profound applications and researched (Table 1) (Chen et al., 2012).

This evolution of big data also has big impact, which has been coined as Data-Driven Decision Making (DDD)[2], the practice of basing decisions on analysis of data rather than intuition (Provost & Fawcett, 2013). The practice of DDD has shown many benefits, one study showed companies in the top third of their industry who engaged in DDD had 5% greater productivity and 6% more profitability than competitors (McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012). The evidence is strong that performance is substantially improved through the use of data; however, this is a difficult to actually implement and requires organizations to invest in technology and trained professionals to increase the chances of being able to turn data into value.

[2] Data-Driven Decision Making is essentially under the same principles of Evidence Based Medicine and Evidence Based Management, using data and best practices to drive the field. The terminology changes depending on the field.

2.4 Process Mining as a Method of Assessing Workflow

Often within an organization various different workflows are executed in order to carry out the organization's intended mission. However, frequently these processes go undocumented, as is there is no formal process laid out for the workflow by, or there is an intended process or flowchart laid out but the execution differs from the ideal. Process mining methodologies fall within the realm of business process management, which aims to provide organizations with the tools to understand and control their process workflows through the use of information technology. Traditionally, the use of process mining has been done through extracting event logs through transitional information systems which reside within the organization (R. Mans et al., 2008). As an individual interacts with a single or multiple information systems, event logs containing unique identifiers for the individuals, an activity name of which the individual engaged in and a timestamp for when the activity was done is generated, forming the essential elements necessary for process mining (R. Mans et al., 2008). The event logs can then be uploaded into a process mining tool to be analyzed.

Figure 2: Scheme for the types of Process Mining (Wil M. P. van der Aalst, 2011)

Figure 2 shows the three types of purposes/analysis that can be conducted with the use of process mining and event logs: 1) Discovery, 2) Conformance and 3) Extension (Wil M. P. van der Aalst, 2011; R. S. Mans, Schonenberg, Song, van der Aalst, & Bakker, 2008). Discovery is done when there is no prior model for the process and the workflow is unknown. It then uses the event logs to uncover the sequence of activities to uncover the workflow. Conformance can be utilized when there is an existing model and the variation between the ideal process and the actual workflow is sought to be understood through delta analysis and conformance testing to see how the actual process "fits" into the ideal (W. M. P. van der Aalst, 2005). And finally, extension is often done for quality improvement to identify areas where the process can be enhanced such as identifying bottlenecks, variations and frequency. Process mining has shown to be an effective tool in healthcare and in other industry sectors to provide organizations with control over their process, identify areas of concern and formulate best practices (W. M. P. van der Aalst, 2005; R. S. Mans et al., 2008). Process mining is useful as it provides organizations a way of assessing and monitoring their processes. The alternative would be extensive manual observation to develop flowcharts, schemes and work diagrams of what is occurring. The use of process mining can provide Student Run Free Clinics with a relatively easy and effective way of understanding their process and highlighting areas for improvement.

2.5 Dashboards for Monitoring and Management

Table 2: Differences between Dashboards and Scorecards (Wayne Eckerson, 2007)

[redacted]

A notable type of data visualization that has become popular are dashboards. Before speaking on the use of dashboards in healthcare for decision making it is important to clarify what is meant by a dashboard, and the similarities and differences from that of a scorecard. While the two tools share similarities and have recently been converging and overlapping in some areas of use, each still has an intended and distinct purpose of use (Table 2). Firstly, both are in the realm of business intelligence (BI), using tools and technology in conjunction with data warehouses, mining, and integration to communicate, monitor, and analyze business technology (Wayne W. Eckerson, n.d.). In regards to their differences, dashboards are used to display performance metrics while scorecards display progress related metrics; additionally dashboards operate in real time to track a various metrics while scorecards are monthly snapshots that capture targets or thresholds (Wayne Eckerson, 2007). Furthermore, dashboards are capable of tapping into next level data analytics and engage in forecasting and predictive activities to give insights to what the future holds based on historical data (LaValle et al., 2011).   It is evident that each has a distinct use, however, dashboards have evolved to incorporate many of the features prevalent in scorecards and thus a single dashboard can be leveraged to highlight the strengths of both tools.

Regarding its use in healthcare, dashboards have been very instrumental as a quality improvement tool to enhance clinical and nonclinical processes. According to one study of 139 health care institutions, essentially all areas in healthcare are influenced by the use of dashboards in order to make decisions, specifically QI projects being ranked first followed by strategic planning and public reporting coming in second and third (Kroch et al., 2006). Generally, the use of dashboards has been most prevalent amongst clinical process, however, there has been increased use in the nonclinical setting to monitor and improve processes related to workflows, errors, readmissions, bed utilization, and operational management due to their wide applicability and benefits. (Egan, 2006; Rosow, Adam, Coulombe, Race, & Anderson, 2003). Additionally, moving from the theoretical benefits described in the literature to the manifest, it has been seen that prolonged use of dashboards was correlated with higher quality index and performance rankings with the study showing a difference of 4.7 points (Kroch et al., 2006). However, the impact of dashboards is not without limitations and restrictions. Effective use of dashboard development, governance, and measure selection are key to obtaining the benefits found within the literature (Kroch et al., 2006).

2.6 Lean Processes to assess Patient Flow and Wait-Times

Wait-times as a result of inefficient processes can have detrimental consequences for not only the organization but also the health of the patient. Studies have shown that there is a strong inverse relationship between wait-times and patient satisfaction; furthermore, this dissatisfaction can increase to the point that the patient may leave without being seen (Chan, Killeen, Kelly, & Guss, 2005; Michael, Schaffer, Egan, Little, & Pritchard, 2013). Increased wait-times are caused by a multitude of reasons: limitations in resources, improper allocation of resources, training, protocols and so on. Many organizations, inside and outside of healthcare have sought performance improvement methodologies, such as Lean Six Sigma. These activities have shown positive results in understanding their processes and optimizing them to reduce wait times (Dickson, Singh, Cheung, Wyatt, & Nugent, 2009; Eitel, Rudkin, Malvehy, Killeen, & Pines, 2010; Ng, Vail, Thomas, & Schmidt, 2010). The tools included in these methods, such as value stream mapping (VSM), process diagrams, simulation, statistical forecasting, demand management, and so on have provided organizations with the ability to make major improvements despite constraints of resources, such as having to add additional beds or staff (Ng et al., 2010). These tools are not only effective for improving efficiency and reducing wait-times but have seen in healthcare to increase patient satisfaction and decrease the rate of patients leaving without being seen (Chan et al., 2005)

2.6.1 Implementing Processes so that to Increase Patient Satisfaction

As briefly mentioned in the previous section, increased wait-times can lead to low patient satisfaction. This can in turn cause the patient to leave without being seen, meaning they never received the care they were seeking. It is worth mentioning that in addition to creating Lean processes in a health organization, which reduce wait-times subsequently increasing patient satisfaction, the processes themselves can be developed to increase the perception of positive care and therefore improve patient satisfaction. A model published in the literature suggests the following formula for satisfaction:

Equation 1: Satisfaction Formula (Soremekun, Takayesu, & Bohan, 2011)

$$Satisfaction\ (S) = Perception\ (P) - Expection\ (E)$$

Where Perception (P) is defined as

$$Perception\ (P) = (Sensory\ Information) * (Psychological\ Processing)$$

The formula essentially highlights that the more Perception exceeds Expectation then the higher the level of satisfaction. Using this principle, five concepts regarding the psychology of waiting have been identified to increase impact the perception of wait-times which are seen in the following Table 3 (Soremekun, Takayesu, & Bohan, 2011).

Table 3: Five Concepts to Impact Perception of Waiting. Developed from (Soremekun, Takayesu, & Bohan, 2011)

Concept	Explanation
1. Design of the service environment	• Proper levels of temperature, lighting and noise level. • Spatial layout (example: segmented ER Dept.) • Visibility of attentive employees engaging in activities
2. Early interactions during the wait period	• "During the wait period, early interactions with staff disproportionately affect the perception of the wait time. Negative interactions early in the wait period increase the perception of the overall wait time, whereas positive interactions have the opposite effect."
3. Occupied time vs. unoccupied time	• Wait times during occupied times feel shorter than unoccupied time • Incorporate video, games, surveys, education, Wi-Fi and etc.
4. Uncertain waits vs. known, finite waits	• "Uncertain waits are associated with anxiety and have been shown to increase the perception of wait times more than known finite wait times." • Provide reasonable estimates in wait times to patients with also erring on the side of caution.[3]
5. Starting a process earlier, regardless of the overall duration of the service interaction	• If multiple services are involved, start other services while waiting for one. Early initiation of a service can decrease perception of wait time even if the overall time will remain unchanged.

[3] While this may seem initially concerning, the article sites a study where this has been implemented and shown to be successful with minimal consequences.

2.7 Summary of Background Literature Review

Our search into background literature revealed several findings relevant to our purpose. Firstly, the need for avenues to serve the uninsured is still warranted; while the ACA has done a great deal to allow more individuals to obtain coverage, gaps still remain that leave many uninsured. A viable option to help aid these uninsured in receiving some level of healthcare and assistance are SRFC. SRFC have shown success at not only training the next generation of healthcare professionals but also at providing quality services that improve the health status of those who they administer care to. While much literature is present regarding the clinical aspects of SRFC, literature on the nonclinical or administrative side has yet to become prevalent. This entails literature regarding workflow, operational efficiency, wait-times, quality measures, resource utilization and other administrative efforts that are prevalent amongst all healthcare organizations. Having an effort of monitoring, reporting and quality improvement is important for any organization but especially so in healthcare as they can impact the success of the organization and more importantly the lives of the patient. Several tools and methodologies have been identified as potential prospects for quality improvement efforts. These include, process mining, data visualization and Lean Six Sigma methodology as effective ways of monitoring, assessing and conveying what is occurring within the processes of an organization. With the use of these tools, organizations such as SRFC generated the data they need to understand their processes and optimize them to improve utilization of resources, cut down on wait-times and improve patient satisfaction.

Chapter Three
Methodology

3.0 Background

MedZou Community Health Clinic offers a range of services during general clinic, held every Thursday of the month. There are between 15-20 patients seen at each clinic. The services that comprise general clinic are Nursing, Med. (Medical) Student Assessment, Assessment Presentation, Physician Assessment, PHT (Preventative Health Treatment), Social Work and Pharmacy. Generally there are two nurses, four medical teams comprised of two medical students[4], two physicians, 1-2 pharmacy teams and one PHT and social work team. The critical pathway during the general clinics is for a patient to arrive, see a nurse who will obtain vital signs, then progress to a medical student team who will conduct an assessment of the patient. The team will then present their assessment to a physician and then the three of them will reassess the patient under the guidance of the physician. After which, the patient may see one or all of the ancillary services: PHT, social work and pharmacy, which may also happen earlier depending on availability of the critical pathway services. A flowchart illustrating this workflow can be seen in Appendix B.

3.1 Study Design

This study was implemented from April 2015 to December 2015 at MedZou Community Clinic during general clinic days, which are held every Thursday of the month. All services mentioned in the previous section were tracked including arrival and

[4] The medical student teams are generally paired M1/M2 and M3/M4 with 'M' standing for 'medical student' and the number the year they are currently in within their program.

departure. Through the implementation of timecards and observation, we collected time data for each activity as the patient received the services. This data was then then inputted into a Microsoft Access Database for easy storage and export. This database would then export as a Microsoft Excel dataset to be uploaded into our data analysis tools, which is Disco for process maps and Tableau for dashboards. The VSM will then be filled out using the data from the Excel dataset and Disco Process Maps.

3.2 Data Collection Method

To collect process times for this study we implemented two observational strategies to collect data quantifiable data, implementing timecards and having volunteers shadow the patient. This process data serviced as the bases for which all other data was derived with some parts being supplemented by demographic data from MedZou's SharePoint.

3.2.1 Timecards

Figure 3: MedZou Process Times Timecard

M/D

MedZou Process Times

Please fill out as the patient progresses through each step

Patient # ___________

Apt. Time: ___________

Activity	Time Started/Ended	PawPrint
Arrival		
Nursing	/	
Social Work	/	
PHT	/	
Pharmacy	/	
Med Students	/	
Resident/ Attending	/	
Departure		

The initial strategy was to implement timecards, as seen in Figure 3, that the patient would receive upon arrival which would then progress along with them as they received each service, being filled out by the volunteer at that station. This protocol initally worked when one of the QI Chair was present to manage the process; however, hand off to the Temporary QI Chair during the summer session was poor and the effort to maintain the protocol a self sustaining process was poorly executed. This resulted in many incomplete timecards and timecards with errounious data.

3.2.2 Shadowing

We switched the data collection strategy in August 2015 to physical observation. Physical observations involved having 1-2 volunteers shadow the patient or observe from a distance in order to mark the start and end times for each rendering of service. The data collection tool the volunteers used while shadowing can be seen in Appendix C. This method produced better data but drastically limited the volume of data that could be collected to 1-3 patients per clinic night. Additionally, occasional confusion between the volunteers sometimes lead to both of them observing the same patient and thus producing duplicate results; this happened three times during the duration of this study. Nonetheless this method was deemed most effective and was utilized for the remainder of the study.

3.2.3 Data Storage, Processing and Export

The timecards or observation sheets the volunteers filled out were then collected and inputted into an Access Database which linked the Patient IDs to the various activities/services they received. The form which was developed for data entry can be seen in Appendix D along with the tables that were needed to appropriately capture the data. During the process of data entry, those observations which contained errors that could be corrected, such as a null departure or end date, were corrected. Those cards which contained too many errors, such as services with the same end time or too many null entries, were thrown out and not considered. Once the data was cleaned it was then exported as an Excel dataset for analysis.

3.3 Data Analysis

In order to conduct our analyses, we sought out industry leading BPM and QI software tools to that are intuitive to use and can easily be implemented in a SRFC. Since SRFC are often price sensitive due to the scale and nature of their operations, the tools would have to have academic or affordable options and also not jeopardize on robustness and analytical power. These tools would have to be able to provide measurable results of our process which we can then use to draw conclusions from in order to implement changes in operations that would improve clinic performance and patient health.

3.3.1 Selection of Technology

Several technologies/software were used in this study to accomplish different purposes. Most were chosen because they were industry standard that met our purposes, as is the case for Microsoft Access for serving as our database, Microsoft Excel for outputting our dataset output and performing a few calculations, and finally Microsoft Visio for mapping and developing flowcharts and VSM.

In our analysis we sought to develop process mining maps and dashboards for which there is no set standard software in industry and thus we were left with several options. For process mining and map development we initially used ProM 6 which is a generic open-source framework of process mining tools, developed by the father of process mining, Professor Wil M.P. van der Aalst (http://www.processmining.org," n.d.). However, the open source nature of the tool proved difficult to use and we were confronted with many technical issues. We sought alternatives and found Disco by Fluxicon which is a commercial and more intuitive process mining tool developed by a few of the students of van der Aalst (*Disco*, n.d.). Additionally, an academic version was available for Disco and preliminary use deemed it appropriate for this study.

Figure 4: Magic Quadrant for Business Intelligence and Analytic Platforms

[redacted]

Our choice in dashboard software would have been more arduous since the market is saturated with vendor solutions. However, familiarity, experience and industry reviews narrowed the search to a few vendors. Tableau was ultimately chosen due to its use by reputable organization consistently scoring well by Garner's review and personal experience with its easy to use interface (Figure 4) (Gartner, n.d.; "Gartner Positions Tableau as a Leader in Magic Quadrant for BI and

Analytics Platforms," n.d.). An academic version for Tableau was also available which was used in this study.

3.3.2 The α-algorithm and Process Mining

Equation 2: α-Algorithm ("Process Mining: Beyond Business Intelligence," n.d.)

[redacted]

Figure 5: Principles within the α-algorithm ("Process Mining: Beyond Business Intelligence," n.d.)

[redacted]

Analysis in Disco is done by the use of classification algorithms, namely the α-algorithm, one of the first and most used process mining algorithms. The algorithm is shown in Equation 2 and some of the principles within it are described in Figure 5 ("Process Mining: Beyond Business Intelligence," n.d.). Essentially the algorithm sequences the activities chronologically in accordance to their timestamp. This however is not enough since activities may or may not be contingent upon one another, occur parallel or by choice ("Alpha Algorithm — Personal Wiki," n.d.). Thus the algorithm takes these into account by first saying that if activity X > activity Y then there is a direct succession. However, if there are no instances in which Y > X then there is likely a causality of X -> Y. In situations in which there is both X > Y and Y> X, the relationship is described as parallel with both activities occurring simultaneously. Situations are indicated as having a choice when there is no X > Y and no Y > X. This is a very crude and simple explanation of what is occurring in the algorithm but by factoring all these principles, the algorithm generates a footprint for that log which ultimately acclimates into a map generated by taking into account all the different footprints.

The classification of steps occurs in the backend of Disco, which the user has no control over. However, through the use of filtering criteria the user can add in and adjust constraints to generate a process map that meets the user specifications and displays a desired view of the process. It could be argued that Disco is also part diagnostic tool, allowing for the user to obtain statistical information, outside of the generated process maps, on each case ID and variate present. This allows for deep analysis of what is occurring within the map to uncover findings and develop hypothesizes. Both of these features were utilized to generate frequency of activity and median duration view process maps along with deeper analysis of specific cases and variations within the maps.

3.3.3 Dashboard Development

Figure 6: Dashboard Scoping Design Tool From Juice Analytics

Scope	☐ **Broad:** Displaying information about the entire organization	☐ **Specific:** Focusing on a specific function, process, product, etc.
Business role	☐ **Strategic:** Provides a high-level, broad, and long-term view of performance	☐ **Operational:** Provides a focused, near-term, and tactical view of performance
Time horizon	☐ **Historical:** Looking backwards to track trends ☐ **Snapshot:** Showing performance at a single point in time	☐ **Real-time:** Monitoring activity as it happens ☐ **Predictive:** Using past performance to predict future performance
Customization	☐ **One-size-fits-all:** Presented as a single view for all users	☐ **Customizable:** Functionality to let users create a view that reflects their needs
Level of detail	☐ **High:** Presenting only the most critical top-level numbers	☐ **Drill-able:** Providing the ability to drill drill down to detailed numbers to gain more context
Point of view	☐ **Prescriptive:** The dashboard explicitly tells the user what the data means and what to do about it	☐ **Exploratory:** User has latitude to interpret the results as they see fit

We opted to develop two types of dashboards, a leadership dashboard and a quality improvement dashboard. The literature suggested that dashboards generally fall into two types; reporting which measures and monitors and exploration which helps facilitate understanding (Figure 6) (Juice Inc., 2009). The leadership dashboard serves more of a reporting purpose, showing a higher view of processes without much detail to understand how the organization is doing as a whole. The quality improvement dashboard has the ability to show the same information but at a much granular view in order to ascertain the inner workings of various processes for improvement, thus serving a more exploration purpose. In order to develop dashboards through Tableau we consulted the literature on the methods, strategies, and principles in developing dashboards to understand what were best and common practices in the field. One of the sources that was very useful in dashboard development was a document from Juice Analytics for “A Guide to Creating Dashboards People Love” (Juice Inc., 2009). Using the tool, we determined that our leadership level dashboard should be broad, strategic, historical, one-size-fits-all, high level of detail, and prescriptive. For a quality level dashboard that is interested in improving performance we wanted a specific focus on operational business roles using historical data. This dashboard can be more customizable depending on who is doing the analysis and therefore also allows a drill-able level of data. The point of view will be exploratory since we want the user to be able to interpret the data in the given context to recommend solutions. Using the guidelines from our resources we built out a series of figures in Tableau which we then converted into dashboards. These include heat maps, boxplots, line graphs and control and run charts.

3.3.4 Value Stream Mapping (VSM) via Visio

We utilized basic principles in Lean Six Sigma to develop our VSM. We chose to show the flow of information and descriptive data for our value and non-value added steps in the critical pathway within MedZou, nursing -> med student -> physician. These services were chosen due to being the core patient encounter and the least variable. Developing the VSM was very straightforward since Visio has the tools within it to formulate them. Using the data, we generated from Disco and a few calculations in Excel, we were able to fill out the VSM to properly convey what was occurring in our process both visually and empirically.

3.3.5 Calculating the Cost of Times

Data from the previous sections gave us an indication of duration of services and wait-times during various aspects of the process. In order to gain a context to what these times can mean we have developed a method of calculating the opportunity cost of the visit for the patient using the data from previous sections of the study. Equation 3 shows the formula we used to calculate the opportunity cost of a visit with the variables defined below. We obtained travel distance and duration data by calculating the difference between the zip code listed for the patient, in MedZou's SharePoint, and the address of the clinic. We did this by leveraging of a Visual Basic module which allows for formulas to be used in Excel to calculate distance and duration via incorporation of Google Maps Distance Matrix API[5] (more information in Appendix F). The SharePoint data for patient address contained many inaccurate or invalid entries; we therefore preprocessed the data to eliminate null or invalid entries and disregard outliers.

The 'Time at Clinic' is pulled from the VSM and is a summation of the value and nonvalue added steps. We chose to look at only the critical pathway since that is the most standard and what most patients come to clinic for. Finally, given that clinic operates from 5:00 PM to 10:00 PM, which includes dinner time for most, we decided to factor in a meal into the equation. Our calculation is limited to only one adult individual per address since we did not have the data to consider additional factories such as children or lost wages.

Equation 3: Opportunity Cost of Visit

$$\left(\left(miles\ travelled\ \times (mileage\ rate)\right) + (travel\ time) + (time\ at\ clinic) + (Meal)\right)$$

$where$:
$miles\ traveled = distance\ from\ patients\ address\ to\ clinic\ (Miles)$
$mileage\ rate = 2016\ Standard\ Mileage\ Rate\ (54\ cents)$
$travel\ time = duration\ from\ patients\ address\ to\ clinic\ in\ minutes\ (Hours)$
$time\ at\ clinic = value\ added + nonvalue\ added\ activities\ (Hours)$
$meal = \ \$6\ based\ of\ the\ cost\ of\ a\ McDonald's\ Big\ Mac\ Meal\ in\ Missouri$
$With\ time\ data\ converted\ into\ a\ dollar\ about\ by\ multiplying\ by\ minimum\ wage.$

[5] Application Program Interface (API)

Chapter Four
Results

4.0 Overview of Data Obtained

Through the implementation of our study design from April to December of 2015 we collected, in total, 66 cases/records that were deemed useable for our study (Figure 7). Our initial method of using timecards yielded 37 records from April to July and from September to December we collected 29 records via observation. 299 services were utilized within the 66 cases/records with a median/mean case duration of 107/110.5 mins. The following contain results for each section of our study.

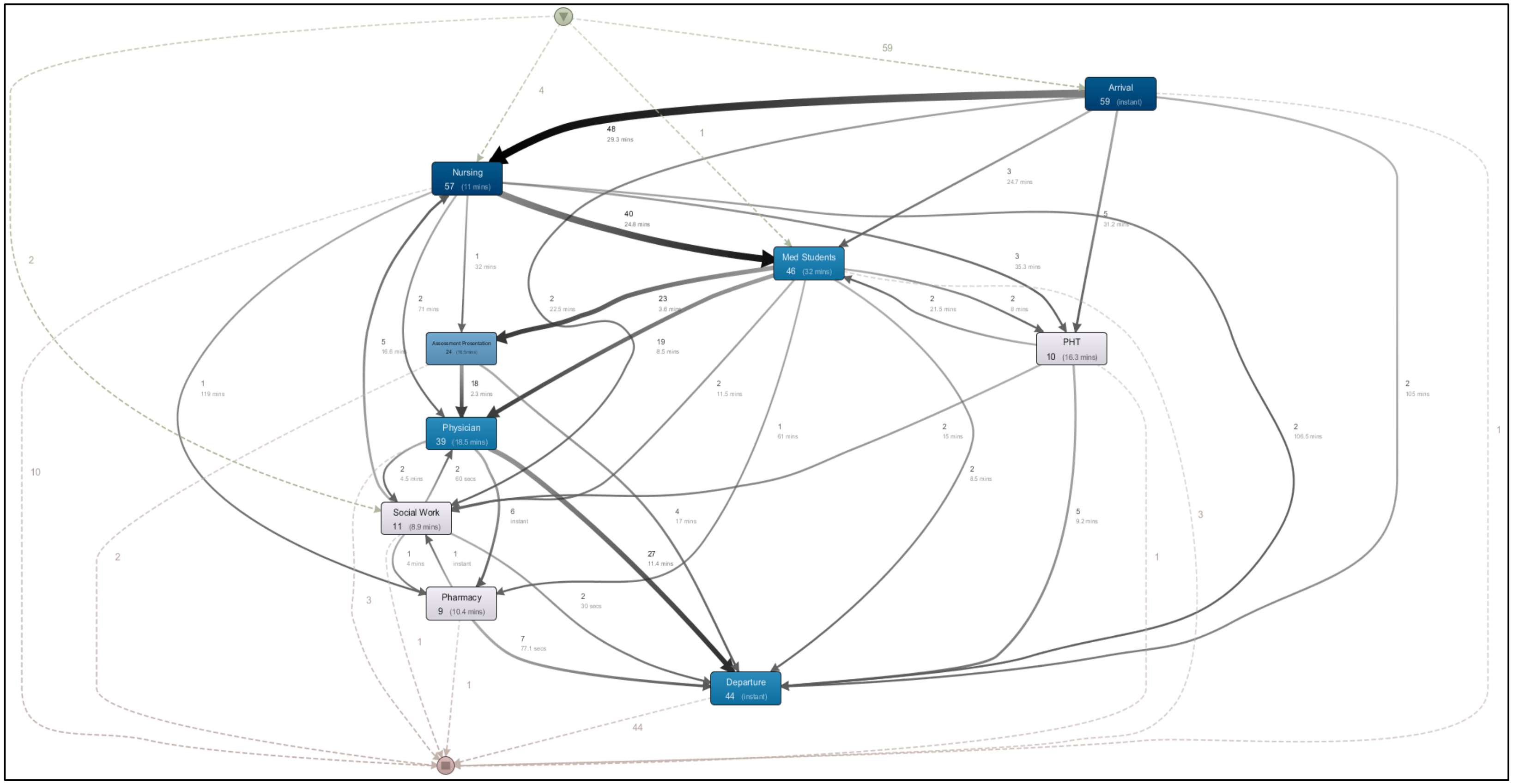
Figure 7: Records Collected During Study Period

Records Collected:
April: 7
May: 21
June: 3
July: 6
August: 0
September: 3
October: 16
November: 7
December: 3
Total: 66

4.1 Process Mining Overview

Through the use of Disco, we were able to develop various process maps and obtain statistical data regarding our workflow. Four maps were generated, Figures 8 and 9 show frequency as the primary metric with mean time in parentheses as the secondary metric and Appendix E contains two performance focused process maps with median duration as the primary metric and frequency as the secondary metric. Figure 8 displays every pathway and variation within our process. In total, 66 cases are contained within 34 variant pathways.

Figure 8: All Paths Process Map (Frequency)

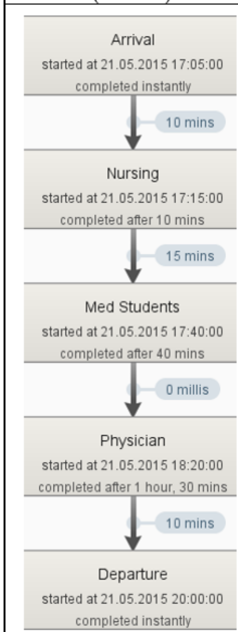
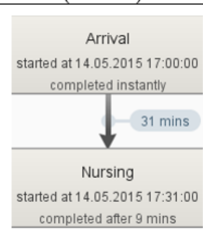
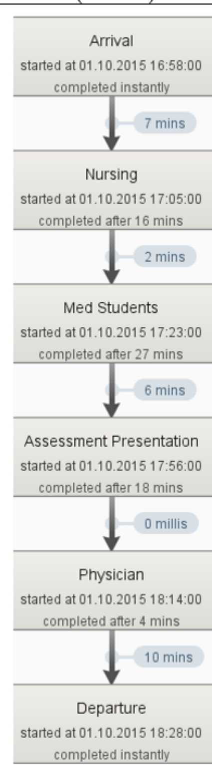
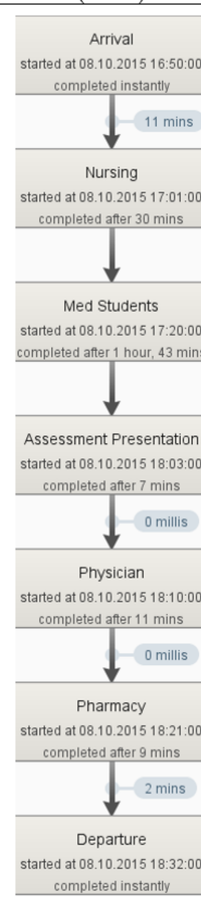


Note: Values in parentheses indicate mean time. For median times consult Appendix: E.

4.1.1 Process Mining Variation

Further analyzes has shown that 48.5% of the cases are found within only four variants (Table 4). Looking at these four variants we saw that Variant 2 was likely a result of a data collection issues since it stops abruptly after Nursing. Variants 1 and 3 are essentially the same with Variant 3 containing the “Assessment Presentation” which was the new activity added when the study was adjusted. Variant 4 is identical to 1 and 3 except that it includes “Pharmacy”. What we take away from these four variants is first, a majority of patients are engaging in the critical pathway in its proper order.

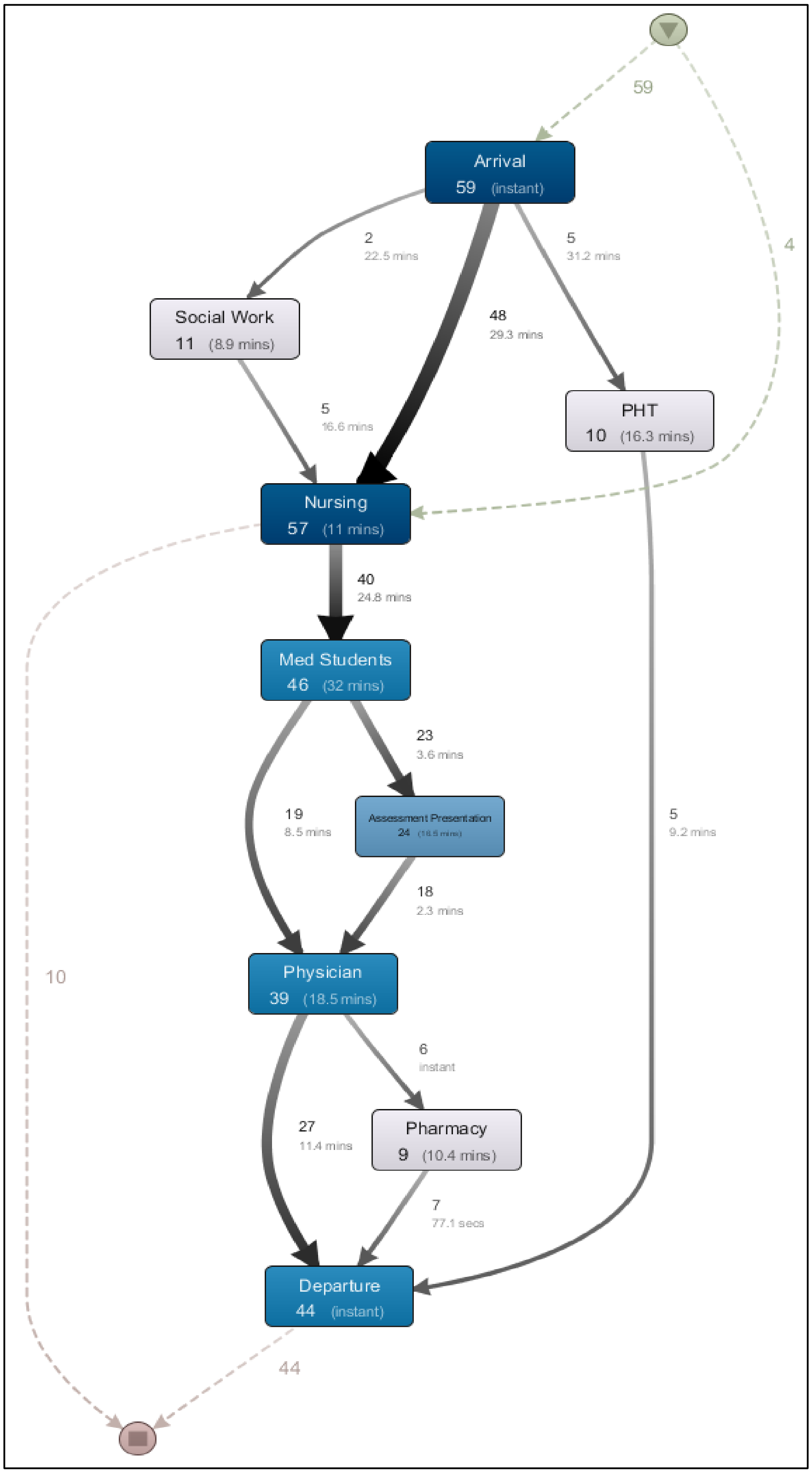
Table 4: Most Frequent Process Flow Variants

<table>
<tr><th>Variant 1, 11 Cases (16.7%)</th><th>Variant 2, 9 Cases (13.6%)</th><th>Variant 3,9 Cases (13.6%)</th><th>Variant 4, 3 Cases (4.5%)</th></tr>
<tr>
<td>
</td>
<td>
</td>
<td>
</td>
<td>
</td>
</tr>
<tr><td>Valid (Identical to 3)</td><td>Invalid</td><td>Valid (Identical to 1)</td><td>Valid</td></tr>
</table>

4.1.2 Process Mining Map: Majority Path

This is further seen in Figure 9 which shows the majority pathways after filtering out the noise from the less frequent variants. Secondly, our data suggests the presence of invalid variants, such as Variant 2, are most likely due to data collection issues. There exists the possibility that these invalid or unexpected variations may actually reflect what is occurring in the process, such as services occurring out of order or patients who walk out. Examining the remaining 30 variants, which contain between 1-2 cases, we found variants that could be deemed invalid but may also be a data collection issue. Until our data collection processes is more controlled, it becomes difficult to identify which is which.

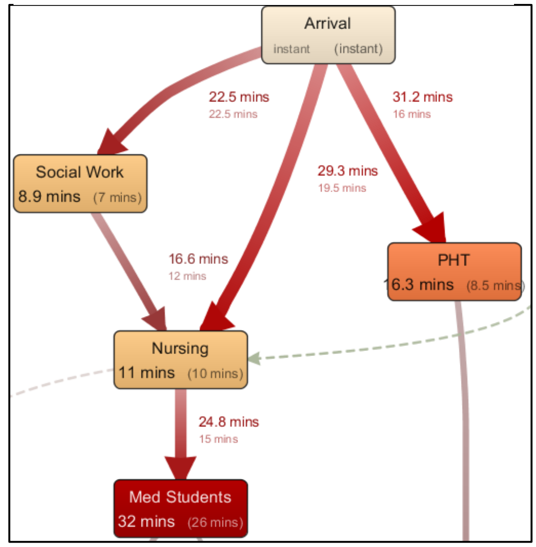
Figure 9: Majority Paths Process Map (Frequency)



Note: Values in parentheses indicate mean time. For median times consult Appendix: E.

4.1.3 Bottlenecks

Figure 10: Bottlenecks/Rate-limiting Services



Duration data suggests that long wait-times and possible bottlenecks are present in various areas of the process. Figure 10 is an excerpt from of a performance view process map showing mean and median duration times between services, with the thickness of the lines indicating higher mean duration. High mean times were present before Social Work, Nursing, PHT and Med Students. Except for Med Students, this is not unexpected since each of these services contains between 1 and 2 volunteers. Despite having the largest number of volunteers, Med Students seems to be the activity that is the most notable bottleneck. This can likely be attributed to the duration of time spent at this service.

4.1.4 Service Utilization

Disco was able to help us uncover insights into our process regarding utilization. Speaking with volunteers at MedZou, we heard that some of the stations felt like they were being underutilized. Our process maps showed that both Social Work and PHT were being underutilized seeing 11 and 10 patients respectably. Both of these services generally occur before the patient engages in the critical pathway, which the average time is 29.3 minutes and the median time is 19.5 minutes. Figure 11 shows the frequency and performance data for both of these services and we found median duration to be between

7 and 8.5 minutes. Aside from what appears to be an outlier in PHT, one or both of these services could fit into the time a patient is likely to wait while waiting for an available nurse. This would thus increase the utilization of these services and allow for the patient to have more value in their visit as opposed to waiting. While the previous section did indicate that both of these services have long wait-times that preceded them, we feel that a change of strategy and scheduling can result in lower wait-times and higher utilization which will be discussed further in our recommendations.

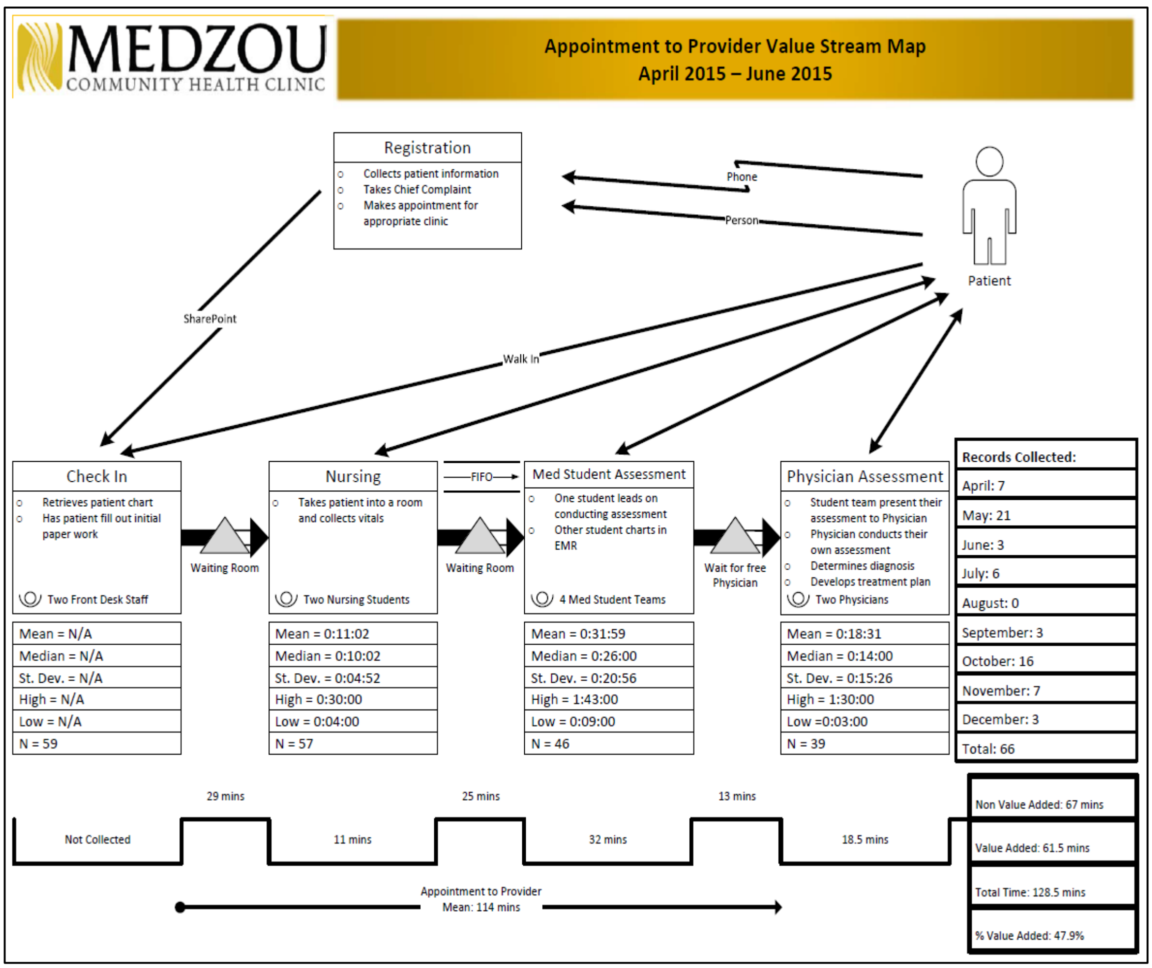
Figure 11: Frequency and Performance of Social Work and PHT

4.2 Critical Path Value Stream Map

The VSM in Figure 12 was developed using the data we obtained through process mining and has yielded several interesting insights. The hallmark feature of a VSM is displaying the difference between value and non-value added steps in a process. This feature was well manifested in our VSM showing that our value added steps amounted to 61.5 mins on average and our non-value added steps amounted to an average of 67 minutes, the percent value add for the entire process being 47.9%. This essentially means that our process is almost half administration of services and half wait-times. This can be most notably attributed to wait-times between Check In/Arrival and Nursing and between

Nursing and Med Student Assessment which is 29 and 25 mins respectably. Furthermore, there is a large duration range within all the services but most pronounced within the Med Student Assessment and Physician Assessments which have standard deviations near 21 and 15 mins. Overall the VSM shows that it takes, on average, 114 mins from appointment to provider with an entire episode of care taking over two hours, half of which is value added. This is likely due to variation in process and bottlenecks in resources.

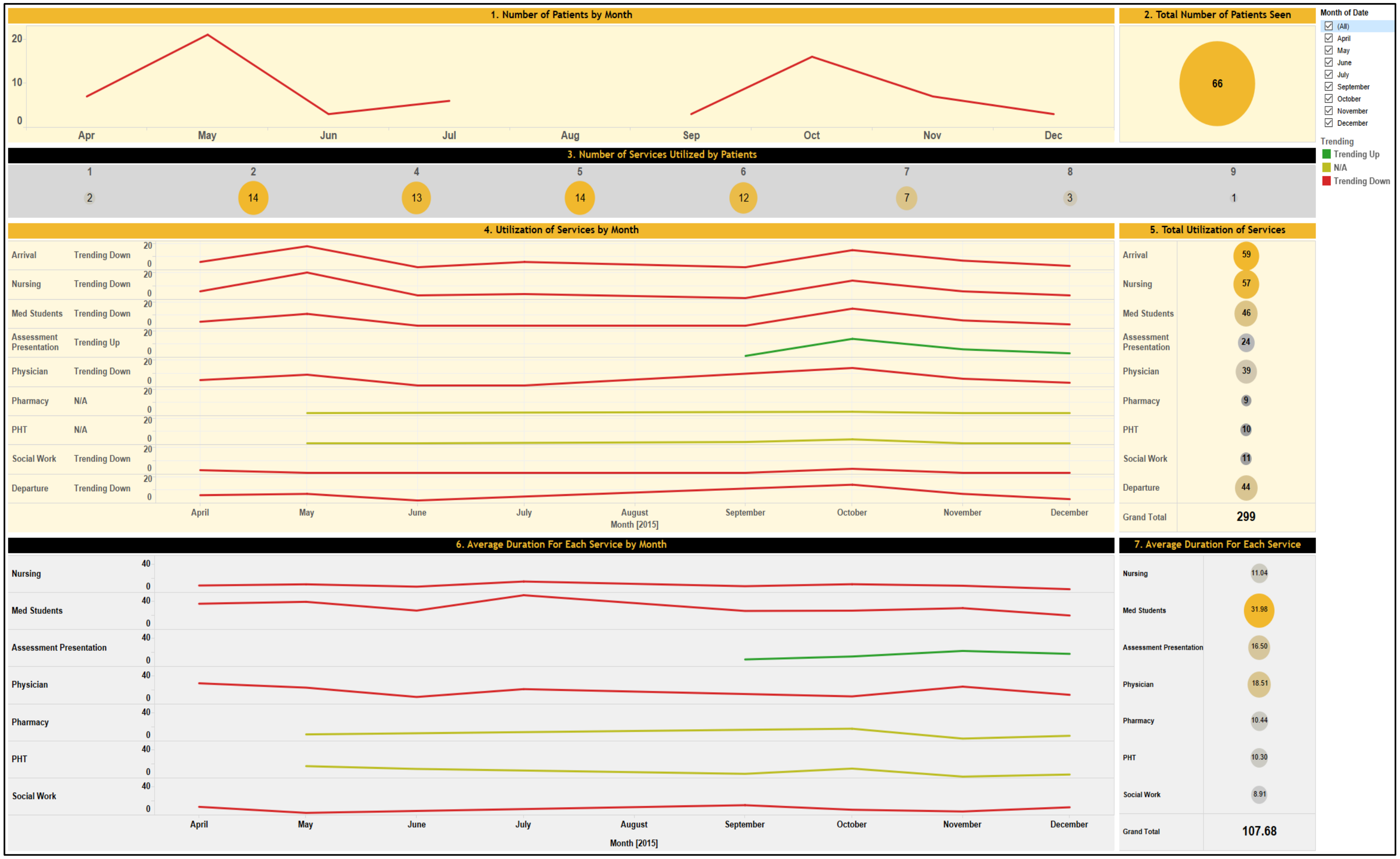
Figure 12: Critical Path Value Stream Map



4.3 Executive Level Dashboard

The executive level dashboard we developed in Tableau can be seen in Figure 13 comprising of 7 different figures/metrics which are filterable by month. The dashboard is structured to follow from top to button by number of patients seen, utilization of services and duration of services. Each metric is designed to provide a quick overview to leadership and present the facts necessary to understanding operations within the clinic. The lines are color coded depending on whether they are trending up, down or neither. The size and shading of the circles corresponds to the degree of the value. An executive will be able to deduce how many patients were seen, which services they utilized, and how long the services took. Using this data, they will be able to see which areas are of concern for the clinic.

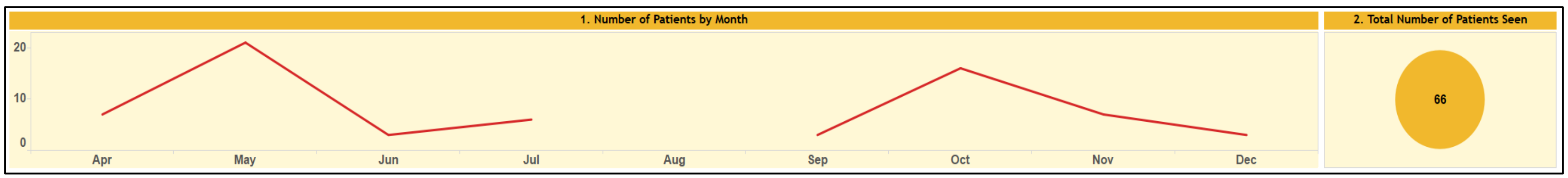
Figure 13: Executive Level Process Dashboard



4.3.1 Number of Patients Seen

The top two metrics deal with number of patients seen; the line graph shows the trend over time and Metric 2 displays the total number seen to date (Figure 14). The line graph indicates a downward trend in patients seen with a notable gap in August from when we did not collect data. We can see that data collection, on patients being seen, was highest in May and October. This shows us that inconsistency in our data collection process was due to the inability to track a large number of patients consistently.

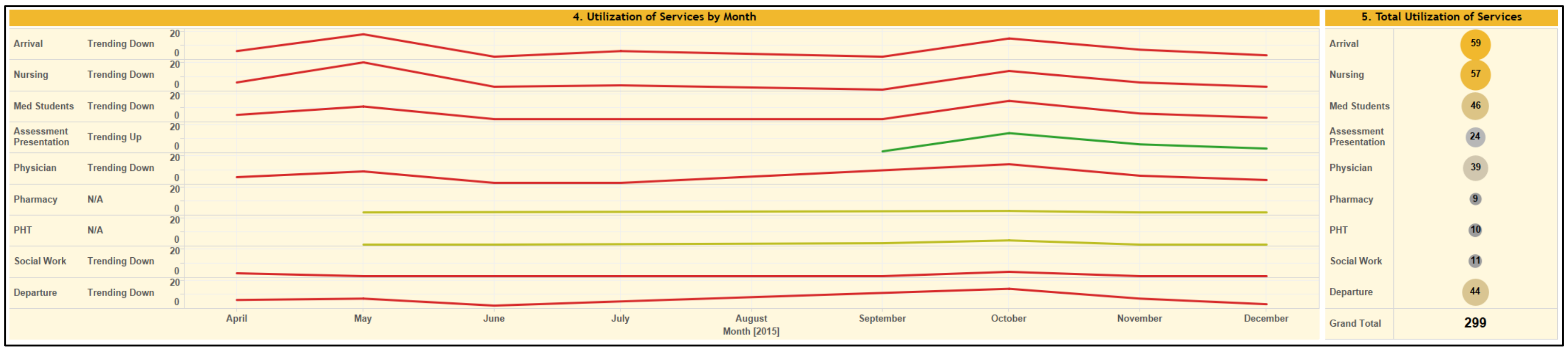
Figure 14: Executive Dashboard: Number of Patients Seen



4.3.2 Utilization of Services

The next three sections deal with utilization of services. Metric 3 contains a series of circles that change size depending on the number of services utilized by the patient (Figure 15). To ensure a holistic and comprehensive checkup, we would like the patient to see as many services as possible when they arrive at the clinic. Our data shows that most patients will see between 2 and 6 services with 2 and 5 services being tied for the number of services most utilized. Moving on to metric 4 we see a familiar line graph indicating the change in utilization for each service over time with metric 5 being the total utilization to date. Most all the services are trending downward for utilization as time progresses with only Assessment Presentation trending upward. This is likely due to its data being collected in the later part of the study. Nursing is the most utilized service followed by Med Students. Since the utilization of the critical path services are inconsistent from each other, this is most likely indicative of a data collection issue. The usage of these metrics can help determine which services are being underutilized and also which services are more in demand so to improve organization preparedness. Like with most of these metrics, they can also indicate directly or indirectly issues with data collection since missing values and inconsistences can be easily seen.

Figure 15: Executive Dashboard: Utilization of Services

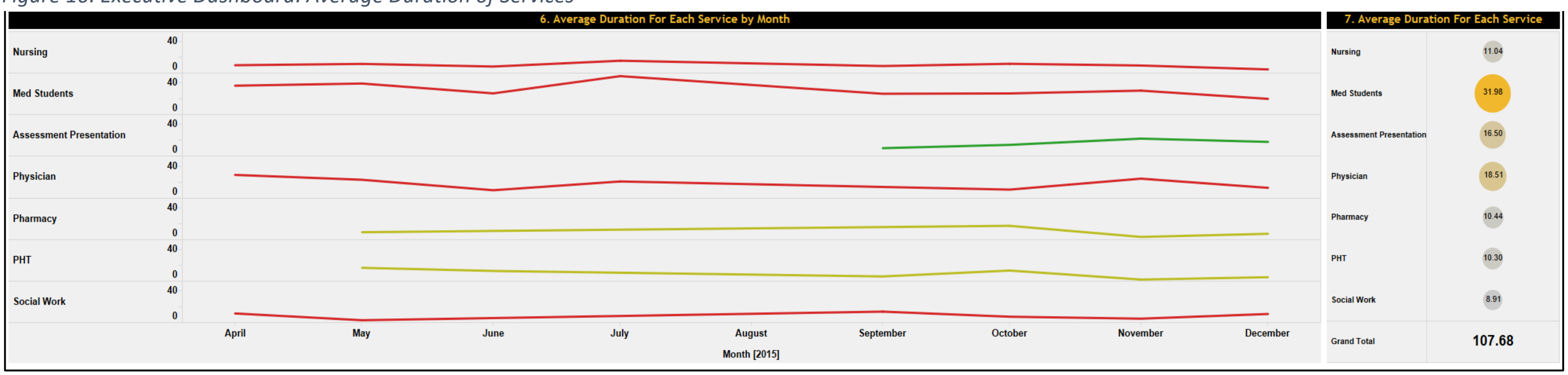


4.3.3 Average Duration of Services

The final two metrics deal with performance data, specifically average duration of services (Figure 16). While we want to make sure the patient is being seen the appropriate amount of time, that does not always translate to a higher average duration for each service. Low duration time may suggest volunteers are not spending enough time with patients and high duration times may be indicative of either complicated patients or inexperienced staff. While the latter is of course expected in a training ground, a certain level of performance is expected and if volunteers are taking too long with patients then it should be seen if specific training or resources can be provided to ensure an appropriate and efficient patient encounter. The same would apply if there was a rise in the influx of complex patients which attributed to volunteers having to spend more time with the patients. These metrics can help identify a trend in the process so that leadership can further inquire about what is occurring and suggest an appropriate response.

Looking at the data we obtain we see the same pattern of trend as seen in the previous metric. Looking at the average duration for each service, the activity Med Students stands out far above the rest with a duration of near 32 minutes. Social work has the lowest duration close to 9 minutes. MedZou leadership should determine the appropriate amount of time each activity should take. The use of this dashboard can help track how far above or below the reality is from its target threshold.

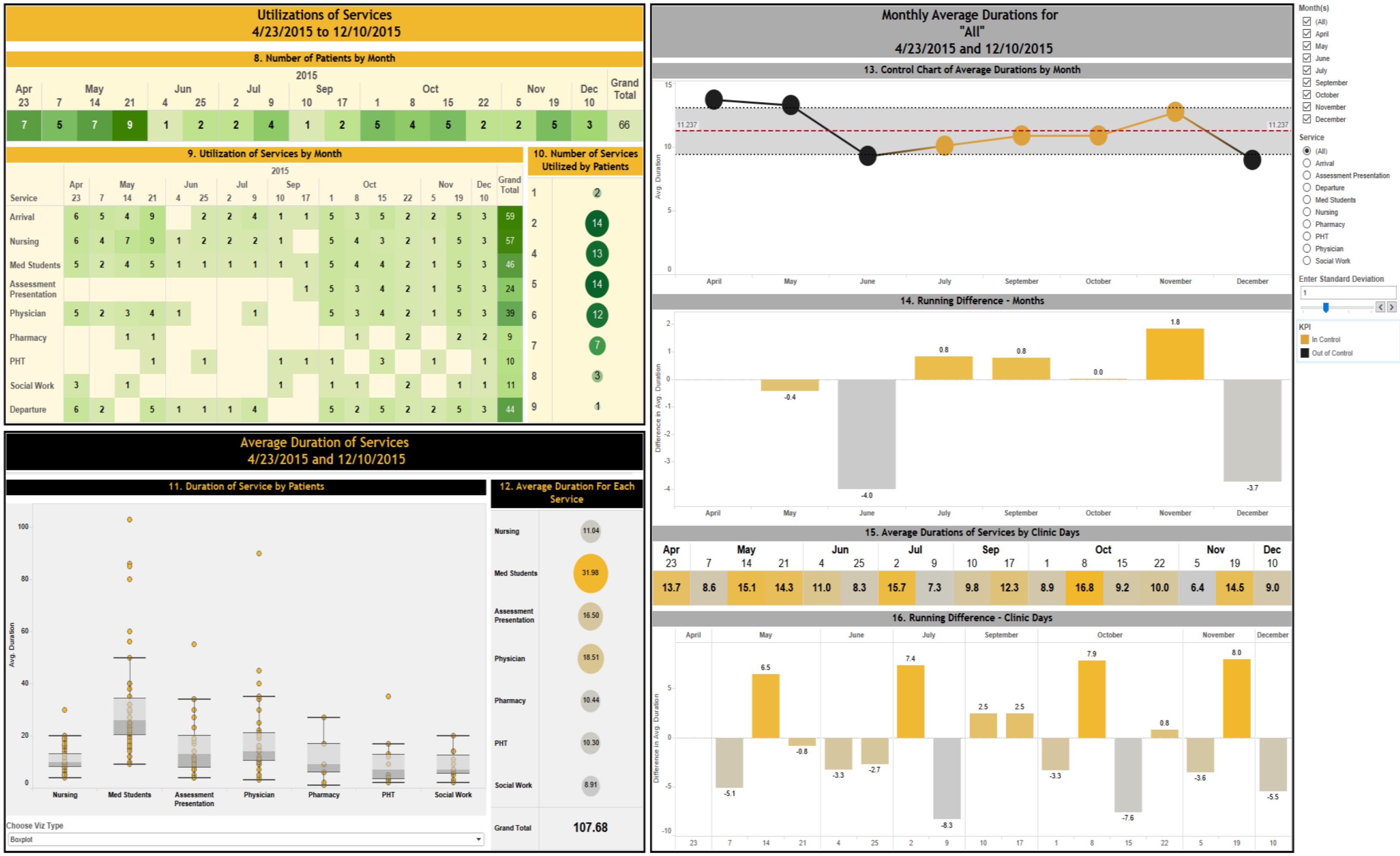
Figure 16: Executive Dashboard: Average Duration of Services



4.4 Quality Improvement Dashboard

The QI dashboard in Figure 17 is structurally with some of the same elements as the leadership dashboard but provides a more granular detail and more filtering options. This allows for drilling deep into various components of the process to uncover areas of improvement and see the effects of interventions. There are 7 metrics within this dashboard; metrics 8-12 on the left side show details for all the services while the right side, metrics 13-16 show detail for specific services. Just like the executive dashboard, the user will be able to see how many services were utilized by the current patient population and how long these services took. Additionally, the user will be able to identify outliers in the process through the boxplot and control chart. The added filtering options will provide detailed information of each service line.

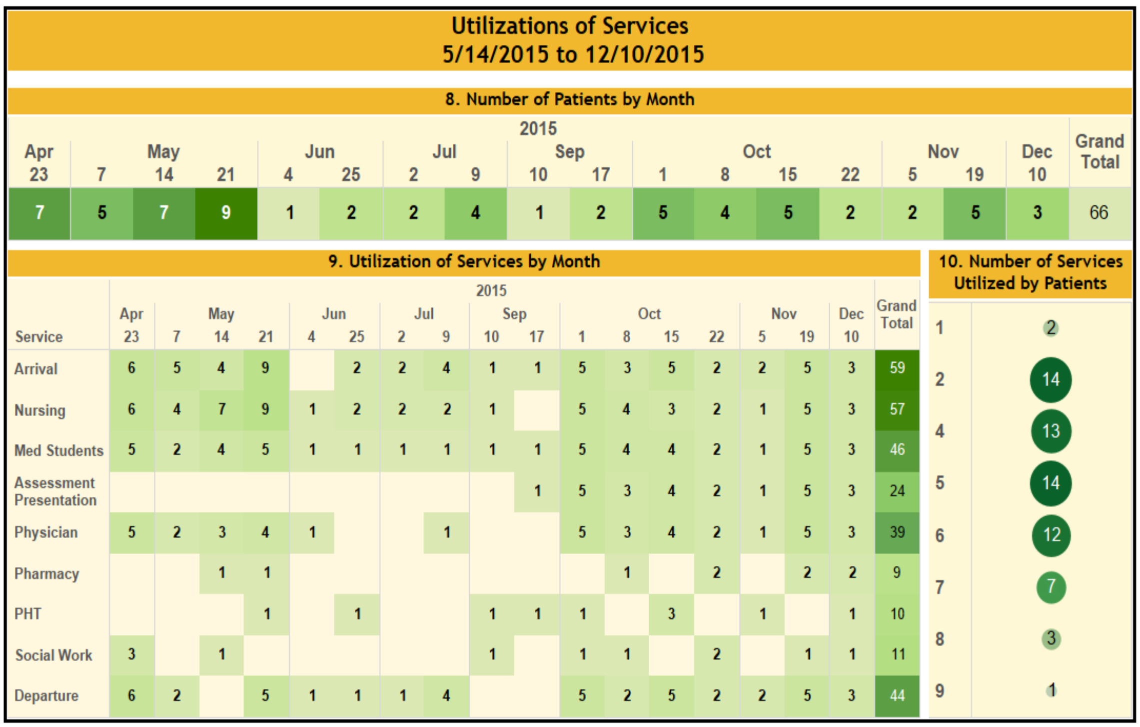
Figure 17: Quality Improvement Dashboard



4.4.1 Utilization of Services

Metrics 8-10 show detailed patient and utilization patterns through various views (Figure 18). The impact of our change in data collection methods can be seen evidently in metric 9; the data in the first half of the study is sparse compared to the second half which is more complete, although not as abundant. This is indication of the effectiveness of our adjusted data collection strategy of having volunteers shadow the patient.

Figure 18: Quality Improvement Dashboard: Utilization of Services



Utilizations of Services
5/14/2015 to 12/10/2015

8. Number of Patients by Month

2015	Apr 23	May 7	May 14	May 21	Jun 4	Jun 25	Jul 2	Jul 9	Sep 10	Sep 17	Oct 1	Oct 8	Oct 15	Oct 22	Nov 5	Nov 19	Dec 10	Grand Total
	7	5	7	9	1	2	2	4	1	2	5	4	5	2	2	5	3	66

9. Utilization of Services by Month

Service (2015)	Apr 23	May 7	May 14	May 21	Jun 4	Jun 25	Jul 2	Jul 9	Sep 10	Sep 17	Oct 1	Oct 8	Oct 15	Oct 22	Nov 5	Nov 19	Dec 10	Grand Total
Arrival	6	5	4	9		2	2	4	1	1	5	3	5	2	2	5	3	59
Nursing	6	4	7	9	1	2	2	2	1		5	4	3	2	1	5	3	57
Med Students	5	2	4	5	1	1	1	1	1	1	5	4	4	2	1	5	3	46
Assessment Presentation										1	5	3	4	2	1	5	3	24
Physician	5	2	3	4	1			1			5	3	4	2	1	5	3	39
Pharmacy			1	1								1		2		2	2	9
PHT				1		1			1	1	1		3		1		1	10
Social Work	3		1						1		1	1		2		1	1	11
Departure	6	2		5	1	1	1	4			5	2	5	2	2	5	3	44

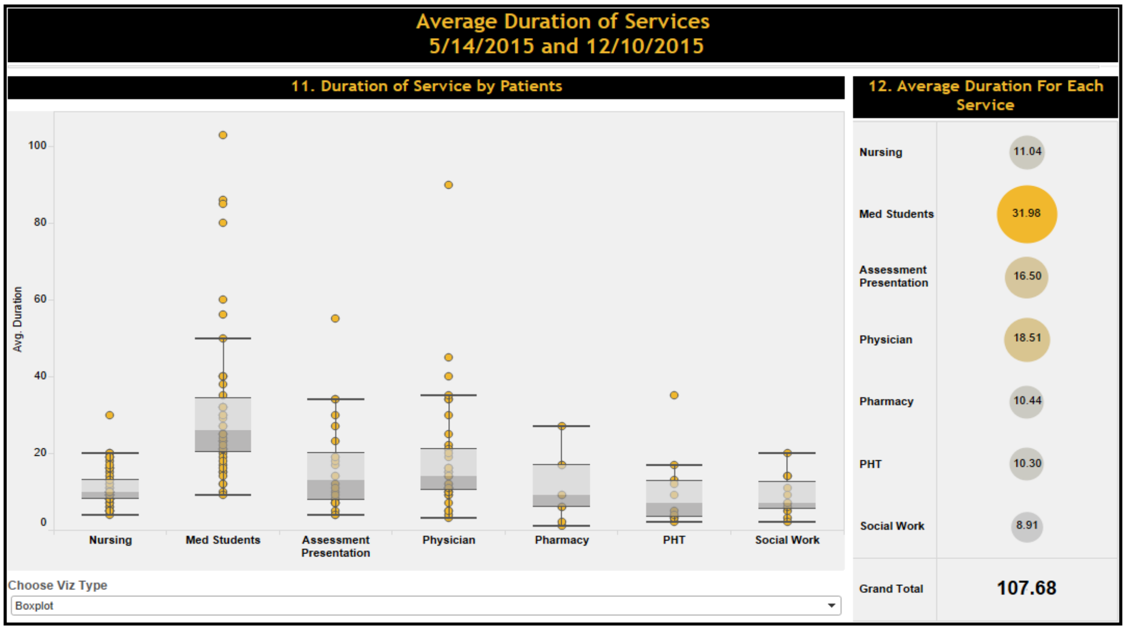
10. Number of Services Utilized by Patients

1	2
2	14
4	13
5	14
6	12
7	7
8	3
9	1

4.4.2 Average Duration of Surfaces

Metrics 11 and 12 deal with average duration of services showing by either patient or total aggregate (Figure 19). Metric 11 provides details into the variation of each services, from here we can see that many of the critical path services have a larger range than the ancillary services. Med student and physician assessment have the largest variations, probably partly due to presence of outliers. Metric 12 shows Med Students as the largest average duration of 31.98 minutes, which can be compared against the other services.

Figure 19: Quality Improvement Dashboard: Average Duration of Services



4.4.3 Monthly Average of Services

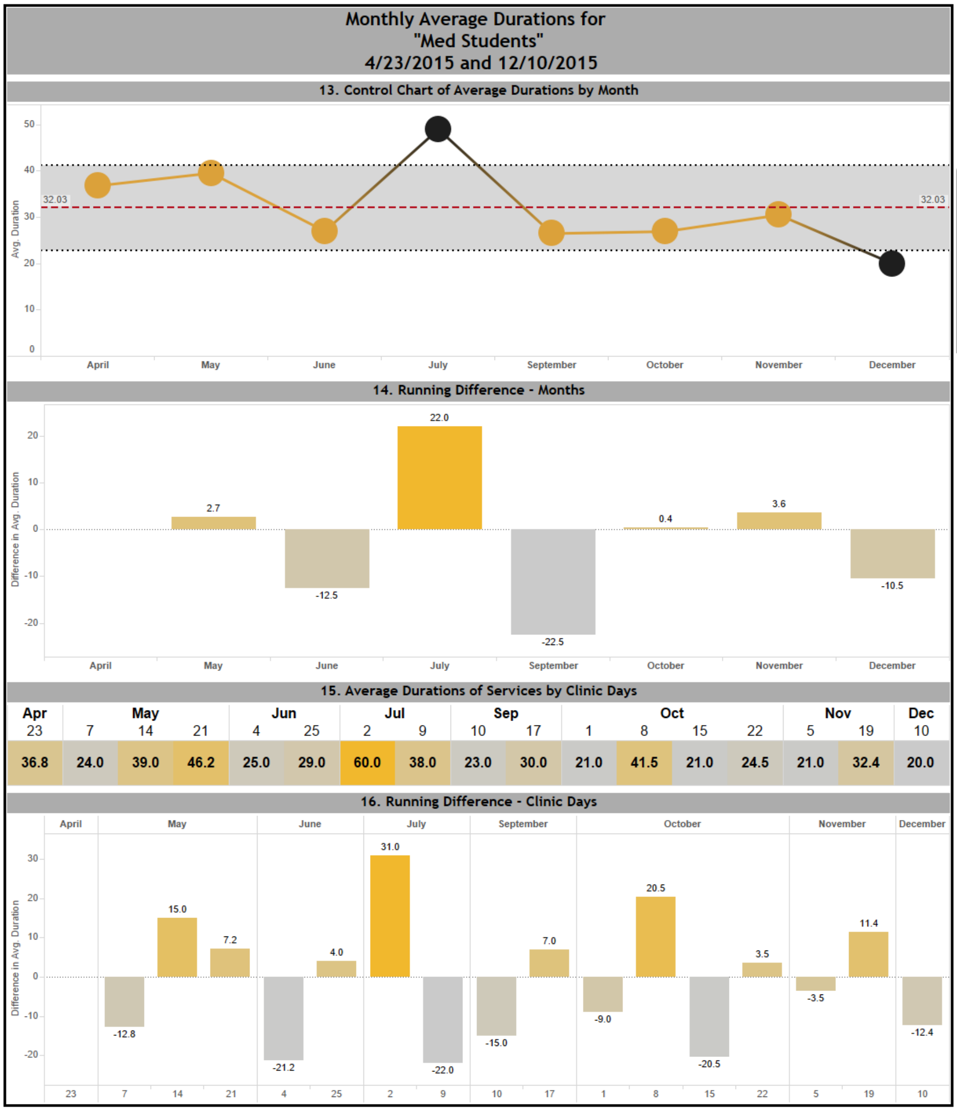
Metrics 13-16 on the right side of the dashboard show monthly duration numbers for a selected service. Metric 13 is a control chart showing the average durations for each month with an average line for the entire year. An upper and lower control limit are also present which are calculated by either 1,2 or 3 standard deviations from the average line depending on what the user selects. Metric 14 is a run chart showing the differences from one month to the next. Metrics 15 and 16 show similar data but at the level of clinic day. Applying these metrics to each service yielded several findings:

1. At 1 standard deviation from the mean, all services had at least two months that were shown as out of control, Physician Assessment had the most with three

months out of control. At 2 and 3 standard deviations all services were deemed in control.

2. The duration of PHT has steadily decreased over the year, starting with an average duration of 17 mins in May and ending with an average duration of 5 mins in December.
3. The most drastic difference in variation from one clinic day to the next occurred for Med Student and Physician Assessments which had differences of around -20 several times throughout the year (3 occurrences for Med Student (Figure 20), 1 occurrence for physician). Similar drastic degrees of variation occurred at the month level as well.

Figure 20: Quality Improvement Dashboard: Monthly Average Duration - Med Students



4.5 Opportunity Cost of Visit

Using the earlier defined methodology along with the data collected, two calculations for average and median total opportunity cost of visit were done. The average opportunity cost of visit was $30.29 and a median opportunity cost of visit was $26.17 (Figure 21). The major attribution to the total cost was the value added time from the clinic. This is what should be the case since that is the primary reason for the visit in the first place. However, the nonvalue added time is not that much different from the value added time, regardless of if you look at average or median. Travel distance was 19% of the cost for the average total opportunity cost but was less than half for the median calculation. The values that the clinic has most control over are the value added and nonvalue added time, the goal would be to increase value added time, thus inversely lowering the nonvalue added time.

Figure 21: Cost of Visit Calculation

Original #	1125						Total Opportunity Cost of Visit		
Filtered #	908							Average	**$ 30.29**
								Median	**$ 26.17**
		Miles	Rate	Dollars		% of Total (Average)	% of Total (Median)		
Distance	Average	10.8	$ 0.54	$ 5.86		19%			
Distance	Median	4.3	$ 0.54	$ 2.30			9%		
Distance	Standard Deviation	19.5	$ 0.54	$ 10.51					
		Mins	Hrs	Dollars					
Duration	Average	16.1	0.27	$ 2.05		7%			
Duration	Median	11.7	0.19	$ 1.49			6%		
Duration	Standard Deviation	19.9	0.33	$ 2.54					
		Mins	Hrs	Dollars					
	Value Added Time	67.0	1.12	$ 8.54		28%	33%		
	Non Value added	61.5	1.03	$ 7.84		26%	30%		
	Total Clinic Time	128.5	2.14	$ 16.38					
	Minimum Wage			$ 7.65					
	Meal			$ 6.00		20%	23%		
					Total	100%	100%		

Note: Color and degree of shading indicates higher percentage of the total opportunity cost of visit within respective column. Conclusions of whether the value is good or bad cannot be drawn from the color alone.

Chapter Five
Conclusion

5.0 Summary of Findings

The study has yielded several major findings into at MedZou's current operations processes and allowed us to develop data driven tools for understanding and managing the processes. The process maps and dashboards showed utilization patterns for the overall clinic and the individual various services. From here it can be seen that there are several services that are greatly underutilized, such as social work and preventative health therapy. Additionally, the process maps highlighted several other insights, specifically the presence of bottlenecks, the most variant pathways and high duration times of some of the services. These results were further highlighted in our VSM and Dashboards, which provided different formats to view the data, depending on the audience and purpose. Ultimately, this data allowed the ability to determine the time, context and cost it takes for patients to see the physician, which was 114 minutes, 47% of which was value added with nonvalue added time costing the patient near $8. Through all our findings and tools, we developed we were able to arrive at several recommendations for the clinic and this study.

5.1 Challenges and Limitations

We are content with the level of data we were able to collect and results we were able to derive; however, this study did experience several challenges and limitations that if addressed should prove to produce higher quality data for subsequent implemenations. We initially had challenges implementing timecards as the primary data collection method, causing us to have to rethink our data collection strategy. Shadowing patients was effective but provided a low yield of results and is not feasible as a continuous operation activity. Furthermore, we did not link patients with diagnosis when tracking our process times, thus but limits our understanding about which diagnosis are associated with higher wait times and utilization of services. Finally, best practices suggest that when developing dashboards, especially ones geared toward leaderships, input from the target audience should be obtained and incorporated, when appropriate. We were not able to conduct this iteration in our dashboards development. Recommendations to mitigate and address some of these challenges and limitations will be explored more so in the subsequent final sections.

5.2 Recommendations

We have listed below several immediate and actionable recommendations to improve operations and establish a stronger informatics foundation. We have also come up with recommendations to improve the study design to increase study effectiveness if replicated or implemented as standard operating protocol. Finally, also listed are recommendations for suggested future research that can be pursued to expand upon this study.

5.2.1 Operational Recommendations

The below recommendations are those that are most pertinent based off our results and the ones deemed most effective at mitigating some of the issues the study uncovered.

5.2.1.1 Increase Service Utilization and Consequently Value

Through the use of the process maps we were able to identify that there is a long wait before patients are seen by nursing. Furthermore, the mean/median durations of our ancillary services are less than the pre-nursing wait-time. Therefore, we suggest that as patients wait to be seen by nursing, they should see one of the ancillary staff such as social work and PHT in order to get the most value out of their clinic and reduce empty wait-times.

5.2.1.2 On Call Nurses

Services that are more likely to be associated as bottlenecks, such as Nursing, should have an additional volunteer on-call in the cause of volunteer being absence or an unexpectedly high patient volume. The functioning of these services is crucial since downstream processes depend on their timely and appropriate execution. If a services are understaffed, it creates a downstream effect that would increase patient wait-times.

5.2.1.3. Develop Benchmarking for Services

Implementation of dashboards allows for leadership and QI to understand the duration of services. Introducing benchmarking for utilization and duration allows the additional ability to determine whether the stations are operating appropriately. This helps ensure that services are being used appropriately; seeing the right number of patients for the appropriate amount of time. If underutilization is present, then efforts can be taken to increase the utilization and if overutilization is present then additional inquiry should be done to determine why this is the case. The results of these interventions can effectively be monitored by the dashboards.

5.2.1.4 Strategic Pairing and Assignment of Medical Students

Currently the medical students are paired M1-M2 and M3-M4, essentially making one pairing structure far more knowledgeable and experienced than the other. Inexperience may cause M1-M2 to take longer when seeing the patients due to a lack of experience. We suggest M1-M3 and M2-M4 structure will result in a more balanced teams and allowing for the less experienced students to better learn from the more experienced students. Furthermore, the appropriate medical student team, more experienced or less experienced, should be assigned to patients according to their level of complexity and severity of chief complaint. This will be of more use for the patient, still allows the medical teams to practice appropriately and improves duration of services for the clinic.

5.2.2 Study Design Recommendations

The below recommendations are related to improving the study design in order to overcome some of the limitations and challenges faced during this study.

5.2.2.1 Coupling Our Data Collection Strategies

There were advantages and disadvantages to both our data collection strategies. Timecards yielded more data but more quality and shadowing produced the inverse result. A combination of the two methods may be the answer to obtaining both high quantity and high quality data. If this study is to be repeated, we recommend using timecards with volunteers overlooking the process. The volunteers can ensure the timecards are moving appropriately throughout the clinic and spot-check for data integrity issues which can be immediately rectified.

5.2.2.2 Pursue Electronic Data Collection Methods

There exist methods of obtaining the relevant process data through electronic measures, which can be looked into if a clinic wanted to have this process more automated. This includes implementing radio frequency identification tags (RFID), extracting data logs through electronic medical record (EMR) and/or information technology (IT) systems, and developing a software for a volunteer to input process time data for multiple patients at a time.

5.2.3 Suggestions for Future Research

The below recommendations are suggested future research that clinics can pursue either right away or once their informatics foundation and process flow are well established and controlled.

5.2.3.1 Link Process Times with Diagnoses

Factoring which diagnoses patients have into this methodology will allow for more context and understanding to be gained. This additional variable can help correlate diagnoses and duration of services, the understanding of which can help further drive clinic operations and interventions.

5.2.3.2 Adding Additional Services

Once the process flow of a SRFC is controlled and understood, clinics such as MedZou which are service based can begin pursing expanding their service-lines. A controlled process means that the effects of expanded services can be quickly studied and optimized. As the clinic expands its services, the value patients receive can be maximized and wait-times reduced.

5.2.3.3 Track Walk-Outs

Patients who walk out of the clinic due to long wait-times are symptomatic of an inefficient clinic. This is especially harmful for the patient since they are unable to receive the care they need and are most likely going to be reluctant to return. Therefore, walk-outs should be tracked and incorporated into the dashboard. Ideally, it would be useful to know how long they waited before walking out. With knowledge of clinic wait-times and the threshold of time it takes a patient walks out, the clinic can begin pursuing efforts to reduce and prevent patient walk-outs from occurring.

5.2.3.4 Implement Perception Improving Efforts

It is inevitable that there will be wait-times. However, our background research uncovered methods to reduce the perception of wait-times experienced the patient. The psychology behind these practices can be exploited to help reduce the effects of long wait-times, dissatisfied patients and the likelihood of walk-outs.

5.2.3.5 Simulation

Higher level data analytics practices include the use of prescriptive tools such as simulation to forecast the results of interventions. These can be effective tools to determine which interventions are worth pursuing, such as seeing the effect of adding additional services or changing the number of volunteers on process flow and wait-times. Arena and Repast are simulation tools which can be used within SRFCs wishing to engage in simulating.

5.3 Conclusion

Through the use of BPM and QI tools, we were able to empirically supported the concerns expressed by many of the volunteers regarding operations within the clinic, specifically in regards to duration and utilization of services. Additionally, these tools enabled us to gain a deeper understanding of clinic processes. This allowed us suggest actionable and measurable recommendations to improve clinic value and reduce wait-times. We feel this methodology is simple enough to be implemented in all SRFC since minimal data elements are required and all the software used are free to students. The implementing of this informatics foundation will allow for the clinic to have control of their processes which can translate into the ability to improve organizational operations and provide more care and value to the patients who come to SRFCs.

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Appendices

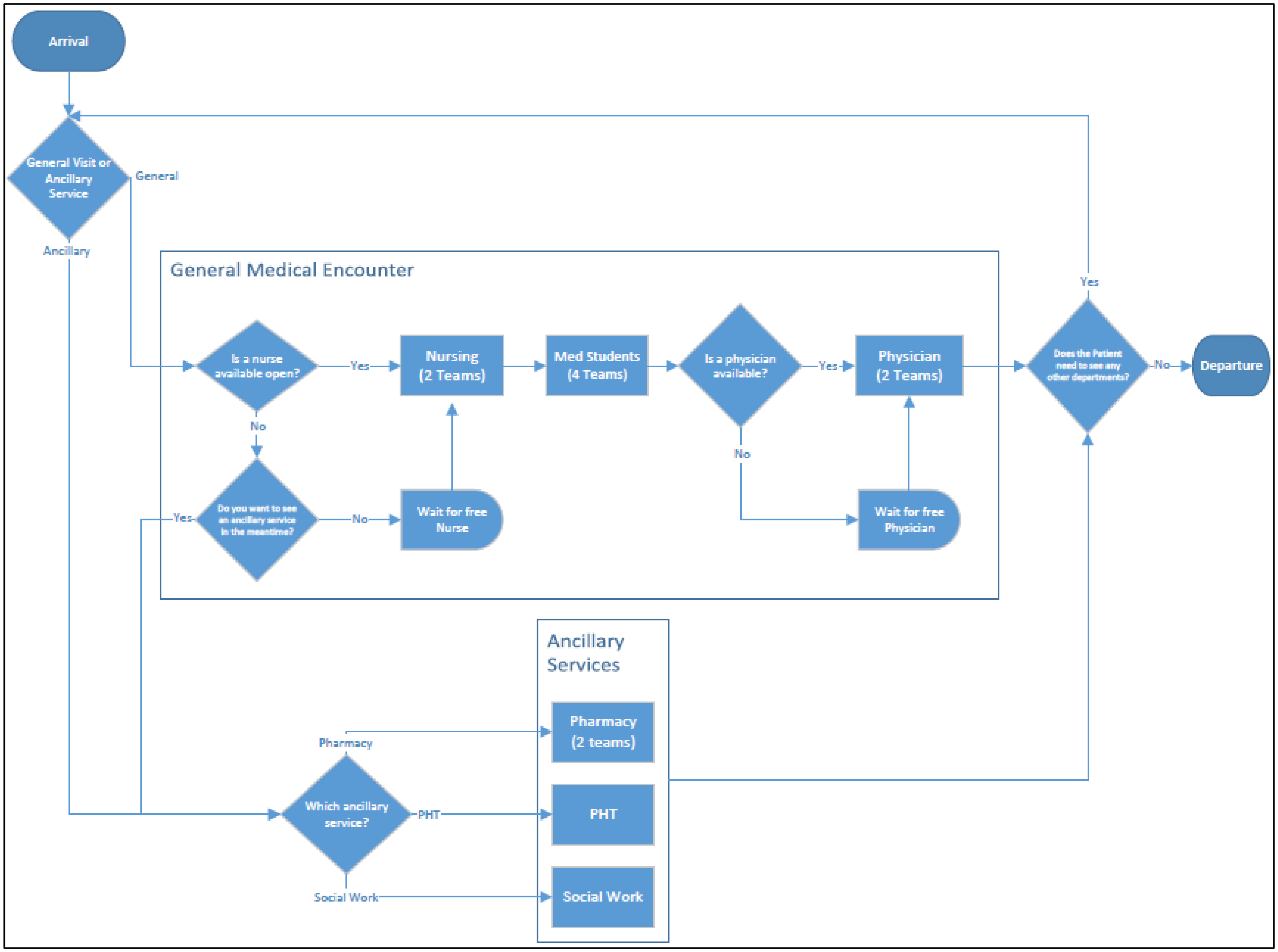
Appendix A: Summery of Literature Related to the Impact of SRFC

Table 5:Summery of Literature Related to the Impact of SRFC

Impact on HealthCare	
(Stuhlmiller & Tolchard, 2015)	"improved health outcomes for the community and cost savings to the health service estimated to be $430,000"
("The Impact of a Student-Run Free Clinic on Reducing Excess Emergency Department Visits," 2015)	"average reported number of ED visits in a three-month period was 0.47 in new patients and 0.24 in returning patients (p=0.0345)"
(Simpson & Long, 2007)	Responses from 59 SRFC reported 36,000 annual patient-physician visits, not included nonvisit encounters.
(Hua, Shih, & Tran, 2015)	$17,332.13 worth of services were rendered to treat 101/patient encounter/visits
(Ryskina et al., 2009)	Clinic rates of such diabetes quality-of-care indicators ranged from 12% to 96%, and in most areas was comparable to or better than averages previously reported for uninsured populations.
Impact on Volunteers	
(Shabbir & Santos, 2015)	"Volunteers showed an improved understanding of the healthcare process and issues relevant to uninsured patients. They also developed favorable attitudes towards primary care medicine and an increased level of interest in pursuing careers in primary care."
(Holmqvist et al., 2012)	"Emphasize health equity, interprofessionalism, and student leadership."
(Riddle et al., 2014)	"The degree to which they felt this experience improved their ability to care for and manage medical conditions was rated as 3.3 (95% confidence interval 2.2–4.5) on a scale from one to five, with five being extremely improved. The degree to which this experience enhanced their medical school education was rated as 3.9 (95% confidence interval 2.8–5.0)."

Appendix B: MedZou Clinical Process Flowchart

Figure 22: MedZou Clinical Process Flowchart



Appendix C: Process Time Observation Sheet

Figure 23: Process Time Observation Sheet

Process Time Observation Sheet
MedZou Quality Improvement

Observer Name: __________ Date: _____________

Patient ID: _____________ Appointment Time: ____________

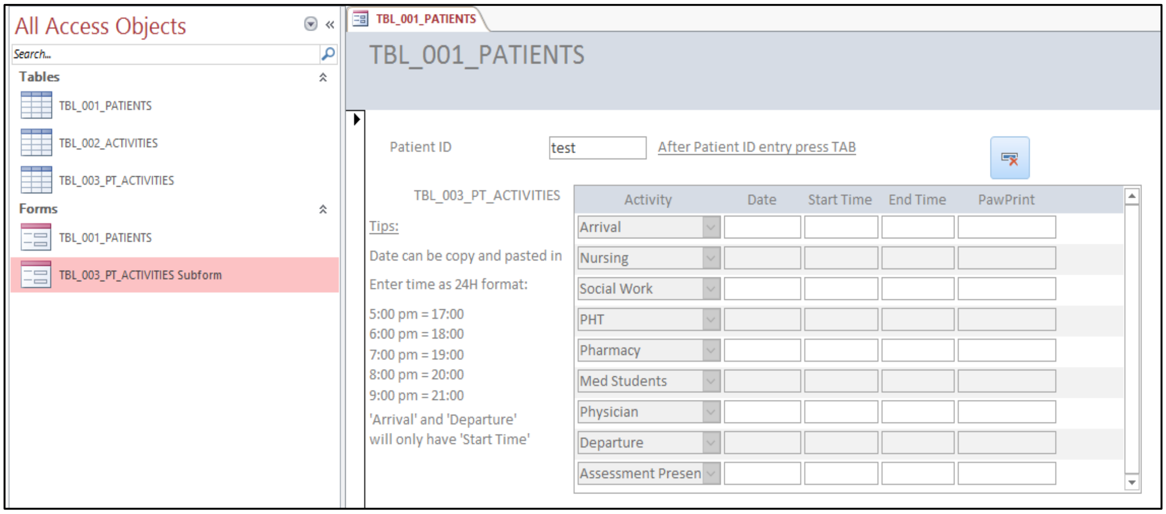
Activity	Start Time	End Time	Notes
Arrival			
Nursing			
Social Work			
PHT			
Pharmacy			
Med Student Assessment			
Assessment Presentation			
Resident/Attending Assessment			
Departure			

Guidelines:

- Enter in times in 24h format (5pm = 17:00, 6pm = 18:00, 7pm =19:00, 8pm = 20:00, 9:00 = 21:00)
- Be sure to simply observe and refrain from intervening. If the rooms get crowded or you are asked to step out then please comply and observe from a distance.
- The timestamp should be when the intervention actually begins and ends. This may mean there are gaps in the sequence of services which is fine. Some End Times for one activity should be the Start Time for the next. For example, The Assessment Presentation's end time should be when the Resident/Attending Assessment begins unless something out of the ordinary occurs.

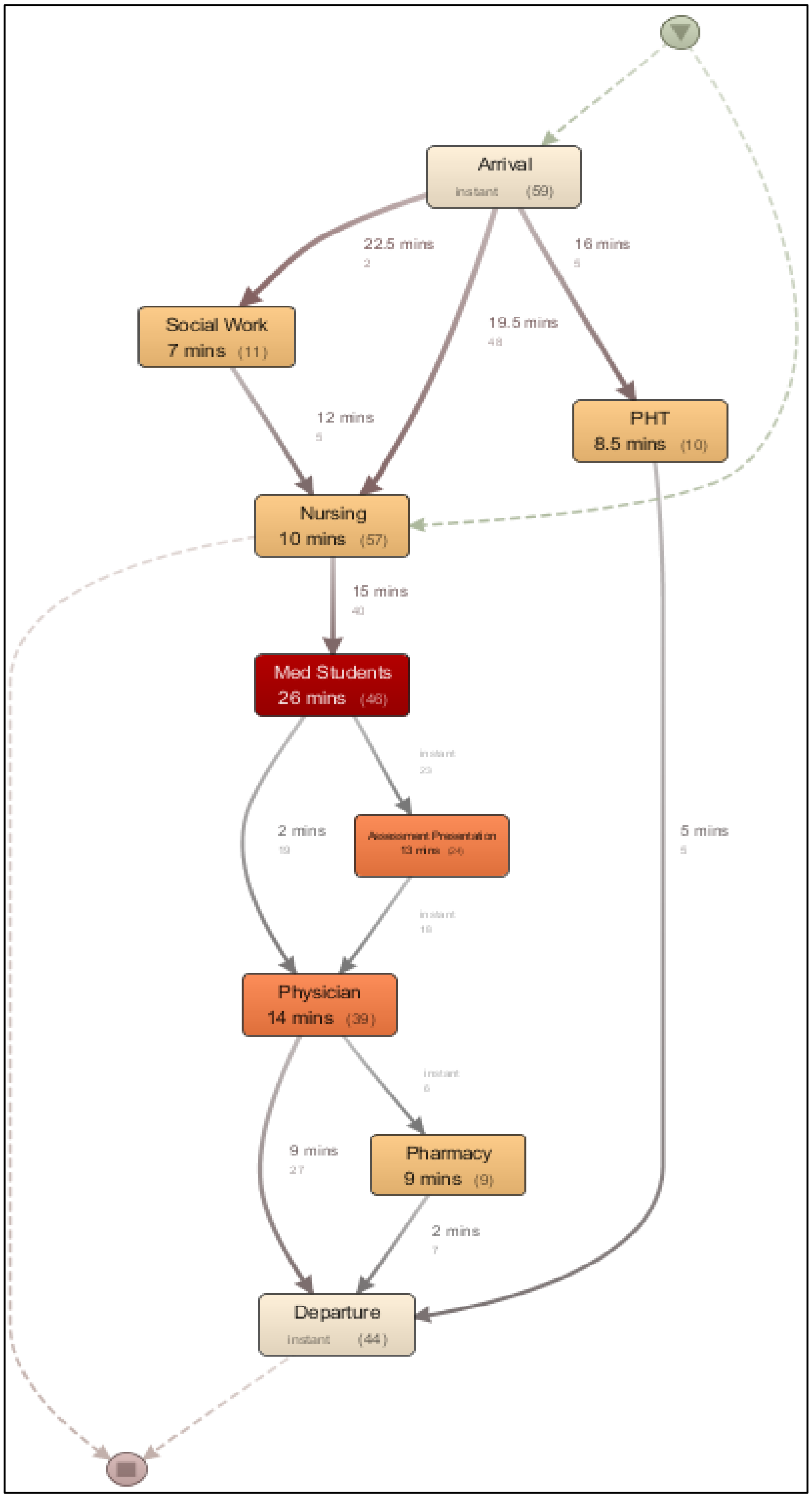
Appendix D: Microsoft Access Data Entry Form and Tables

Figure 24: Microsoft Access Data Entry Form and Tables



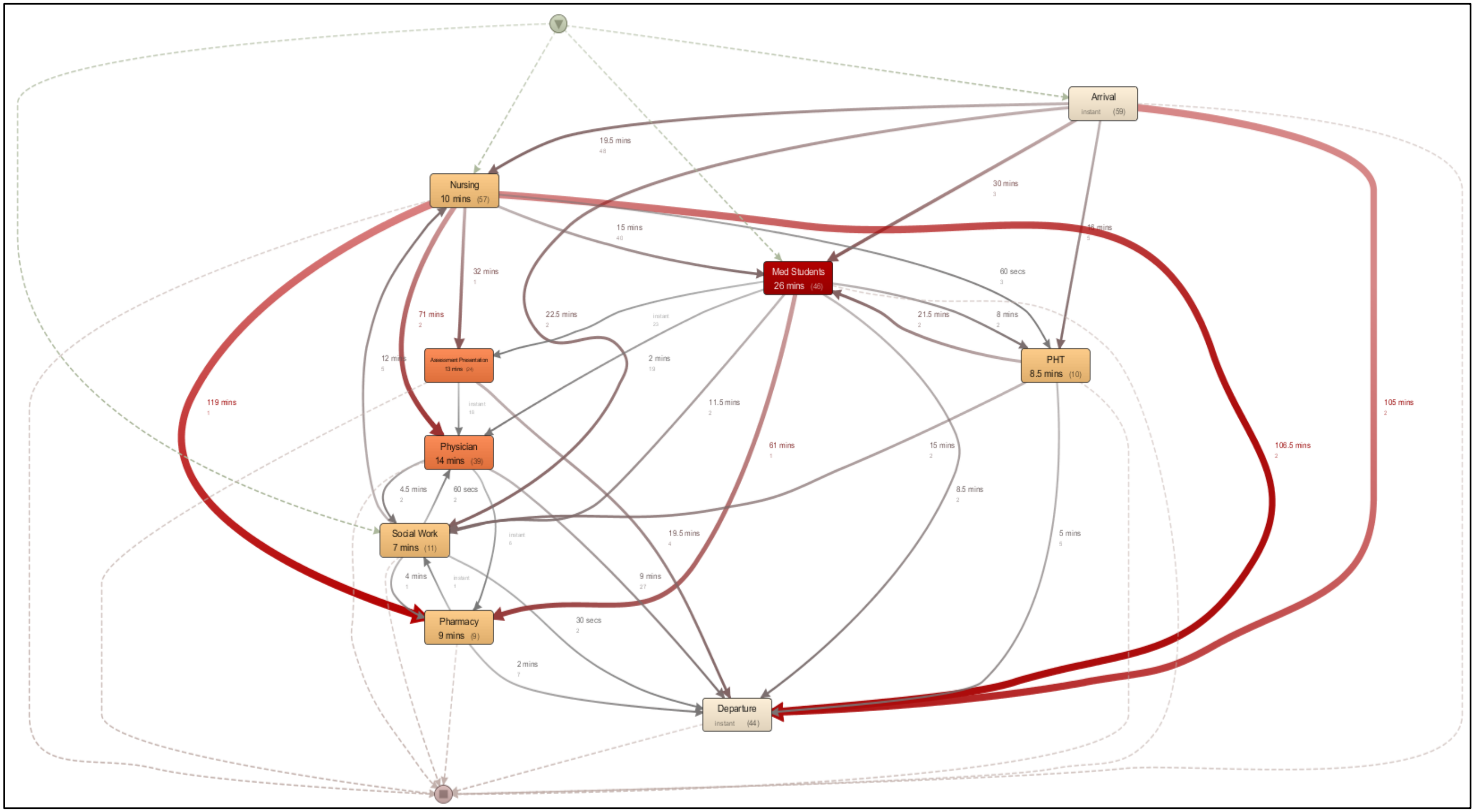
Appendix E: Median Duration View Process Maps

Figure 25: Majority Paths Process Map (Median Duration)



Note: Values in parentheses indicate frequency.

Figure 26: All Paths Process Map (Median Duration)



Note: Values in parentheses indicate frequency.

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Appendix F: Excel Distance and Duration Calculation

The below two Visual Basic modules were taken from Analystcave.com that use the Google Distance Matrix API to calculate distance and duration from two points (AnalystCave, 2014). The formulas were tested and spot checked for accuracy and deemed appropriate for use in this study. GetDistance returns the value in meters and GetDuration returns the value in seconds.

GetDistance

```
Public Function GetDistance(start As String, dest As String)
   Dim firstVal As String, secondVal As String, lastVal As String
   firstVal = "http://maps.googleapis.com/maps/api/distancematrix/json?origins="
   secondVal = "&destinations="
   lastVal = "&mode=car&language=pl&sensor=false"
   Set objHTTP = CreateObject("MSXML2.ServerXMLHTTP")
   URL = firstVal & Replace(start, " ", "+") & secondVal & Replace(dest, " ", "+") &
lastVal
   objHTTP.Open "GET", URL, False
   objHTTP.setRequestHeader "User-Agent", "Mozilla/4.0 (compatible; MSIE 6.0;
Windows NT 5.0)"
   objHTTP.send ("")
   If InStr(objHTTP.responseText, """distance"" : {") = 0 Then GoTo ErrorHandl
   Set regex = CreateObject("VBScript.RegExp"): regex.Pattern = """value"".*?([0-
9]+)": regex.Global = False
   Set matches = regex.Execute(objHTTP.responseText)
   tmpVal = Replace(matches(0).SubMatches(0), ".",
Application.International(xlListSeparator))
   GetDistance = CDbl(tmpVal)
   Exit Function
ErrorHandl:
   GetDistance = -1
End Function
```

GetDuration

```
Public Function GetDuration(start As String, dest As String)
    Dim firstVal As String, secondVal As String, lastVal As String
    firstVal = "http://maps.googleapis.com/maps/api/distancematrix/json?origins="
    secondVal = "&destinations="
    lastVal = "&mode=car&language=en&sensor=false"
    Set objHTTP = CreateObject("MSXML2.ServerXMLHTTP")
    URL = firstVal & Replace(start, " ", "+") & secondVal & Replace(dest, " ", "+") &
lastVal
    objHTTP.Open "GET", URL, False
    objHTTP.setRequestHeader "User-Agent", "Mozilla/4.0 (compatible; MSIE 6.0;
Windows NT 5.0)"
    objHTTP.send ("")
    If InStr(objHTTP.responseText, """duration"" : {") = 0 Then GoTo ErrorHandl
    Set regex = CreateObject("VBScript.RegExp"): regex.Pattern =
"duration(?:.|\n)*?""value"".*?([0-9]+)": regex.Global = False
    Set matches = regex.Execute(objHTTP.responseText)
    tmpVal = Replace(matches(0).SubMatches(0), ".",
Application.International(xlListSeparator))
    GetDuration = CDbl(tmpVal)
    Exit Function
ErrorHandl:
    GetDuration = -1
End Function
```

End of Thesis