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THESIS

**PHARMACY AUTOMATION IN NAVY MEDICINE: A
STUDY OF NAVAL MEDICAL CENTER SAN DIEGO**

by

Abbie J. Merkl

September 2015

Thesis Advisor:
Second Reader:

Lyn Whitaker
Nedialko Dimitrov

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**PHARMACY AUTOMATION IN NAVY MEDICINE: A STUDY OF NAVAL
MEDICAL CENTER SAN DIEGO**

Abbie J. Merkl
Lieutenant, United States Navy
B.S., United States Naval Academy, 2010

Submitted in partial fulfillment of the
requirements for the degree

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September 2015**

Approved by: Lyn Whitaker
Thesis Advisor

Nedialko Dimitrov
Second Reader

Patricia A. Jacobs
Chair, Department of Operations Research

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ABSTRACT

In August 2012, Naval Medical Center San Diego implemented a state-of-the-art pharmacy automation system in an effort to reduce cost and improve efficiency. The objective of this study is to quantify the increase in efficiency after installation through a focus on observed post-automation prescription fill times during calendar year 2014 (CY2014) and a simulated pre-automation process. With a response of average daily prescription fill time, automatic prescription fills in CY2014 are quicker than manual prescription fills in CY2014 by 6.97 ± 0.97 (standard error) minutes, and post-automation prescription fills are quicker than pre-automation prescription fills by 4.4 ± 0.34 minutes. The difference between pre-automation and post-automation prescription fills is used as the response in a linear regression to determine which factors most contribute to the decrease in prescription fill time. The proportion of prescriptions automated is influential: if this proportion is held constant at 0.37, the workload for each pharmacy technician can be reduced by an estimated 2.34 ± 0.03 (standard deviation) hours per day. A cost analysis of the pharmacy automation system is conducted, and it is estimated that a lower bound on the annual cost savings after implementation is over \$300,000.

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LIST OF ACRONYMS AND ABBREVIATIONS

BUMED	Bureau of Medicine and Surgery
CY2014	Calendar Year 2014, January 2014 – December 2014
E-4	Petty Officer Third Class
FTE	Full Time Equivalent
NDC	National Drug Code
NMCSD	Naval Medical Center San Diego
RDS	Robotic Delivery System

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EXECUTIVE SUMMARY

In today's healthcare environment, healthcare facilities continue to seek ways to reduce cost and improve efficiency; the pharmacy is one of many avenues to accomplish this task. In 2012, Naval Medical Center San Diego (NMCS D) installed a state-of-the-art pharmacy automaton system in an attempt to increase efficiency within their pharmacy.

Prior to 2012, pharmacy technicians manually filled all prescription orders within the NMCS D pharmacy. The new pharmacy automation system is capable of autonomously completing all the steps in the prescription fill process prior to pharmacist verification. While the automation system at NMCS D does not completely eliminate the need for manual prescription fills, it has the potential to greatly reduce the workload placed on pharmacy technicians. The objective of this study is to quantify the increases in efficiency experienced after the installation of pharmacy automation at NMCS D.

Of interest is the total prescription fill time for each medication, which is the time elapsed between when a customer orders the prescription at the intake window and the time pharmacist verification is completed. Analysis of prescription fill times is based on one data set that follows each individual prescription in calendar year 2014 (CY2014) through the entire prescription fill process. Because data from prior to the implementation of automation is unavailable, medication demand and prescription characteristics are estimated from this post-automation data to simulate the pre-automation process.

On average, prescriptions filled automatically in CY2014 are completed 6.97 ± 0.97 (standard error) minutes faster than prescriptions filled manually in CY2014. During periods of high demand, automatic fills were quicker than manual fills 84.5 percent of the time, with a 95 percent confidence interval of [80.2, 87.4]. On average, prescriptions filled after the installation of automation are 4.4 ± 0.43 (standard error) minutes faster than prescriptions filled prior to the installation of automation. These results are found to be statistically significant.

The difference in daily average prescription fill times pre-automation and daily average prescription fill times post automation is used as the response in a linear

regression to determine which characteristics of the data most heavily influence this difference; a negative value of the response represents a day in which the average prescription fill time pre-automation is quicker than post-automation. Results indicate the number of hours of high demand experienced in the day negatively impacts the response, while the post-automation proportion of medications filled through automation and the pre-automation proportion of highly prescribed medications positively impact the response.

With all other factors held constant, an automation workload proportion of 0.37 is related to an increase in the difference of average prescription fill time of 2.98 ± 1.95 (standard error) minutes; if this proportion can be maintained over the course of an entire year, assuming an average daily weekday demand is 1186 prescriptions, this alone could reduce yearly workload by 636 days, compared to pre-automation. Assuming there are 25 pharmacy technicians working within the pharmacy, this is also associated with a reduction in daily workload of 2.34 ± 0.03 hours per technician. Figure 1 illustrates the yearly reduction in weekday workload and daily reduction in workload based on proportion of prescriptions filled through automation.

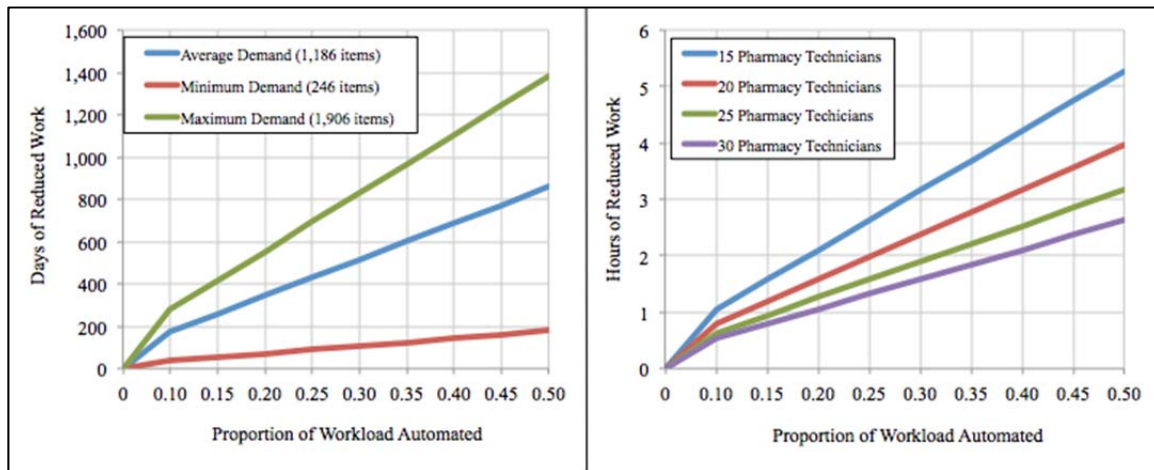


Figure 1. *Estimated Yearly and Daily Reduction (per Technician) in Weekday Workload Based on Proportion of Prescriptions Filled through Automation Demand.*

It is also important to consider the implementation from a cost perspective. The pharmacy automation system at NMSCD carried an individual implementation cost of \$2.4 million of the total \$49 million contract. There is a reduction in total time spent filling prescriptions of 14.2 percent from pre-automation to post-automation. This reduction in time is associated with \$330,000 reduction in cost, the amount of money it would cost to pay for the equivalent amount of work from enlisted military pharmacy technicians. With these calculations, it would take roughly seven years to recoup the cost of implementation at NMCS D based on increased efficiency. This cost analysis does not account for efficiencies based on the storage and supply of medications, increased patient satisfaction, increased access to care, increased accuracy of dispensed medications, or recapture costs based on a reduction of non-military prescription fills.

After the implementation of pharmacy automation at NMCS D, there is an increase in efficiency, defined as the total prescription fill time. This efficiency can be quantified as reduction in total time to fill a prescription, FTEs, or equivalent salary of pharmacy technicians. This data is collected after a little more than one year of implementation; with better training and more emphasis placed on the optimal automation workload, these savings in efficiency will continue to increase.

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I. INTRODUCTION

In today's healthcare environment, healthcare facilities continue to seek ways to reduce cost and improve efficiency; the pharmacy is one of many avenues to accomplish this task. The current pill-counting machines in most pharmacies within Navy Medicine are obsolete, and more advanced replacement technology is available. In particular, facilities that service a larger population of customers have a greater opportunity to benefit from technological advances in pharmacy automation, because their pharmacies experience a higher demand. Replacing legacy systems with updated technology could have extreme impacts on efficiency, accuracy, patient satisfaction, and access to care.

Prior to 2012, pharmacy technicians manually filled all prescriptions at the Naval Medical Center San Diego (NMCS D) pharmacy, supplemented by an AccuMed pill-counting machine. This pharmacy received an upgrade in August 2012, when the Bureau of Medicine and Surgery (BUMED) installed a state of the art pharmacy automation system at this location. The new automation machine is capable of autonomously completing all steps of the prescription fill process prior to pharmacist verification without assistance from pharmacy technicians. Because every prescription filled using this new technology collects data through barcode scanning, its implementation provides a unique opportunity to objectively evaluate its contributions to efficiency.

A. OBJECTIVES AND METHODOLOGY

The objective of this study is to quantify the increases in efficiency after the installation of pharmacy automation at NMCS D. In order to evaluate these objectives, this study focuses on individual prescription orders filled at NMCS D during calendar year 2014 (CY2104), from January to December 2014. Because this data set only contains information for one year post-automation, a pre-automation data set is generated through simulation for use as comparison. All statistical analysis and simulation is completed using R (2013).

A customer placing a prescription order at the intake window in the pharmacy signals the beginning of the prescription fill process; the total prescription fill time is of

interest, which is the difference in time between the placement of an order and the completion of pharmacist verification. To evaluate the efficiency of the machine, the total prescription fill times for all observed manual prescriptions fills in CY2014 are compared to the total prescription fill times for all observed automatic prescriptions fills in CY2014. Similarly, the entire post-automation data set is also compared to the simulated pre-automation process. The results of these comparisons determine if the differences are statistically significant.

B. SCOPE, LIMITATIONS, AND ASSUMPTIONS

This study focuses solely on data obtained from NMCS D. Because this study focuses on one specific location, its results can only be directly applied to NMCS D; however, medical facilities of similar size and patient population should expect to see similar increases in efficiency after the installation of a pharmacy automation system at their location. The techniques used to evaluate the efficiency of the automation system at NMCS D can also be easily applied to another location with a similar automation system.

Data from prior to the installation of the automation system is unavailable, leading to the most significant limitation of this study: if this data was obtainable, a considerably better comparison of changes in efficiency could be completed. In order to address this limitation, manual fill times and daily demand distributions are estimated from the existing data and used to construct a simulation of the pre-automation process. In addition, with only one complete year of post-automation data, it is impossible to validate significant departures from the mean average fill time observed during specific months as a recurring trend. To compensate for this volatility, the month of February is eliminated from the data set for most of the analysis to prevent this month with unusually high prescription fill times from unduly influencing the results.

The most basic assumption of this study is that the automation machine is running properly and efficiently for the entire data collection period. In the absence of information on the breakdown and repair of the machine, this assumption is necessary to conduct analysis. In addition, the use of simulation to generate information for the pre-automation process requires two major assumptions. First, it is essential to assume that

there is no significant variability in the prescription filling abilities of the pharmacy technicians performing manual prescription fills in CY2014. Second, because the demand in the simulation is estimated from the demand observed in CY2014, it is assumed that demand experienced during that year is characteristic of any year in the NMCSD pharmacy. Additional assumptions required by this study are addressed as necessary.

C. COURSE OF STUDY

This study consists of four additional chapters. Chapter II, Background, explains the history of the implementation of the pharmacy automation system at NMCSD and presents a review of existing literature on the topic of pharmacy automation. The objective of Chapter III, Data, and Chapter IV, Methodology and Analysis, is to quantify the efficiencies experienced after the implementation of automation. Chapter V, Results, Conclusions, and Recommendations, highlights the results and conclusions of the study, makes recommendations about automation within Navy Medicine, and suggests topics for future work.

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II. BACKGROUND

All pharmacies face a variety of concerns, such as quality assurance, pharmacy workflow, patient satisfaction, and cost control. With these challenges in mind, the Bureau of Medicine and Surgery (BUMED) looked toward pharmacy automation to upgrade their prescription fulfillment process at several high-volume sites throughout the enterprise. Specifically at NMCS D, this upgrade converted the pharmacy from a manual system to an automated system, supplemented by pharmacy technicians.

A. MANUAL PRESCRIPTION FILLS

Prior to 2012, pharmacy technicians manually filled all prescription orders within the NMCS D pharmacy. To fill a prescription manually, pharmacy technicians received the order, obtained the specific medication from its place of storage, and then physically counted each pill; thirty-six AccuMed automated pill counting machines supplemented the pharmacy technicians in NMCS D, which simply counted a specific number of pills, loaded by the user (St. Onge Company, 2011). Once counting was completed, the technician bottled the medication, capped the bottle, and then printed and affixed the label. At this stage, all bottled prescriptions were physically carried to the pharmacist for verification, who certified the medication filled fit the prescription entered for each customer. Manual completion required the pharmacy technicians and pharmacists to physically complete each step in the process, as well as retrieve medications from the storage shelves and walk the medication between the different stages.

The customer experienced a “bank-teller” queuing system within the NMCS D pharmacy while getting a prescription filled. Specifically, when a customer first arrived in the pharmacy, he entered a queue to be received at the window. Once called to the window, he placed his order, and then waited at the window while the order was filled. When the order was completed, the customer’s prescription was reviewed with him, he accepted the order, and then he departed the pharmacy (B. Detlef, BUMED, personal communication, July 30, 2015). Figure 1 illustrates both the customer queuing system and the manual fill process.

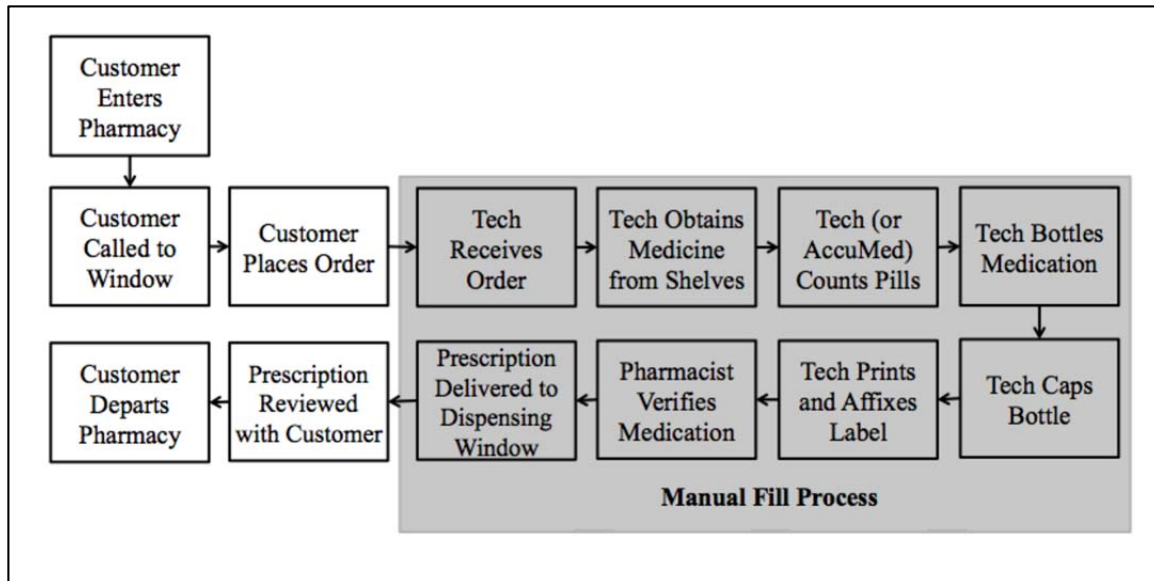


Figure 1. *Bank-Teller Queuing System with Manual Fill Process.* Once a customer places an order, he waits at the dispensing window while his prescription is filled manually.

B. AUTOMATION IMPLEMENTATION

In August 2012, the United States Navy awarded a \$49 million contract to Innovation, makers of the PharmASSIST pharmacy automation technology, to supply pharmacy automation to its high-volume sites (Innovation, 2012). This included the installation of pharmacy automation in NMCS D in 2013; this site currently has the most technologically advanced and fully functional system in Navy Medicine. This automation system is capable of handling and storing 360 unique medications, and consists of a conveyor system that is activated once a customer places an order (B. Detlef, BUMED, personal communication, April 8, 2015). The conveyor system is not used solely for prescription fills that have been automatically counted, capped, and labeled; pharmacy technicians also use the conveyor system to quickly route manual prescription fills. Figure 2 is a photograph of the actual conveyor system installed at NMCS D.



Figure 2. *Conveyer Belt Installed at Naval Medical Center San Diego.* Once the customer places an order, the conveyer system directs each prescription through the different steps of the fill process. Manual fill stations are located to the right side of the conveyer belt; as pharmacy technicians complete a manual fill, they place completed orders onto the conveyer belt for routing to pharmacist verification.

Once the customer order is loaded, the automation system dispenses a vial, affixes the label, and delivers the empty bottle to the Robotic Delivery System (RDS). The RDS inserts the labeled vial into the inventory container containing the appropriate medication, dispenses the pills, caps the vial, releases the vial, and routes the medication to the pharmacist for verification. Figure 3 shows the RDS inserting the labeled bottle into an inventory container. This automatic procedure is used to supplement the manual fill process described in Section A.

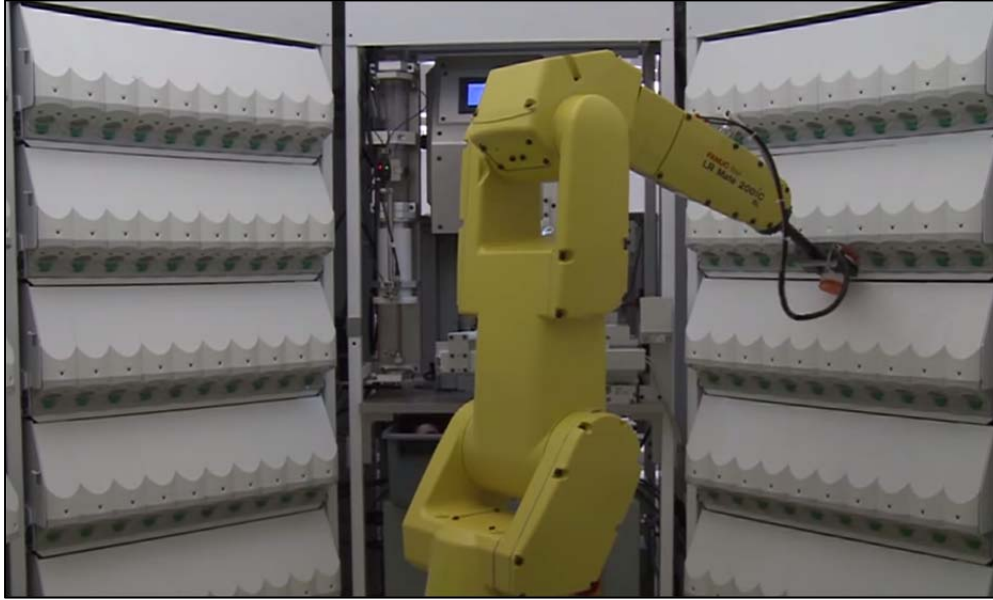


Figure 3. *Robotic Delivery System Installed at Naval Medical Center San Diego.* Each container houses an inventory of medication. The RDS selects a vial, inserts it into the container to receive dispensed medication, caps the vial, and affixes the label. This completed prescription is then placed on the conveyer belt for routing to pharmacist verification.

Along with the implementation of the pharmacy automation system, NMCS D underwent changes to their customer queuing system; instead of a bank-teller system, customers experience an “in-and-out” system. When a customer first arrives in the pharmacy, he takes a ticket number from an automated kiosk, and waits for that ticket number to be called. Once the number is called, the customer is received at the window, where he places his order. This signals the beginning of the prescription fill process. The customer is dismissed from the window, where he waits for his ticket number to be called for a second time. After his ticket number is called again, the customer enters a queue to wait for order pickup. At his turn, the customer is received at the dispensing window, the customer’s prescription is reviewed with him, he accepts the order, and then he departs the pharmacy (B. Detlef, BUMED, personal communication, July 30, 2015). Figure 4 illustrates the customer queuing process combined with the manual and automatic fill process. By dismissing a customer from the window, this queuing system allows for

greater window utilization than the bank-teller model; the customer is not occupying a window while prescription operations are occurring.

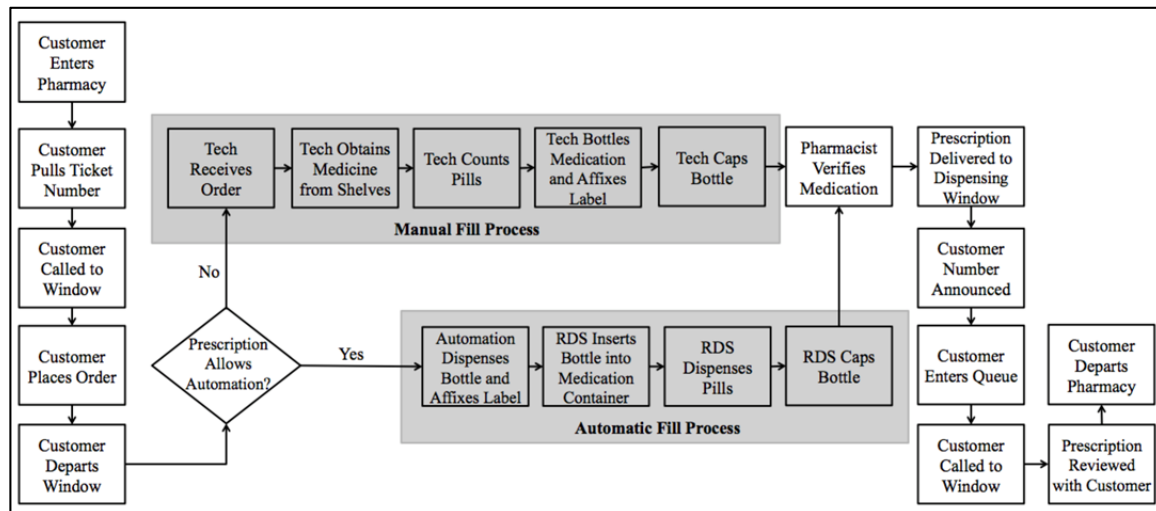


Figure 4. *In-and-Out Queuing System with Manual and Automatic Fill Process.* Using the in-and-out model, the queuing process for the customer is different, and the prescription fill process is more streamlined. The automation is capable of performing all steps, including transportation, up to pharmacist verification via the conveyor belt. Manual fills are located along the conveyor system for increased efficiency.

While the automation system at NMCS D does not completely eliminate the need for manual prescription fills, it has the potential to greatly reduce the workload placed on pharmacy technicians. This reduction in workload occurs not only in the physical number of orders filled manually, but also decreases the need for pharmacy technicians to constantly retrieve and stock medication; most of the high-demand medications are stored within the RDS system. In addition, each step in the automatic process is triggered by barcode scanning, which, in theory, should lead to more accurate prescription fills. Through barcode scanning, the PharmASSIST software ensures that every step in the process is automatically double checked for accuracy prior to the pharmacist verification.

C. LITERATURE REVIEW

There exists extensive literature surrounding the implications of changing pharmacy operations within a hospital; much of this literature specifically identifies the outcomes related to the implementation of different automation systems. Due to an environment of rapidly changing technology, the ability to understand the impact of such a change is of significant interest to any healthcare organization. A review of existing literature concerns the topic of efficiency. This review is limited to studies conducted in hospital pharmacies as opposed to community pharmacies, which are of similar size and scope to NMCSO, but are varied in the types of automation systems implemented.

The use of emerging technologies within pharmacies is, in part, directly aimed at increasing productivity while reducing customer wait times. One way to quantify the productivity of the pharmacy is to measure the total output of prescription items over time; through statistical inference, the quantity of items produced prior to installation can be compared to after installation and evaluated for significance. Though many other factors, such as staff training and competency, can impact this metric, the impact of automation on the number of items produced per day varies widely from study to study. This increase can range from as little as nineteen percent to as much as 43 percent; see Fitzpatrick, Cooke, Southall, Kauldher, and Waters (2005), Angelo, Christensen, and Ferreri (2005), and James et al. (2013). Many of these numbers have significant standard deviations, and items produced per hour can vary by as much as 68 percent of the mean (Angelo, Christensen, & Ferreri, 2005). In addition, staffing practices must be adjusted to maximize this effect on productivity. While automation can reduce the average time spent filling prescriptions by seventeen percent after the introduction of automation, this reduction is associated with eighteen percent increase in time spent doing non-productive activities if staffing levels remain unchanged (Lin, Huang, Punches, & Chen, 2007).

Because of the cost associated with automation machines, many healthcare organizations turn to simulation as a reduced cost method to influence decision-making. With proper modeling and input parameters, simulations can provide valuable insights into important aspects of pharmacy management, especially when used as a queuing model. Customer satisfaction surveys indicate that pharmacy customers value a wait time

of less than 30 minutes as the third most important factor in a pharmacy experience, after only prescription accuracy and affordability of medicine (Vincent & Lim, 1997). This goal of a 30-minute customer wait time is used as target metric in Tan, Chua, Yong, and Wu's simulation of the impacts of automation on a hospital pharmacy in Singapore (2009). The results of this simulation indicate that the implementation of automation alone is not substantial enough to reduce the 95th percentile customer wait time to below 30 minutes; in addition to automation, pharmacies must change their staffing procedures and workflow management to achieve this goal (2009).

Based on the unavailability of data collected prior to the installation of the automation machine at NMCS D, this study takes a hybrid approach, incorporating both empirical evaluation and simulation. The post-automation data indicates whether a prescription is filled manually or automatically; therefore, inferences are made about manual fill times, in general. The data also provide demand signals that assist in determining customer requests on an hourly, daily, and weekly basis. This information is used to simulate the pre-automation environment, which is the basis for statistical inference in Chapter IV.

D. SUMMARY

The efficiency of medication dispensed in a hospital pharmacy will always be of the utmost importance to any healthcare organization. Navy Medicine has attempted to address these issues through the implementation of pharmacy automation of varying degrees at its high volume sites. At NMCS D, in particular, the most advanced and fully functional automation machine has been in use for nearly three years; this type of automation has the potential to greatly reduce workload on pharmacy technicians and pharmacists, which in turn, will increase efficiency and patient satisfaction. These benefits will be addressed in the following chapters.

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III. DATA

Analysis of prescription fill times is based on one data set generated by Innovation, the system that runs the automation machine procedures to fill, verify, and stage prescriptions at NMCS D. Improvement Path Systems, an organization contracted to perform healthcare analytics, provided this data via the BUMED. This data set follows each individual prescription in CY2014 through the entire fill process; the time lapse between automation implementation in 2012 and data collection in 2014 reduces the possibility of an adjustment period influencing the results. Specifically, this accounts for technician training and modifications to standard operating procedures. Medication demand and prescription characteristics are estimated from this post-automation data to simulate the pre-automation process, because data from prior to the implementation of an automation system is unavailable. Using both the simulated pre-automation and observed post-automation data, it is then possible to conduct the statistical analysis completed in Chapters IV and V.

Each observation, 403,900 in total, represents an individual prescription request at the pharmacy during CY2014, and includes a unique prescription identification number, dispensed medication name, and fill type (manual or automatic). In addition to these descriptive fields, the data set contains fifteen tracked processes for each prescription. Each process is represented by the date and time in which the process occurred, accurate to the second. Table 1 details the eight processes relevant to this study; other processes of interest, but not used to this study, are found in Appendix A.

Table 1. *Processes Tracked in Prescription Data.* The prescription data contains the date and time, accurate to the second, of eight relevant processes during the entire prescription order procedure.

Process	Description (date/time)
Scheduled	Entered into the system
Counted	Count of quantity of medication is complete
Added to Tote	Counting, bottling, capping, and labeling is complete
Verified	Pharmacist verification for errors is complete
Added to Bag	Combined with remaining customer order
Added to Location	Complete order is placed in assigned cubby location
Ready for Pickup	Order is complete and ready for customer pick up
Pickup	Customer picks up completed order.

Figure 5 illustrates the flow of the prescription order process within the pharmacy. For this analysis, total time to fill a single prescription is of interest. Total time is defined as the difference in time between scheduling and verification; all processes after that are possibly dependent on the other items contained in a customer order, or the actions of the customers themselves. The difference in scheduled time and verified time is found for each observation, and this time difference is used as the response during analysis

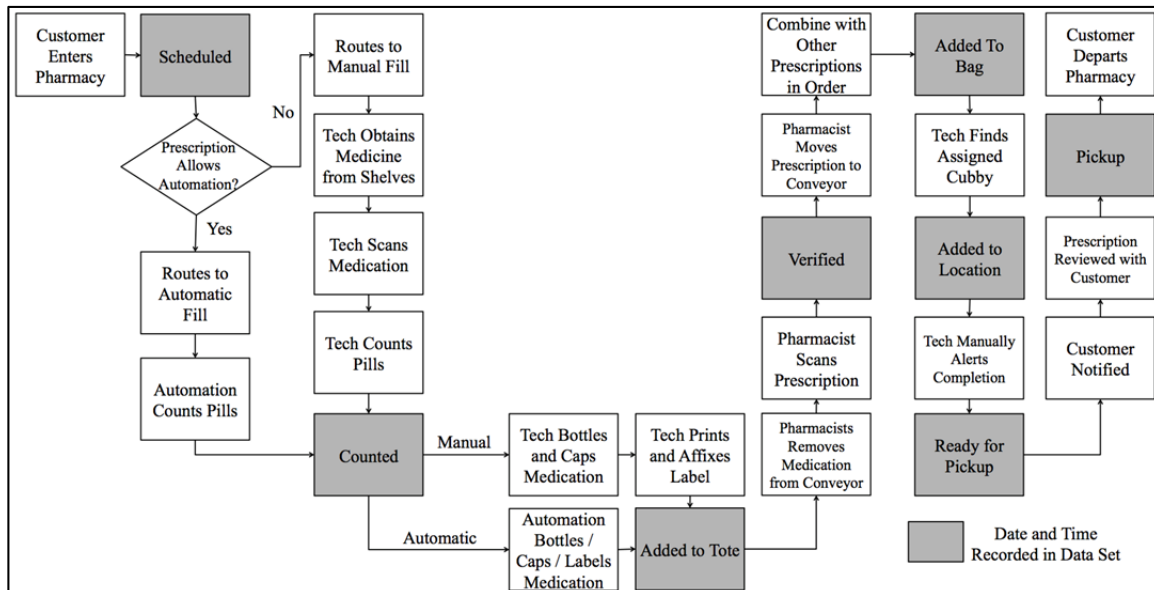


Figure 5. *Prescription Fill Flow Chart.* The general prescription fill process is outlined, including indication of which steps in are recorded in the data set.

Of the 403,000 observations identified in the post-automation prescription data, 32,841 items are eliminated based on issues with observed scheduled, verified, and pickup times. Observations without these times recorded are excluded. In addition, all observations with another process recorded at a point in time prior to scheduling are removed; scheduling is the very first step in the prescription fill process, and observations contrary to this are treated as errors. These times are important because their difference is used as the measure of total prescription fill time. Another 109 observations are eliminated because the type of fill, either manual or automatic, is not specified. Lastly, 7,017 observations have a total prescription fill time of either less than two minutes or greater than one day. Because the median prescription fill time is 16.3 minutes, including these observations, observations greater than one day are considered extreme outliers and excluded from analysis. Similarly, based on the number of steps in the prescription fill process, any observation of less than two minutes is uncharacteristically quick. The result is a final data set consisting of 364,529 observations, as illustrated in Figure 6.

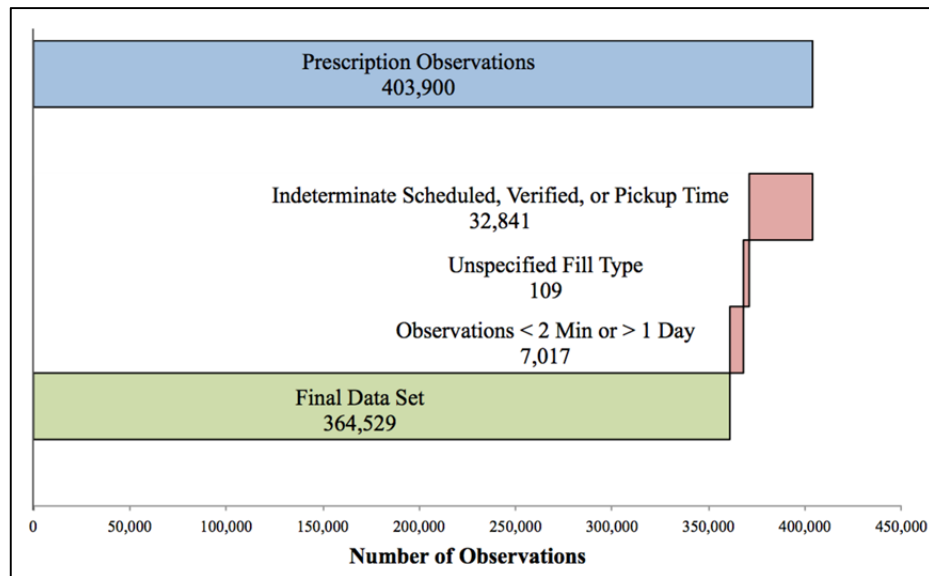


Figure 6. *Reduction of 403,900 Initial Observations to Final Data Set of 364,529. An analysis of available prescription data results in a final sample size of 364,529 observations for CY2014 at NMCSD.*

In the final data set, the automation machine completes 37.3 percent of all prescription fills; the rest are filled manually. Summary statistics for the final data set, distinguishing prescriptions filled automatically from manually, are contained in Table 2.

Table 2. *Summary Statistics of Prescription Fill Times (Minutes)*. In the final data set, 37.3 percent of all prescription fills for CY2014 are filled through automation.

Type	Number of Fills	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
Total	364,529	2.00	8.95	15.98	26.09	28.10	1440.00
Auto	136,068	2.00	7.07	12.90	21.74	23.48	1435.00
Manual	228,461	2.00	10.38	17.95	28.68	30.75	1440.00

A. POST-AUTOMATION PRESCRIPTION FILL

The final data set contains the entirety of information used to analyze post-automation prescription fills. It is of interest to examine trends in demand and prescription fill times based on different time periods; assuming these tendencies are consistent with the typical pharmacy environment at NMCSD, they are used as the basis to simulate the pre-automation process. Data is binned by day, day of the week, and hour of the day to determine significant time periods in order to better understand the workload and demand signals within the pharmacy.

1. Daily Trend Analysis

First, the number of prescriptions observed is totaled by day of the year. This procedure results in 365 observations, and serves as the basis for the first stage of analysis, see Figure 7. Upon inspection, a weekly trend is apparent; there are roughly four local minima and maxima during each month, corresponding to the number of weeks in a month. In addition, the number of prescriptions appears to increase in the month of February, while the rest of the year remains fairly consistent.

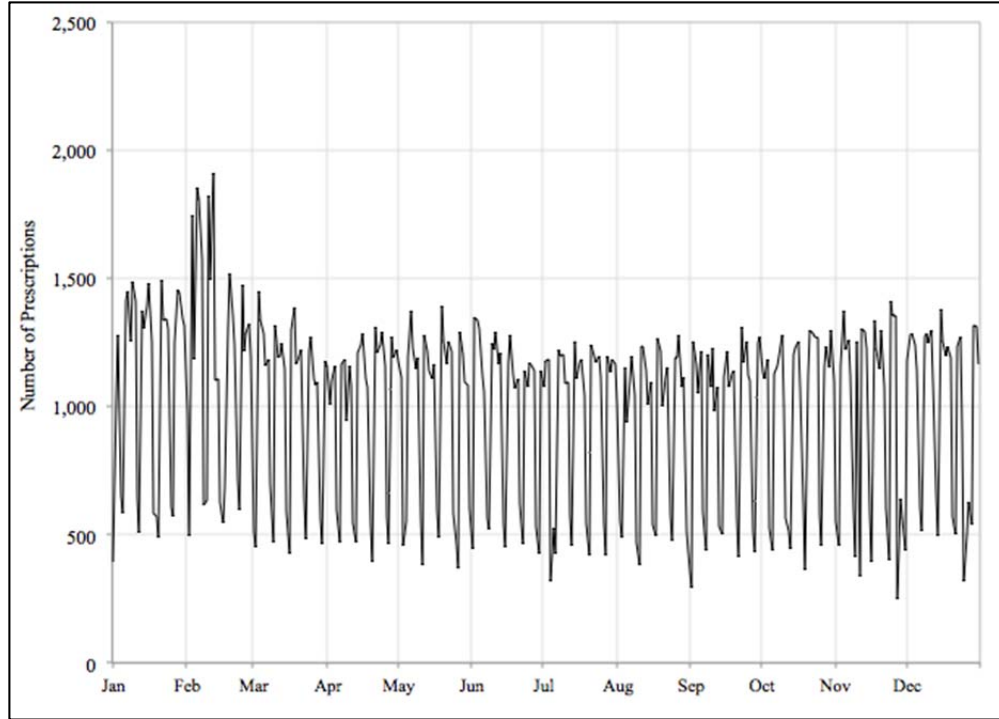


Figure 7. *Total Number of Prescriptions.* This includes prescriptions filled both manually and automatically. The maximum number of daily prescriptions is 1,911 observations, occurring on February 12, 2014. The minimum number of prescriptions is 246, occurring on November 27, 2014. The sharp increases and decreases in the number observations during each month indicate a weekly trend.

Similarly, prescription fill time is averaged by day of the year, resulting in 365 observations; see Figure 8. Average daily prescription fill times experience an increase during the month of February, while they are at their lowest during the month of August. This spike in prescription fill time during the month of February corresponds with an increase in customer orders during that month. With only one year of observations, this cannot be validated as a recurring seasonal trend. This departure from the mean proves to be problematic throughout this study; as a result, the month of February is eliminated during most analysis conducted in Chapters IV and V.

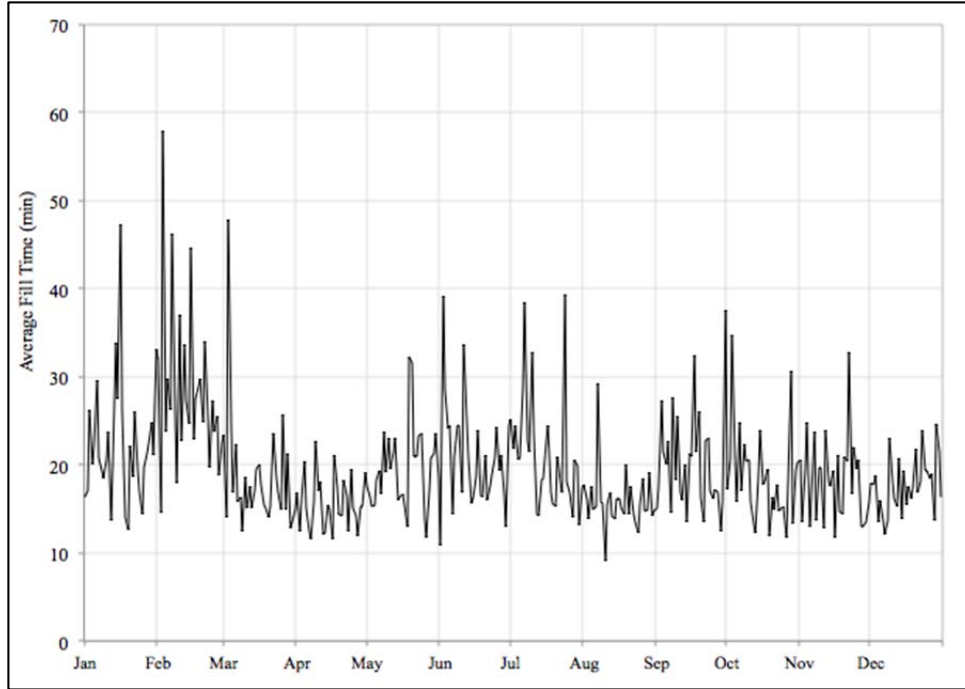


Figure 8. *Average Prescription Fill Times.* This includes prescriptions filled both manually and automatically. The maximum average fill time of 57.9 minutes occurred on February 5, 2014, while the minimum of 9.04 minutes occurred on August 10, 2014.

2. Day of Week Trend Analysis

Next, the number of prescriptions filled and their fill times are analyzed based on day of the week. It is noted previously that there is a significant weekly trend in the number of prescriptions filled within a day. The pharmacy at NMCS D is open seven days a week; however the regular workweek for the base is Monday through Friday. Therefore, it is expected that there are significantly fewer customer orders on weekends than on weekdays, because patients tend to make appointments during the business week. In order to validate this expectation, observations are binned by day of the week, and then averaged within that bin. Demand decreases on the weekends, which is also associated with a lower average prescription fill time. Of more interest, the average prescription fill time on Mondays is higher than other weekdays without a corresponding increase in demand. Figure 9 illustrates the effect that day of the week has on average number of prescriptions filled and average prescription fill time.

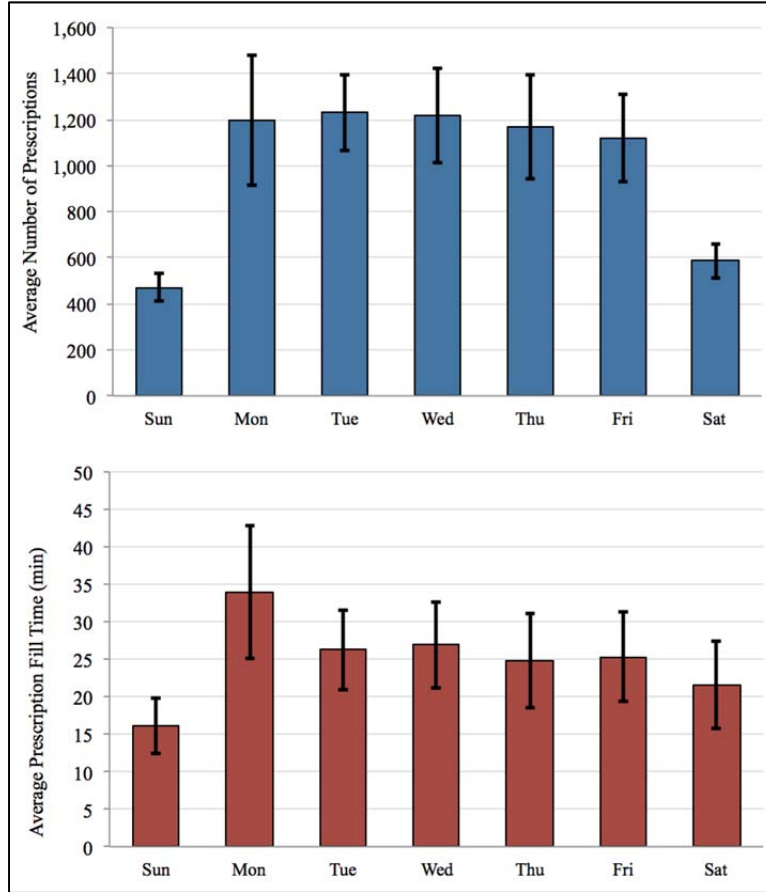


Figure 9. *Average Prescription Fill Time and Average Number of Customer Prescription Orders, Binned by Day of Week.* The black bars represent standard error of the mean. Demand decreases on weekends, which is also associated with a lower average prescription fill time. On weekdays, demand for prescriptions remains fairly constant. Mondays have an increased average prescription fill time without a corresponding increase in demand.

3. Hour of Day Trend Analysis

A normal workday for the outpatient pharmacy at NMCS D begins at 0800 and ends at 2100, Monday through Friday. On Saturday and Sunday, business hours are from 0800 to 1800. At all other times, the outpatient pharmacy is officially only open for prescription fills associated with Emergency Department visits. Because of this schedule, it is expected that customer demand will be higher during working hours and lower during non-working hours. In order to validate this expectation, observations are binned by hour of the day, and then averaged within that bin. Prescription demand experiences a

sharp increase at 0800, and then tapers off after 1700. Prescription fill times experience delays around 0700 and 1800. Figure 10 illustrates the relationship between hour of the day, prescription demand, and prescription fill times.

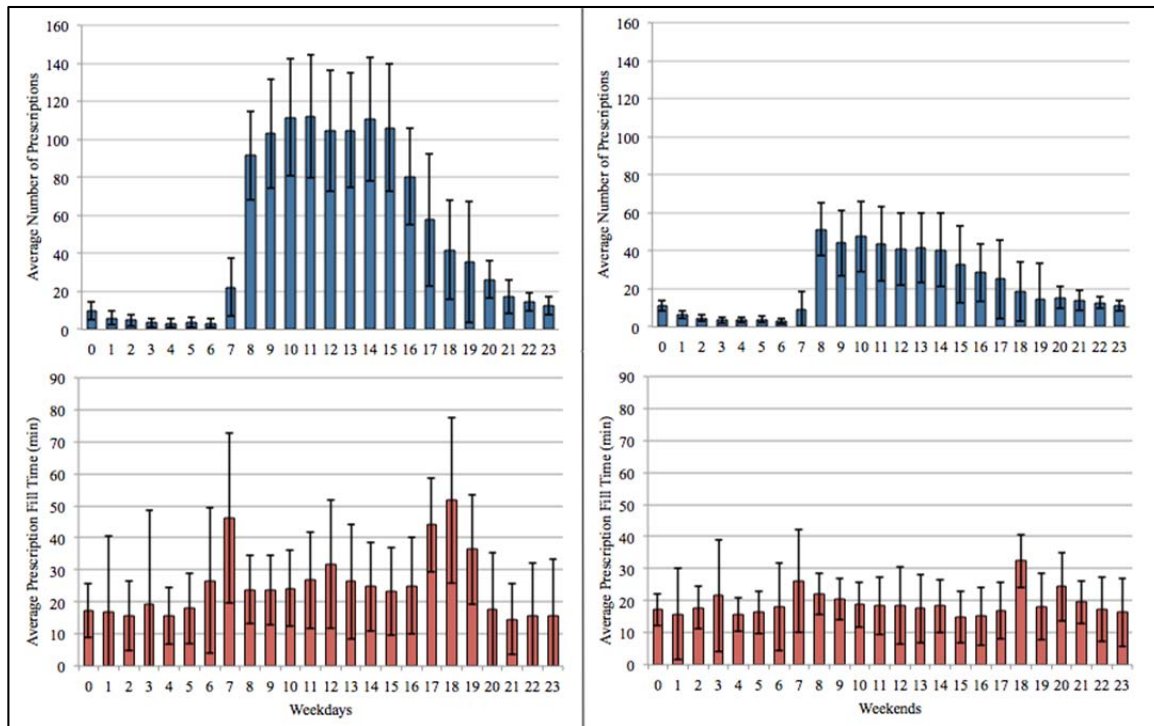


Figure 10. *Average Prescription Fill Time and Average Number of Customer Prescription Orders, Binned by Hour of the Day.* The black bars represent standard error of the mean. Weekends and weekends are separated because there are different working hours, depending on the day. Prescription demand experiences a sharp increase at 0800, and then tapers off after 1700. Prescription fill times experience delays around 0700 and 1800.

Based on the observed increase in prescription fill times without an increase in demand on Mondays, this day is evaluated individually. Figure 11 illustrates the average prescription fill time, per hour, during working hours on Monday; there is an extreme increase in the fill time from 1700 to 1900. This hourly increase directly contributes to the overall increase in average daily prescription fill times on Mondays, compared to the rest of the week.

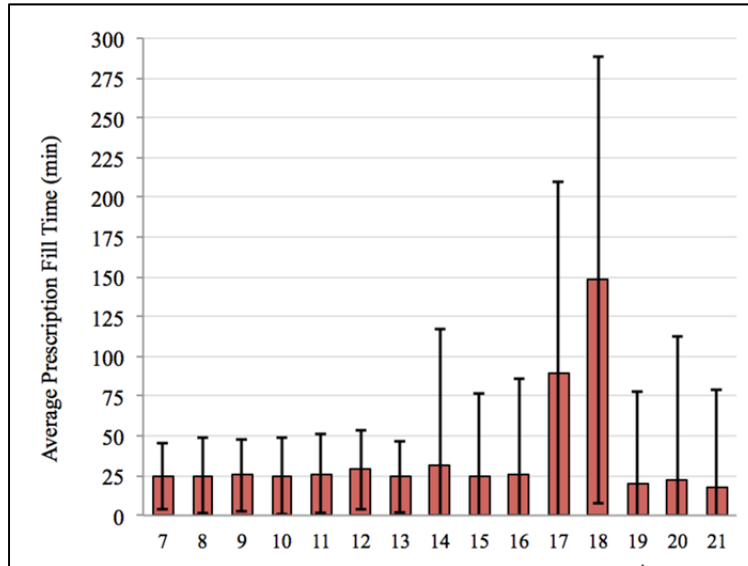


Figure 11. *Average Hourly Prescription Fill Time During Working Hours, Monday.* The black bars represent standard error of the mean. There is an extreme increase in the average hourly prescription fill time from 1700 to 1800, where the fill times jumps to a maximum of 147 minutes.

B. PRE-AUTOMATION PRESCRIPTION FILL

A significant limitation of this study is the unavailability of data collected pre-automation. To evaluate the effectiveness of the automation system, a pre-automation data set is constructed using simulation to model the process prior to automation implementation. Two major assumptions are made in order to construct this simulation: first, the CY2014 medication demand is representative of typical yearly demand, and second, the manual fill times of the pharmacy technicians in CY2014 is characteristic of typical manual fill times per prescription.

1. Design

Using the name of the dispensed medication as an identifier in the CY2014 data set, it is observed that there are 2,340 unique medications—the same type of medication in a different dosage is counted as a unique medication. Of those medications, the ten most prescribed medications account for 21.3 percent of the total prescription in CY2014; a distribution of the 25 most prescribed medications can be found in Appendix B.

Prescription fill time is dependent on the type of medication ordered. Figure 12 and Figure 13 illustrate the difference in manual prescription fill time and demand for four of the most frequently filled medications.

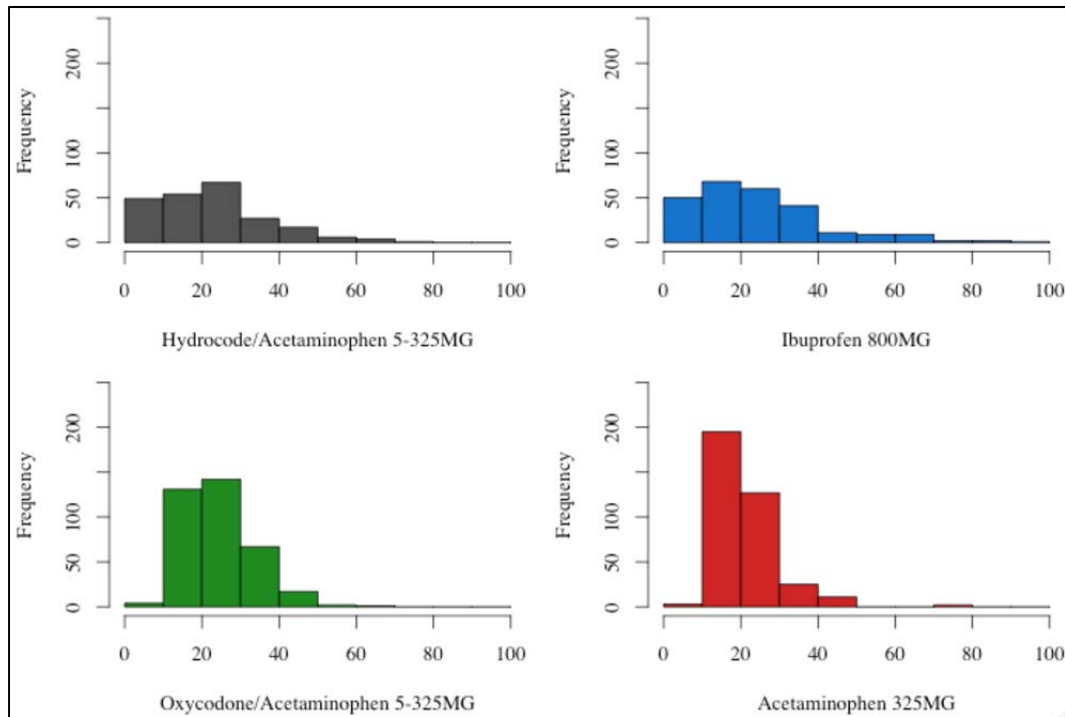


Figure 12. *Histogram of Daily Average Manual Fill Time (Minutes) for Four Frequently Prescribed Medications.* The manual fill time varies based on medication.

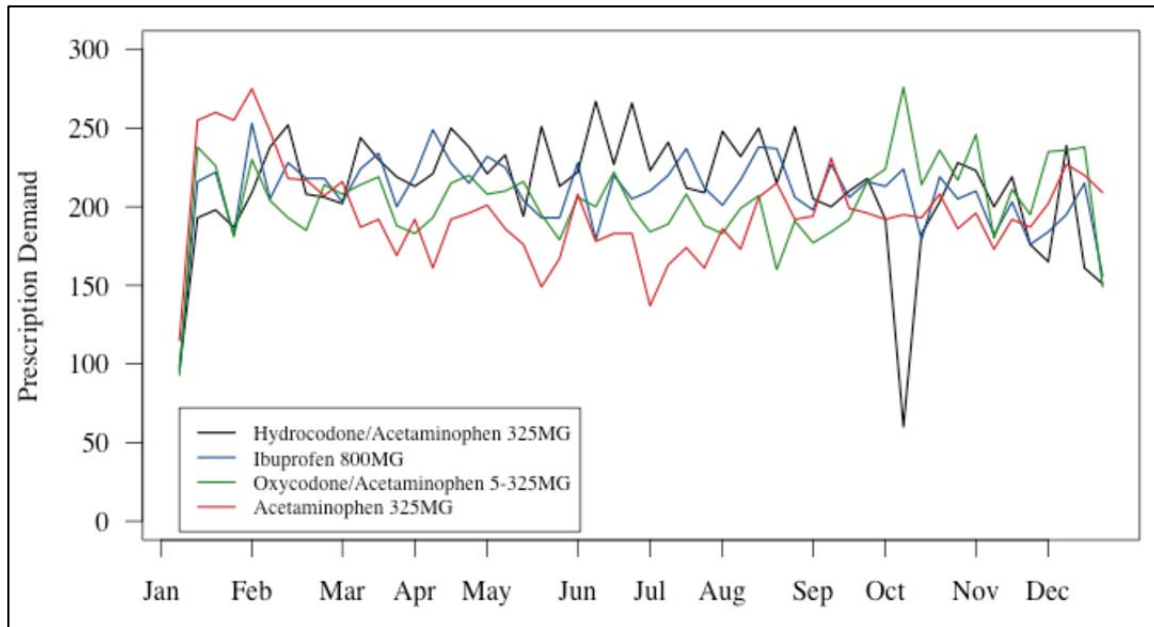


Figure 13. *Prescription Demand for Three Frequently Prescribed Medications.* Demand for different medications varies throughout the year, based on the unique medication. For example, the demand for Hydrocodone/Acetaminophen 326MG tends to be larger than the demand for Acetaminophen 325MG during the middle portion of the year.

Monthly and weekly trends are used as the basis for simulation; it is not essential to detail hourly trends at this level. Because it is assumed that the demand and manual prescription fill times are consistent with CY2014 data, it is only necessary to simulate the extra demand placed on the pharmacy technicians in the absence of automation. For this simulation, this means that the actual fill times observed in CY2014 for manual transactions each day of the year are left unchanged; only the additional manual workload not supplemented by the automation machine is simulated. The variables of interest for the simulation include total prescription demand, medication demand, and prescription fill times, as defined in Table 3.

Table 3. *Indices, Derived Data, and Calculated Variables for Simulated Pre-Automation Process.* The additional manual workload not supplemented by the automation machine is simulated to create a pre-automation data set.

	Notation	Description
Indices	i	Day of the Year, $i \in \{1, \dots, 365\}$
	j	Day of the Week, $j \in \{1, \dots, 7\}$, where $j = 1$ is Sunday
	k	Month, $k \in \{1, \dots, 12\}$
	m	Medication, $m \in \{1, \dots, 2340\}$
Derived Data	$total_fills_i$	Total number of prescriptions filled on each day of the year, i .
	$manual_fills_i$	Total number of prescriptions filled manually on each day of the year, i .
	$medication_demand_{j,k}$	Vector of medications demanded on each day of the week, j , for each month of the year, k .
	$manual_fill_time_{m,j,k}$	Vector of manual fill times associated with medication m for each day of the week, j , for each month of the year, k .
Calculated Variables	$sd_{j,k}$	Standard deviation of daily demand on each day of the week, j , and month, k .
	$upper_bound_i$	Upper bound for simulated total prescription demand on each day of the year, i .
	$lower_bound_i$	Lower bound for simulated total prescription demand on each day of the year, i .
	$simulated_total_i$	Total simulated prescription demand on each day of the year, i .
	$excess_manual_i$	Excess manual workload on each day of the year, i .

First, the medication demand at NMCSD pharmacy in CY2014 is aggregated by day of the week, j , and month, k , resulting in 84 vectors of varying length, **medication_demand** _{j,k} . This vector contains the names of all medications filled on day of the week, j , in month, k ; individual medications appear in this vector with the same frequency as observed in CY2014. Similarly, all manual fill times associated with the demanded medications are aggregated by medication, m , day of the week, and month of the year, **manual_fill_time** _{m,j,k} . This results in 196,560 vectors of varying length, one for every medication, m , on every day of the week, j , in each month, k . Then, total number of prescription fills and manual prescription fills completed on each day of the year, i , are calculated. This results in 365 observations of two variables, $total_fills_i$ and $manual_fills_i$, respectively; on average, the automation machine accounts for 37.3 percent of prescription fills per day. The total number of prescriptions ordered on a specific day of the week within each month is modeled as uniformly distributed. The lower and upper bounds of the uniform distribution are calculated the observed total fill for that day, $total_fills_i$, and the standard deviation of the daily demand corresponding to the day of the week and month, $sd_{j,k}$; this is shown in Equations (1) and (2).

$$upper_bound_i = total_fills_i + sd_{j,k} \quad (1)$$

$$lower_bound_i = total_fills_i - sd_{j,k} \quad (2)$$

$$i \in \{1, \dots, 365\}, j \in \{1, \dots, 7\}, k \in \{1, \dots, 12\}$$

For each day of the year, a random uniform number within the calculated lower and upper bounds is drawn to determine the day's simulated total demand, $simulated_total_i$. Because the observed manual prescription fills from CY2014 will remain unchanged, the observed manual fills, $manual_fills_i$ are removed from the simulated total demand, leaving only the excess workload per day, $excess_manual_i$, as shown in Equation (3).

$$excess_manual_i = simulated_total_i - manual_fills_i, i \in \{1, \dots, 365\} \quad (3)$$

For each day of the year, a random medication sample of size $excess_manual_i$ is selected at random from $medication_demand_{j,k}$, based on the appropriate day of the week and month. Using the medications in the sample, manual fill times are chosen with replacement from $manual_fill_time_{m,j,k}$, the actual manual fill times for each medication observed during that month and day of the week. If a medication does not have an associated manual fill time for a specified day of the week within month k , the manual fill time is assigned as the average manual fill time for the specified medication in month k . If a medication does not have an associated manual fill time in all of month k , the manual fill time is assigned as the average manual fill time for the specified medication over the entire year. If a medication does not have an associated manual fill time in the entire year, the manual fill time is assigned as the average manual fill time for all medications; there are only seventeen medications in CY2014 filled solely through automation, accounting for 0.07 percent of total observations. This entire process is repeated with 1,000 replications.

Through this technique, 135,972 data points are created using simulation, representing the excess demand within the pharmacy not supplemented by automation. These simulated observations are then combined with the observed manual prescription fill times, resulting in a pre-automation data set consisting of 364,443 total data points. Figure 14 illustrates the observed and simulated prescription demand.

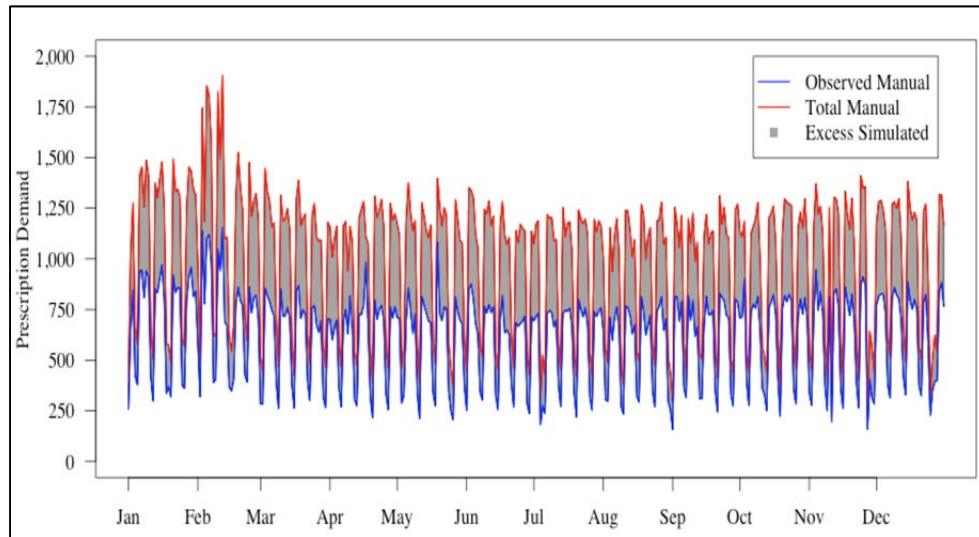


Figure 14. *Simulated Excess Demand Combined with Observed CY2014 Prescription Demand.* Through simulation, the excess demand not supplemented by automation is generated to produce a pre-automation data set.

2. Validation

In order to confirm the validity of this simulated process, the automation demand for CY2014 is generated through a similar technique, using only monthly and weekly trends. Again, the manual fill times observed in CY2014 are left unchanged; only the automatically filled prescriptions are simulated. By simulating the automated prescription fills and combining these data points with the observed manual fill times, simulated data set can be compared to the observed CY2014 data. The variables of interest for this validation include total prescription demand, medication demand, and prescription fill times, as defined in Table 4.

Table 4. *Indices, Derived Data, and Calculated Variables for Simulated Automation Process.* The additional manual workload not supplemented by the automation machine is simulated to create automation data.

	Notation	Description
Indices	i	Day of the Year, $i \in \{1, \dots, 365\}$
	j	Day of the Week, $j \in \{1, \dots, 7\}$, where $j=1$ is Sunday
	k	Month, $k \in \{1, \dots, 12\}$
	m	Medication, $m \in \{1, \dots, 2340\}$
Derived Data	$total_fills_i$	Total number of prescriptions filled on each day of the year, i .
	$manual_fills_i$	Total number of prescriptions filled manually on each day of the year, i .
	$medication_demand_{j,k}$	Vector of medications demanded on each day of the week, j , for each month of the year, k .
	$auto_fill_time_{m,j,k}$	Vector of automatic fill times associated with medication m for each day of the week, j , for each month of the year, k .
Calculated Variables	$sd_{j,k}$	Standard deviation of daily demand on each day of the week, j , and month, k .
	$upper_bound_i$	Upper bound for simulated total prescription demand on each day of the year, i .
	$lower_bound_i$	Lower bound for simulated total prescription demand on each day of the year, i .
	$simulated_total_i$	Total simulated prescription demand on each day of the year, i .
	$simulated_auto_i$	Simulated automatic workload on each day of the year, i .

The $medication_demand_{j,k}$ vector remains unchanged for validation. All automatic fill times associated with the demanded medications are binned by medication, day of the week, and month of the year, $auto_fill_time_{m,j,k}$. This results in 196,560 vectors of varying length, one for every medication, m , on every day of the week, j , in

each month, k . Again, the total number of prescriptions ordered on a specific day of the week within each month is modeled as uniformly distributed. The lower and upper bounds of the uniform distribution are calculated the observed total fill for that day, $total_fills_i$, and the standard deviation of the daily demand corresponding to the day of the week and month, $sd_{j,k}$; this is shown in Equations (1) and (2).

For each day of the year, a random uniform number within the calculated lower and upper bounds is drawn to determine the day's simulated total demand, $simulated_total_i$. Because the observed manual prescription fills from CY2014 will remain unchanged, the observed manual fills are removed from the simulated total demand, leaving only the automation workload, $simulated_auto_i$, as shown in Equation (4).

$$simulated_auto_i = simulated_total_i - manual_fills_i, i \in \{1, \dots, 365\} \quad (4)$$

For each day of the year, a random medication sample of size $simulated_auto_i$ is selected at random from **medication_demand** _{j,k} , based on the appropriate day of the week and month. Using the medications in the sample, automatic fill times are chosen with replacement from **auto_fill_time** _{m,j,k} , the actual automatic fill times for each medication observed during that month and day of the week. If a medication does not have an associated automatic fill time for a specified day of the week within month k , the fill time is assigned as the average automatic fill time for the specified medication in month k . If a medication does not have an associated automatic fill time in all of month k , the fill time is assigned as the average automatic fill time for the specified medication over the entire year. If a medication does not have an associated automatic fill time in the entire year, the fill time is assigned as the average automatic fill time for all medications. This entire process is repeated with 1,000 replications.

Through this technique, 136,074 data points are constructed using simulation, representing the automation workload within the pharmacy. These simulated observations are then combined with the observed manual prescription fill times, resulting in a data set consisting of 364,535 total data points. Figure 15 illustrates the observed daily demand and the daily demand with simulated automation workload; Figure 16 illustrates the

observed average daily prescription fill time and the average daily prescription fill time with simulated automation workload.

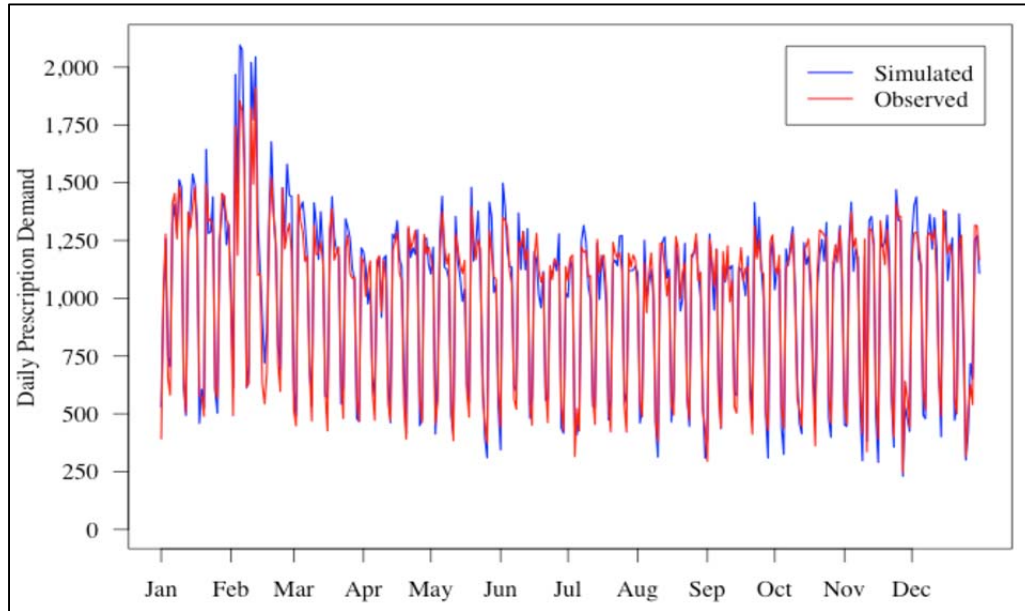


Figure 15. *Observed and Simulated Daily Demand.* With the same simulation techniques used to create the pre-automation manual workload, a simulated automation workload is generated.

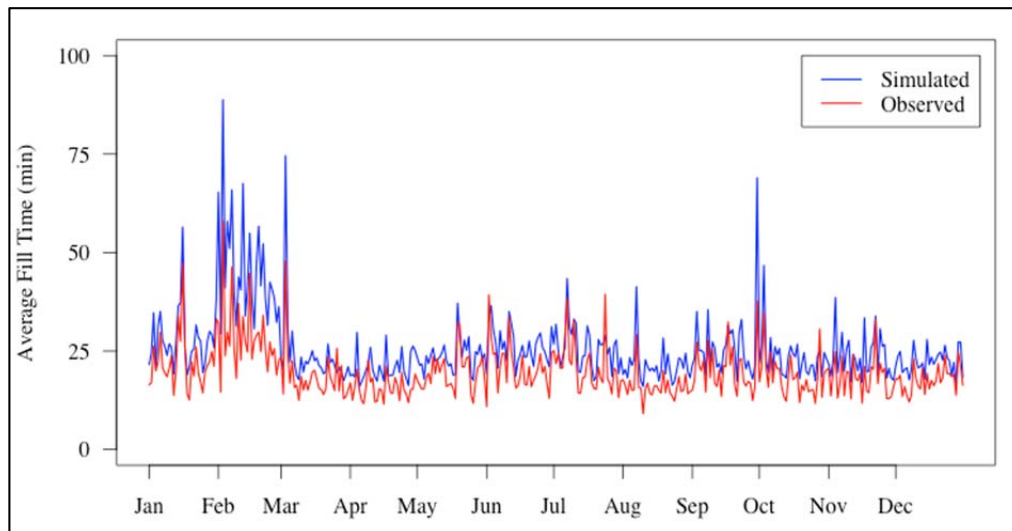


Figure 16. *Observed and Simulated Automation Average Prescription Fill Time.* With the same simulation techniques used to create the pre-automation manual workload, a simulated automation workload is generated.

This simulated automated workload provides a degree of validity to the techniques used to simulate the pre-automation data. The simulated automatic data set tends to overestimate both the daily demand and the average daily prescription fill time; this suggests that the simulated pre-automation data set will be an upper bound of the manual workload. The absolute mean difference between daily observed demand and daily simulated demand is 72.9 ± 51.2 (standard deviation) items; 70 percent of the differences fall within 100 items. February is a month with uncharacteristically large differences, and if excluded from the data set, the mean difference between daily observed demand and daily simulated demand is 67.4 ± 40.6 items. Figure 17 illustrates the difference in the demand for the observed and simulated data sets throughout an entire year. The mean difference between average daily observed prescription fill time and average daily simulated prescription fill time is 6.3 ± 4.8 minutes; 83 percent of observations fall within ten minutes. With February excluded, the mean difference between average daily observed prescription fill time and average daily simulated prescription fill time is 5.4 ± 2.9 minutes. Figure 18 illustrates the difference in prescription fill time for the observed and simulated data set throughout an entire year. Evaluation of the difference in the observed and simulated data set aggregated by month and day of week, is conducted; other than the month of February, there does not appear to be any patterns in the average differences based on month or day of week. These plots can be found in Appendix C.

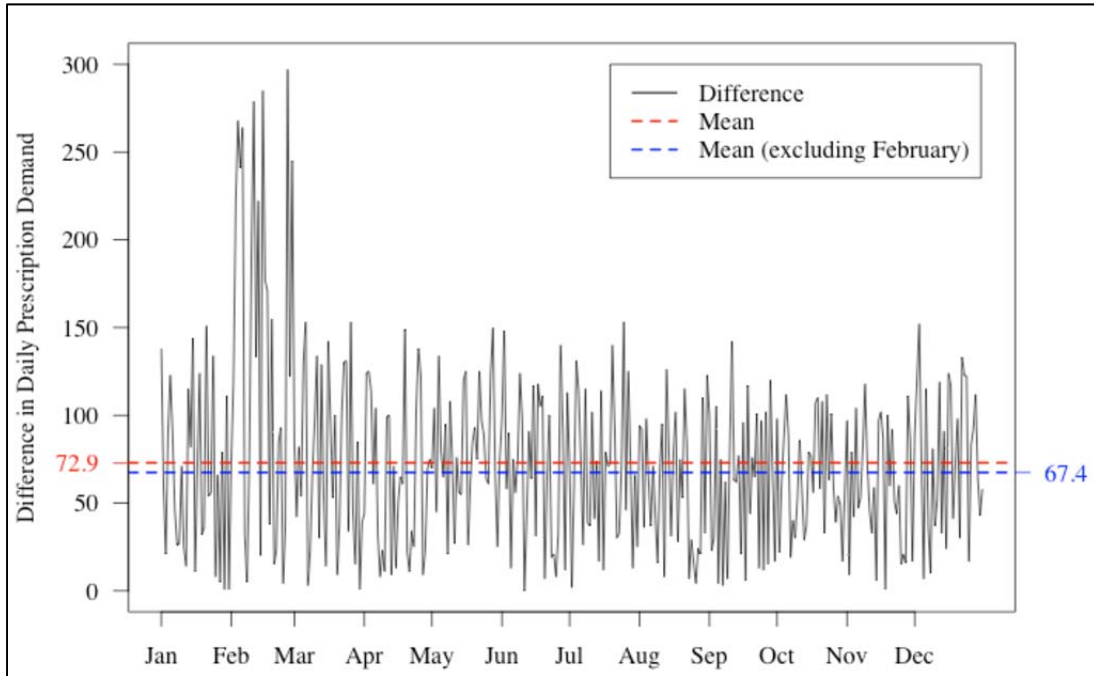


Figure 17. *Difference in Daily Observed Demand and Daily Simulated Demand.* After simulating the automated workload, the mean difference between the daily observed demand and the daily simulated demand 72.9 observations with a standard deviation of 51.2 observations. The month of February is extremely volatile; without this month, the mean difference is 67.4 observations with a standard deviation of 40.6 minutes.

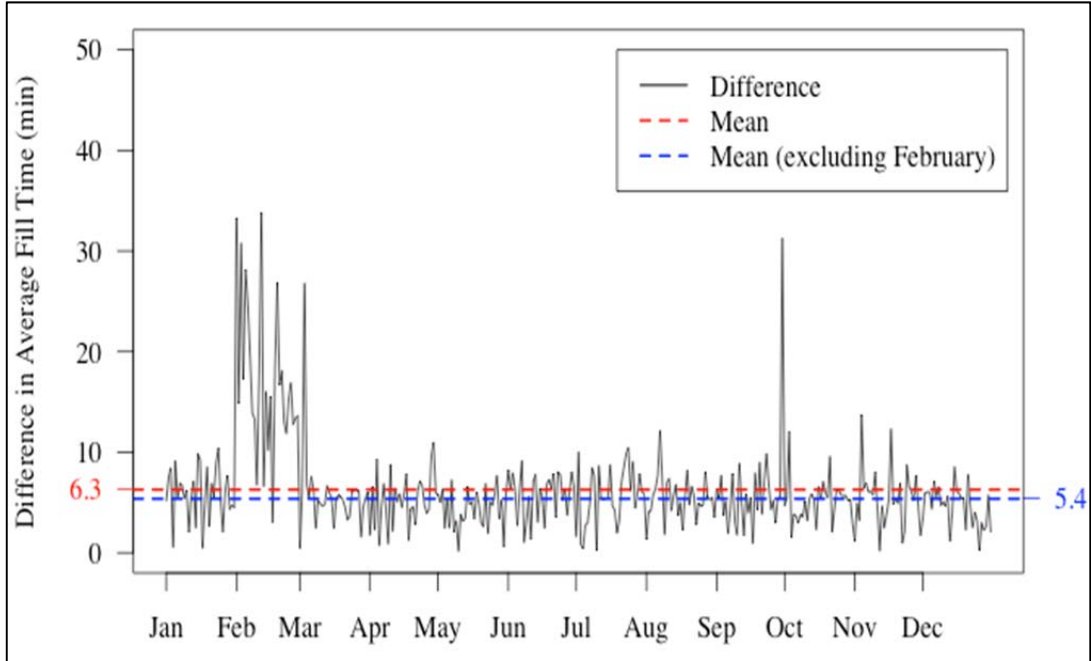


Figure 18. *Difference in Average Daily Observed Prescription Fill Time and Average Daily Simulated Prescription Fill Time.* After simulating the automation workload, the mean difference between the observed average daily prescription fill time and the simulated daily prescription fill time is 6.3 minutes with a standard deviation of 4.8 minutes. The simulated data set is more volatile during the month of February; without this month, the mean difference is 5.4 minutes with a standard deviation of 2.9 minutes.

To determine if there are any systematic trends over time, two statistical tests are performed on the difference in average daily observed prescription fill time and average daily simulated prescription fill time; February is an extremely volatile month, and is removed from the data set. First, a two-sided runs test for detecting non-randomness is performed, and the results indicate there is no evidence to suggest dependence in the differences over time (Bradley, 1968). The standardized runs test statistic is -1.36 with a p-value of 0.17. Next, a Durbin-Watson test is conducted to detect autocorrelation, and the results are consistent with the two-sided runs test, indicating independence in the differences over time (Durbin & Watson, 1950). The Durbin-Watson test statistic is 1.98 with a p-value of 0.44. The difference in average daily prescription fill time and average daily simulated prescription fill time does not show any evidence of non-randomness or autocorrelation.

C. SUMMARY

There are significant trends in the demand and prescription fill times of prescriptions filled at NMCSD in CY2014. With these trends, monthly and weekly indicators are used to generate the increased manual demand that is expected without the automation; this simulated manual demand is combined with the observed manual demand to create a pre-implementation data set. To validate this simulation, the automatic workload is also simulated using the same technique. The construction of the pre-automation data facilitates analysis of the effectiveness of the automation implementation at NMCSD conducted in Chapters IV and V.

IV. METHODOLOGY AND ANALYSIS

The objective of this study is to quantify any efficiencies experienced due to the implementation of pharmacy automation at NMCSD. In addition, linear regression is used to evaluate which characteristics of the pre-automation and post-automation data sets most heavily impact the difference in average prescription fill time. The results of this analysis provide a foundation for the implementation of pharmacy automation at similarly sized medical facilities.

A. MANUAL VS. AUTOMATIC FILLS IN CY2014

Using the observed post-automation data set, the prescription fill times for manual prescription fills and automatic prescription fills are compared; see Figure 19. In order to remove any evidence of autocorrelation, the observations are aggregated by week. A two-sided runs test for detecting non-randomness in data is performed, and the results indicate there is no evidence to suggest the data points were produced in a non-random manner (standardized runs statistic = -0.58, p-value = 0.56). On average, prescriptions filled automatically are completed 6.97 ± 0.97 (standard error) minutes quicker than prescriptions filled manually. In CY2014, automatic fills were faster than manual fills in 96.2 percent of weeks, with an approximate 95 percent confidence interval for the probability that the automatic fills are quicker than manual fills of (0.87, 0.99). This confidence interval does not include 0.5, which is the expected probability if this result occurred by chance; therefore, this result is statistically significant.

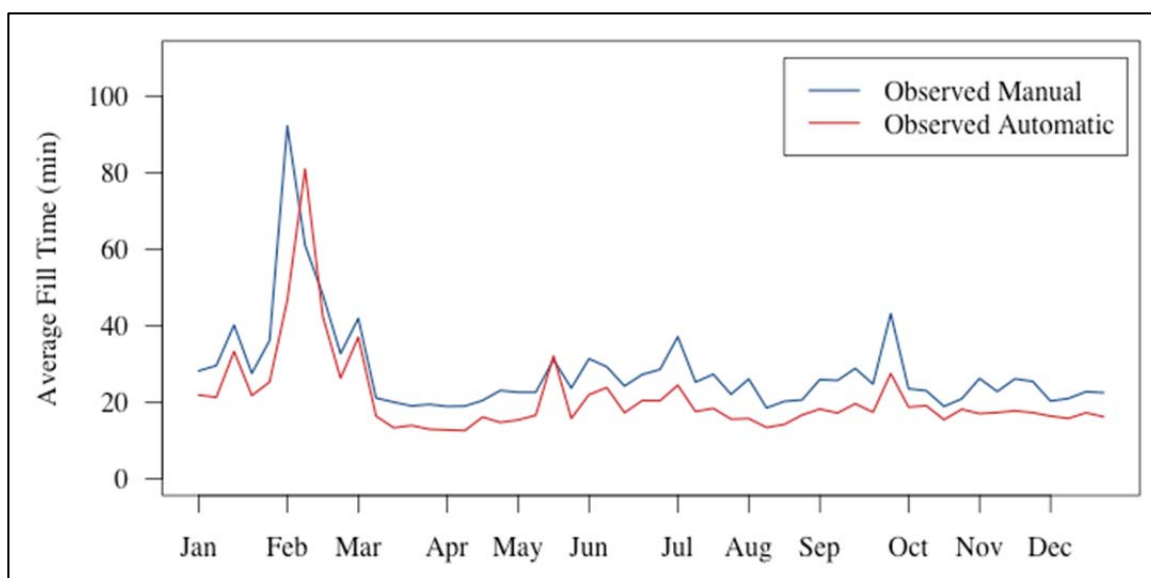


Figure 19. *Observed Manual and Automatic Fills in the Post-Automation Data Set.* The average weekly prescription fill time for medications filled automatically tend to be quicker than manually in 96.2 percent of weeks in CY2014.

It is also of interest to see if there is a significant difference in the average fill time during periods of high demand in the pharmacy. A period of high demand is defined as an hour during business hours (0800 to 2100 Monday through Friday and 0800 to 1800 Saturday and Sunday) in which customer demand exceeds the mean yearly demand during that time period; the mean demand on weekdays is 83 prescriptions per hour, and the mean demand on weekends is 34 prescriptions per hour. These observations are aggregated by day, and the average daily prescription fill times during hours of high demand is illustrated in Figure 20. A two-sided runs test for detecting non-randomness is performed, and the results indicate there is no evidence to suggest dependence in the differences over time (standardized runs statistic = -1.49, p-value = 0.14). During periods of high demand, automatic fills were quicker than manual fills on 84.5 percent of days with an approximate 95 percent confidence interval for the probability that automatic fills are quicker than manual fills during hours of high demand of [0.80, 0.87]. This confidence interval does not include 0.5, which is the expected probability if this result occurred by chance; therefore, this result is statistically significant.

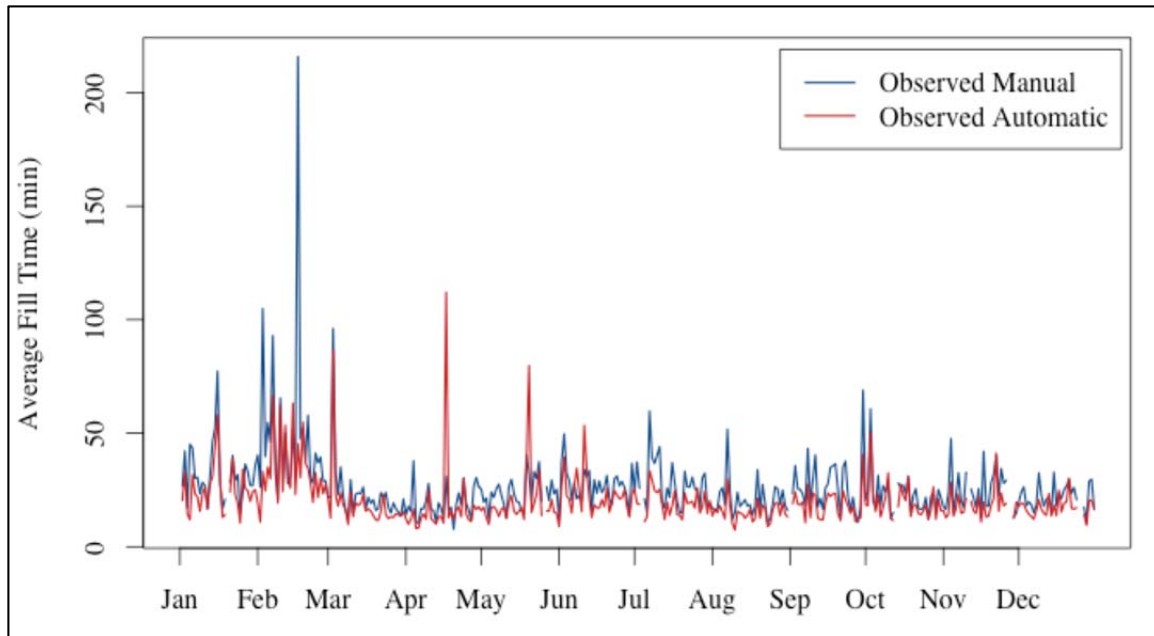


Figure 20. *Manual and Automatic Fills During Hours of High Demand.* During periods of high demand, automatic fills tend to be quicker than manual fills 84.5 percent of days in CY2014.

B. PRE-AUTOMATION VS. POST-AUTOMATION

Using both the pre-automation data set generated in Chapter III and the observed post-automation data set, the average daily prescription fill times pre-automation, $Y_{DailyAvgPre}$, are compared with the average daily prescription fill times post-automation, $Y_{DailyAvgPost}$; see Figure 21. On average, prescriptions filled after the installation of automation are completed 4.4 ± 0.34 minutes faster than prescriptions filled prior to the installation of automation. The average daily prescription fill time post-automation is faster than the average daily prescription fill time pre-automation on 92.6 percent of day with an approximate 95 percent confidence interval for the probability that post-automation fills are quicker than pre-automation fills of $[0.89, 0.95]$. This confidence interval does not include 0.5, which is the expected probability if this result occurred by chance; therefore, this result is statistically significant.

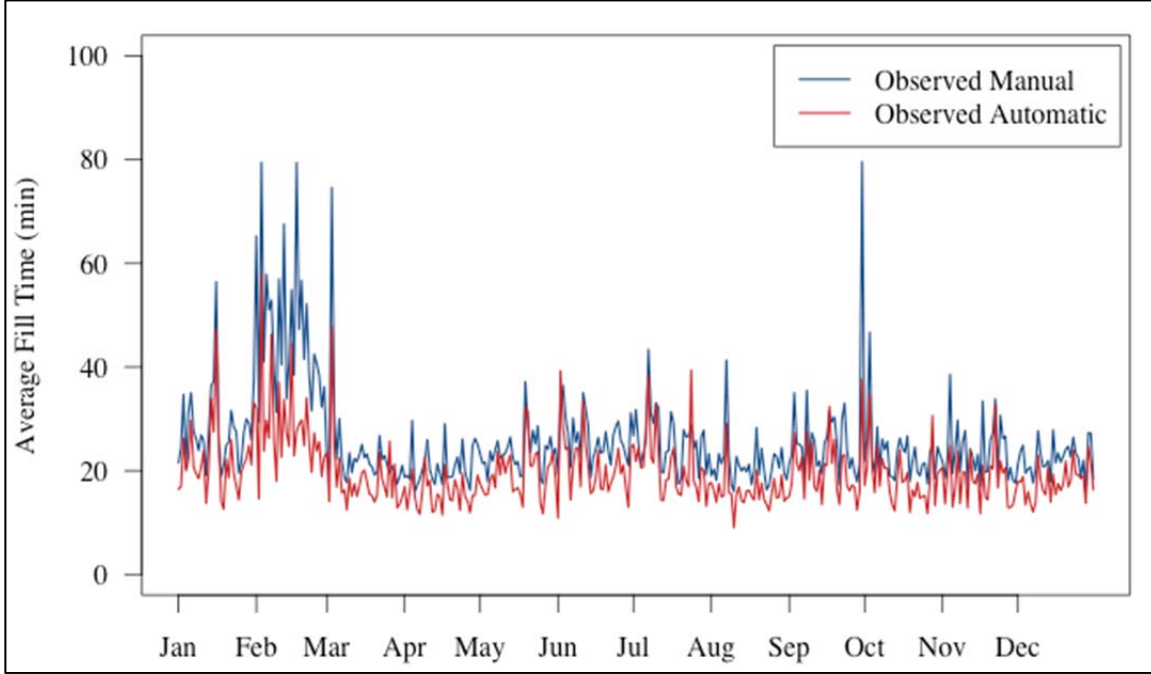


Figure 21. *Average Daily Prescription Fill Time Pre-Automation and Post-Automation.* The average daily prescription fill time for medications filled post-automation is quicker than medications filled pre-automation on 92.6 percent of days.

Next, linear regression is used to study which characteristics of the data most heavily impact the difference in $Y_{DailyAvgPre}$ and $Y_{DailyAvgPost}$. This difference is the new response variable, Y_{Diff} , defined in Equation (5). A negative value of Y_{Diff} represents a day in which the average prescription fill time pre-automation is quicker than post-automation.

$$Y_{Diff} = Y_{DailyAvgPost} - Y_{DailyAvgPre} \quad (5)$$

Equation (6) gives the linear regression model, where Y is the response variable, Y_{Diff} , given x_1, \dots, x_n regressors; the constants, β_0 through β_n , are the unknown parameters, and ε is the error term. The errors are modeled as independent and normally distributed with a mean of zero and constant variance (Faraway, 2015). Several different characteristics, including daily proportion of orders automated, proportion of highly prescribed medications, and number of daily high demand hours, are used as regressors.

In this analysis, the entire month of February is eliminated from consideration due to its relative extremes.

$$Y = \beta_0 + \beta_1 x_1 + \dots + \beta_n x_n + \varepsilon \quad (6)$$

1. Variable Selection

In total, ten variables are considered for impact on Y_{Diff} : total number of hours in the day above the mean demand ($x_{HighDemand}$), proportion of daily demand fill by automation in the post-automation data set ($x_{PropAutoPost}$), proportion of medications demanded in the top five most prescribed medications pre-automation and post-automation ($x_{PropTop5MedsPre}$ and $x_{PropTop5MedsPost}$, respectively), proportion of medications demanded in the top ten most prescribed medications pre-automation and post-automation ($x_{PropTop10MedsPre}$ and $x_{PropTop10MedsPost}$, respectively), proportion of medications demanded in the top 25 most prescribed medications pre-automation and post-automation ($x_{PropTop25MedsPre}$ and $x_{PropTop25MedsPost}$, respectively), day of the week (x_{DOW}), and month (x_{Month}). Summary statistics for the ten considered variables are shown in Table 5. Variable selection is performed using backwards elimination; the full model with all ten variables and the final model after variable selection is validated using regression diagnostic techniques, and it is found that the error terms can be modeled as independent with mean zero and constant variance. There is some indication that the errors may not be normally distributed, but with the large number of observations, inference results are not affected (Faraway, 2015). In addition, none of the outlying observations are found to be influential. Diagnostic plots can be found in Appendix D. Prior to the discussion of the final model in Section 2, univariate analysis on the selected variables is performed.

Table 5. *Summary Statistics for Considered Variables.* The selected model contains three continuous variables. The coefficient estimates and regressor summary statistics for the regressors contained in the final model can be found in Table 6.

Variable	Final Model	Type	Minimum Value	Maximum Value	Mean	Standard Deviation
$x_{HighDemand}$	X	Continuous	0	10	6.8	2
$x_{PropAutoPost}$	X	Continuous	0.11	0.48	0.38	0.04
$x_{PropTop5MedsPre}$	X	Continuous	0.11	0.29	0.17	0.03
$x_{PropTop5MedsPost}$		Continuous	0.08	0.28	0.16	0.03
$x_{PropTop10MedsPre}$		Continuous	0.14	0.35	0.21	0.04
$x_{PropTop10MedsPost}$		Continuous	0.16	0.41	0.23	0.05
$x_{PropTop25MedsPre}$		Continuous	0.24	0.49	0.32	0.05
$x_{PropTop25MedsPost}$		Continuous	0.25	0.53	0.34	0.05
x_{DOW}		Categorical	7 Levels		N/A	N/A
x_{Month}		Categorical	11 Levels (Excl. Feb)		N/A	N/A

a. Hours of High Demand

As defined in Section A, an hour of high demand is an hour during business hours in which the prescription demand is greater than the mean hourly prescription demand for weekends and weekdays, as appropriate. This means that instead of customers arriving to the pharmacy at a relatively steady pace, there are hours of peak demand. For each day, the number of hours the pharmacy functioned in high demand is totaled, and this becomes $x_{HighDemand}$; 13.1 percent of days experienced 8 or more hours of high demand. Figure 22 reflects a slightly decreasing trend, indicating that as the hours of high demand increase, the difference in the pre-automation prescription fill time and the post-automation prescription fill time decreases.

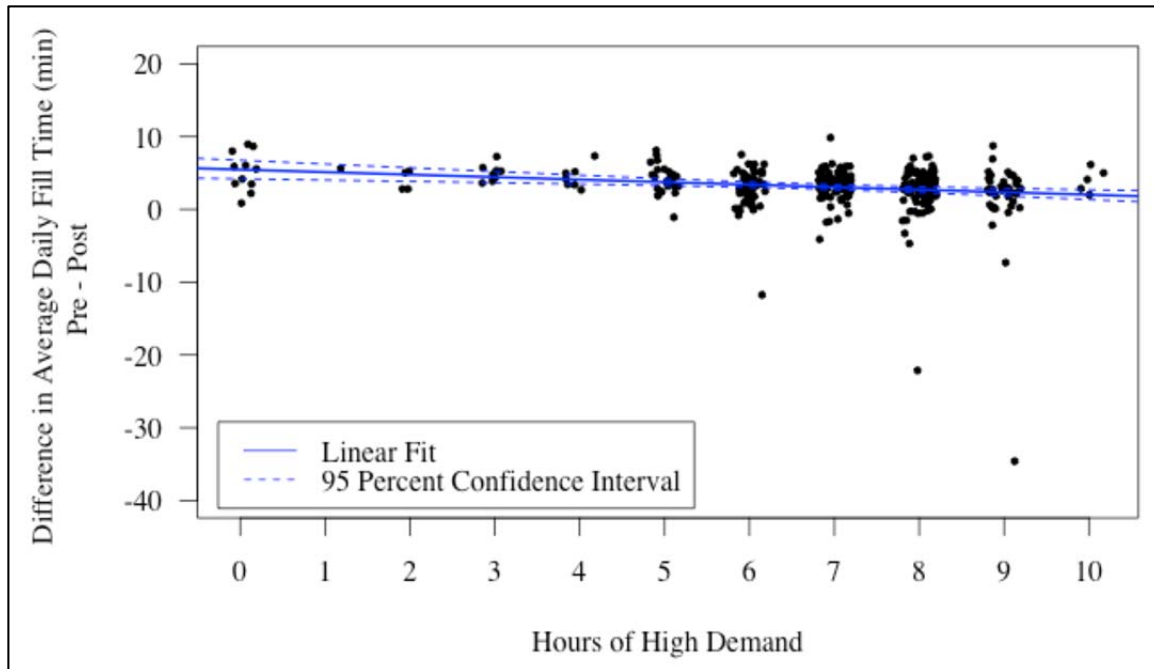


Figure 22. *Difference in Average Daily Prescription Fill Times Based Hours of High Demand.* As the number of hours of high demand increases, the difference in average daily prescription fill time between pre-automation and post-automation decreases.

b. Proportion Filled by Automation

On average, automation filled 37.3 percent of prescriptions in CY2014; however, there are days in which automation accounted for significantly more of the total demand, 47.7 percent, or significantly less than the total demand, 11.3 percent. In addition, prescriptions filled automatically have a mean fill time that is 6.94 minutes faster than prescriptions filled manually. The proportion of post-automation medications filled through automation, $x_{PropAutoPost}$, is calculated for each day. The linear fit of $x_{PropAutoPost}$ shown in Figure 23 reflects a slightly increasing trend, indicating that a higher proportion of prescriptions automated causes an increase in Y_{Diff} .

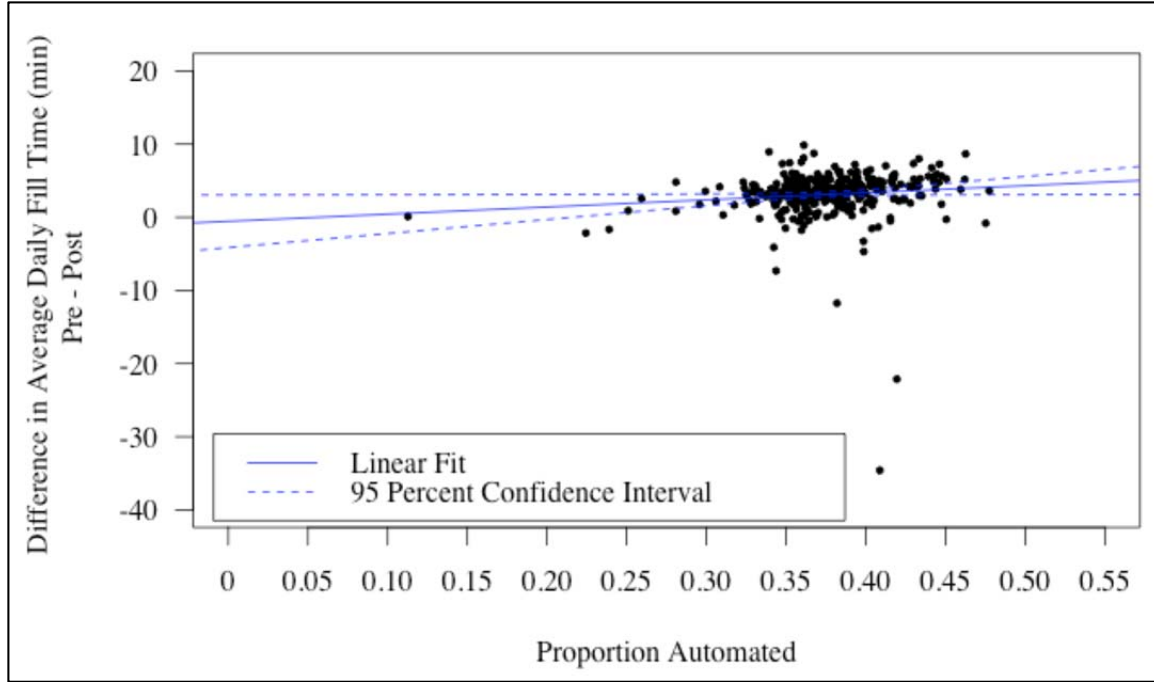


Figure 23. *Difference in Average Daily Prescription Fill Times Based Daily Proportion of Prescriptions Automated, Post-Automation.* The linear fit reflects a slightly increasing trend, indicating that a higher proportion of prescriptions automated increases the difference in average daily prescription fill time.

c. Frequently Prescribed Medications

As noted in Chapter III, the type of medication ordered influences the prescription fill time. The distribution for the 25 most frequently prescribed medications can be found in Appendix B. These medications account for 30.5 percent of total prescriptions filled pre-automation, and 31.7 percent of total prescriptions filled post-automation. For both the pre-automation and post-automation data, the daily proportion of medications that are the top 25, ten, and five most prescribed medications is found to create the variables $x_{PropTop5MedsPre}$, $x_{PropTop5MedsPost}$, $x_{PropTop10MedsPre}$, $x_{PropTop10MedsPost}$, $x_{PropTop25MedsPre}$, and $x_{PropTop25MedsPost}$. These variables are all highly correlated with each other; therefore, it is only appropriate to select one of them for use in the linear regression. After performing backwards elimination, $x_{PropTop5MedsPre}$ is selected as the variable with the most impact on Y_{Diff} . This is a reasonable selection because frequently prescribed medications are stored

in more convenient locations, and therefore, their fill times should be faster than less frequently prescribed medications. When all prescriptions are filled manually, this convenience could make a large difference in the overall daily prescription fill time. The linear fit of $x_{PropTop5MedsPre}$ shown in Figure 24 reflects a slightly increasing trend, indicating that a higher proportion of prescriptions automated causes an increase in Y_{Diff} . Linear fits of $x_{PropTop5MedsPost}$, $x_{PropTop10MedsPre}$, $x_{PropTop10MedsPost}$, $x_{PropTop25MedsPre}$, and $x_{PropTop25MedsPost}$ can be found in Appendix E.

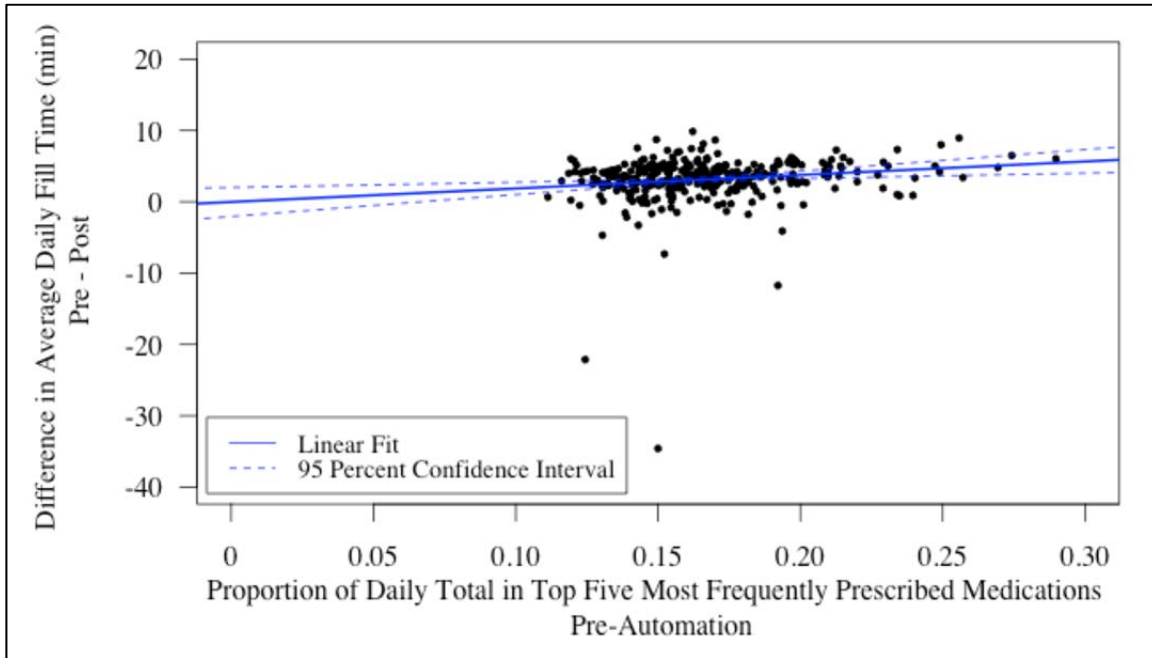


Figure 24. *Difference in Average Daily Prescription Fill Times Based Daily Proportion of Prescriptions that are the Five Most Prescribed Medications, Pre-Automation.* The linear fit reflects a slightly increasing trend, indicating that a higher proportion of highly prescribed medications increases the difference in average daily prescription fill time.

2. Regression

A simple linear regression is fit using the three selected continuous variables: $x_{HighDemand}$, $x_{PropAutoPost}$, and $x_{PropTop5Pre}$. Equation (7) shows the resulting model, where each estimate of the coefficients are rounded to the corresponding standard error. A

positive value of the response signifies that the post-automation prescription fills were, on average, faster than the pre-automation prescription fills on that particular day. A positive (negative) value of a coefficient indicates that as the variable increases, the difference in the average daily prescription fill time between pre-automation and post-automation becomes more positive (negative). Additional details for the regressors can be found in Table 6.

$$\hat{Y}_{Diff} = -.2x_{HoursHigh} + 8x_{PropAutoPost} + 12x_{PropTop5Pre} \quad (7)$$

Table 6. *Model Term Coefficient Estimates, Standard Error, T-Ratio, and Statistical Significance.* Each coefficient is rounded in the final regression model according to the corresponding standard error. Each variable is significant to the 0.1 level.

Term	Estimate	Standard Error	T-Ratio	P-Value
Intercept	0.55	2.53	- 0.22	0.8265
$x_{HighDemand}$	- 0.25	0.10	- 2.45	0.0150
$x_{PropAutoPost}$	8.86	4.79	1.85	0.0651
$x_{PropTop5Pre}$	12.30	6.74	1.83	0.0688

This linear regression model has three degrees of freedom with 333 residual degrees of freedom. These values correspond to an F-ratio of 6.870, and a model p-value of 0.0002; this result indicates there is a significant relationship between the variables in the linear regression to the response. The R_{adj}^2 value, which is a measure of the proportion of the variability of the response explained by the regressors, is 0.058 (Faraway, 2015). Though this is an extremely low value for this measure, it is not inherently limiting. The regressors are still statistically significant, and conclusions can still be drawn about how changes in the regressors are associated with changes in the response. The intention of this study is not to predict the difference in average daily prescription fill times for pre-automation and post-automation, but to determine the factors that impact this response.

The impact of these three regressors on the difference in average daily prescription fill time pre-automation and post-automation can be inferred from the values of their coefficients. The value of the coefficient for $x_{HighDemand}$ suggests that for every increase in hours of high demand experienced by the pharmacy, the estimated expected response decreases by 0.2 minutes, holding the values of the other two regressors constant. The maximum value of the variable found in the data is ten hours; therefore, this variable could potentially decrease the response by two minutes. A decrease in the response indicates that the implementation of automation had a lesser impact on the overall average daily prescription fill time.

The proportion of prescriptions filled through automation, $x_{PropAutoPost}$, causes an increase in response. This variable can take on values between zero and one, and the maximum value of $x_{PropAutoPost}$ observed in the data set is 0.48; this indicates that $x_{PropAutoPost}$ could potentially increase the response by 3.84 minutes, holding the values of the other two regressors constant. An increase in the response indicates that the implementation of automation has a greater impact on the overall daily prescription fill time. Figure 25 depicts the change in the response for different values of $x_{HighDemand}$ for fixed values of $x_{PropAutoPost}$.

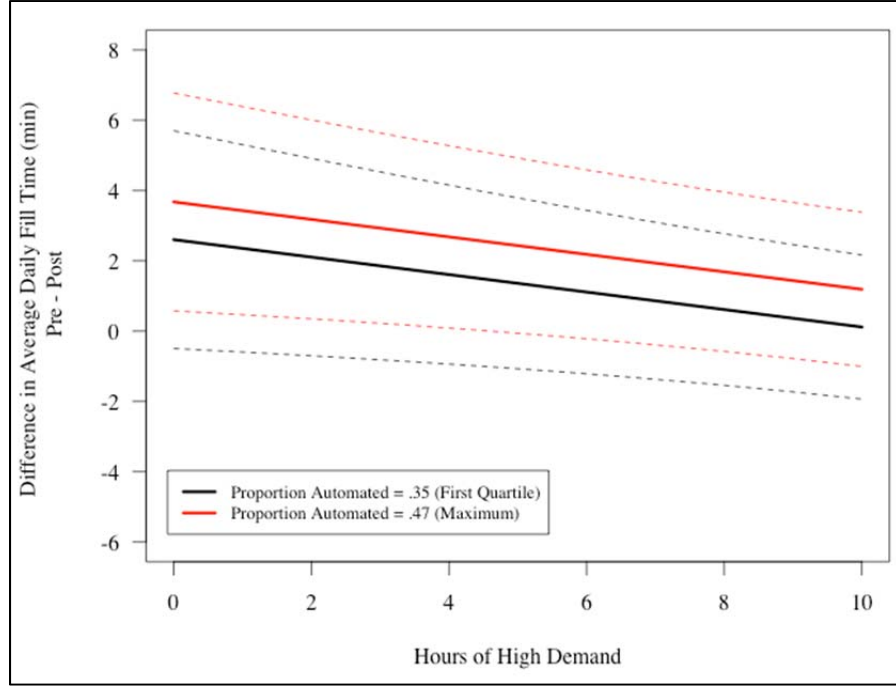


Figure 25. *Estimated Expected Difference in Average Daily Prescription Fill Time as Hours of High Demand Increases for Fixed Values of Proportion of Prescriptions Automated.* The proportion of automated prescription fills is fixed at the first quartile and maximum values, while the hours of higher than average demand are varied. As the hours of higher than average demand increase, the estimated expected difference in average daily prescription fill time decreases. The dotted lines represent 95 percent confidence intervals.

The proportion of highly prescribed medications pre-automation, $x_{PropTop5Pre}$, also positively impacts Y_{Diff} . This variable takes on values between zero and one and the maximum value of $x_{PropTop5Pre}$ observed in the data set is 0.29. Based on this information, an increase in $x_{PropTop5Pre}$ could potentially increase the difference in average daily prescription fill times by 3.48 minutes, holding the values of the other two regressors constant. This increase is an interesting result, because frequently ordered medications tend to be stored in more convenient locations; it is expected that this would cause a decrease in Y_{Diff} . The observed result, an increase, could be explained by an optimized loading of medications into the automation machine. Figure 26 depicts the change in the response for different values of $x_{HighDemand}$ or fixed values of $x_{PropTop5Pre}$.

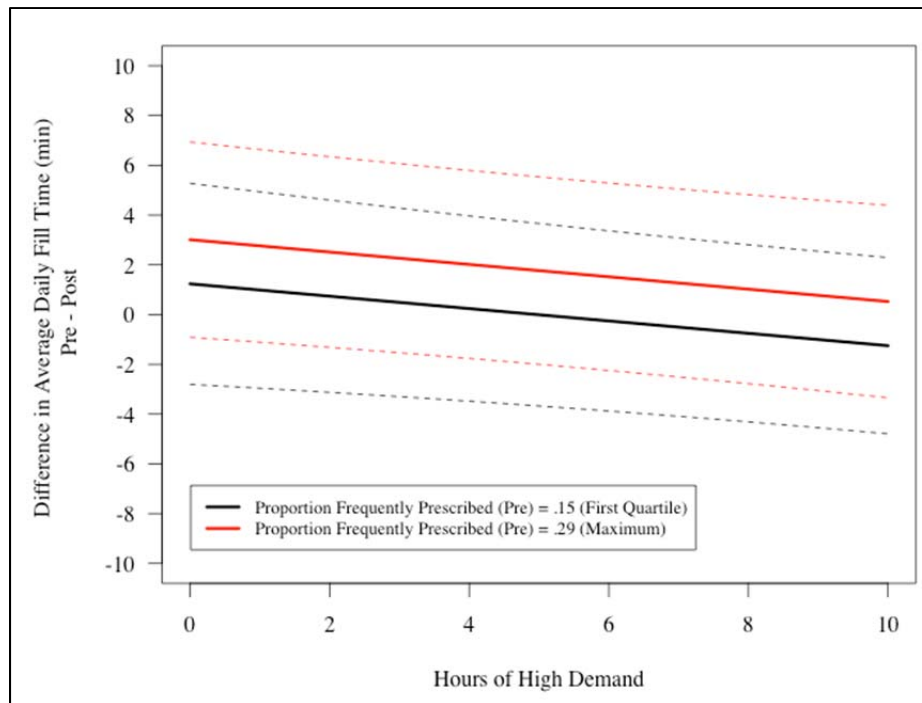


Figure 26. *Estimated Expected Difference in Average Daily Prescription Fill Time as Hours of High Demand Increases for Fixed Values of Proportion of Frequently Prescribed Medications.* The proportion of frequently prescribed medications is fixed at the first quartile and maximum values, while the hours of higher than average demand are varied. As the hours of higher than average demand increase, the estimated expected difference in average daily prescription fill time decreases. The dotted lines represent 95 percent confidence intervals.

C. SUMMARY

Through analysis of the data, it is revealed that the difference in average daily prescription fill times is statistically significant, both between manual and automatic fills in CY2014, and between pre-automation and post automation. In addition, linear regression reveals that there are three main factors that affect the difference in average daily prescription fill times: the number of hours of high demand experienced within the pharmacy, the proportion of prescriptions filled by automation, and the proportion of highly prescribed medications demanded by customers. As the number of hours of high demand increases, the response decreases, while as the two proportions increase, the response also increases.

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V. RESULTS, CONCLUSIONS, AND RECOMMENDATIONS

This thesis demonstrates a method to evaluate the changes in efficiency experienced at the NMCS D pharmacy after the implementation of pharmacy automation. The introduction of barcode scanning for each step in the prescription fill process provides a unique opportunity to objectively evaluate this process. With the increase in emerging technologies now available throughout different areas of healthcare, it is in the Navy's best interest to invest in items that could potentially lead to better access to care; this, in turn, leads to healthier Sailors and Marines.

A. POST-AUTOMATION TRENDS

Several items of interest emerged during exploratory analysis of the post-automation data set. With more than one year's worth of data, these trends could be further studied to determine if they are reoccurring, or specifically related to events in CY2014. The most significant and problematic item is the sharp increase experienced in the month of February. During this month, the average prescription fill time during working hours on weekdays is 63.3 ± 162.2 (standard deviation) minutes. In comparison, the average prescription fill time for the rest of the year during this time same time period is 24.3 ± 55.9 minutes. The month of February also experiences an increase in average daily demand of 197 prescriptions compared to every other month in the year. It can be hypothesized that this departure from the norm is associated with the cold and flu season and an increase in patient visits to NMCS D; if it is determined that this increase in demand and prescription fill time is not an anomaly, extra pharmacists and pharmacy technicians should be staffed during this month to account for the increase in demand.

Next, data is aggregated by day of the week. There is an obvious difference in both demand and average prescription fill time between weekdays and weekends; this is expected based on the NMCS D's primarily military patient population. A more interesting observation is the average prescription fill time is significantly higher on Mondays than every other day of the week, but that there is no corresponding increase in

demand. During working hours, the average time to fill a prescription on Mondays is 34.9 ± 108.1 minutes, compared to every other weekday, which is 26.1 ± 61.6 minutes

Again, much of this increase can be attributed to the volatile month of February. Excluding February, the average hourly prescription fill time during working hours on Mondays is 26.8 ± 66.4 minutes, while in February alone, the average hourly prescription fill time on Mondays is 114.6 ± 275.5 minutes. Figure 27 compares the hourly prescription fill times in February to the rest of the year. While the times are considerably higher during February, there is still a substantial difference in the fill times from 1800–1900 during the rest of the year. Excluding February, the average prescription fill time during this hour on Mondays is 81.6 ± 267.9 minutes. This increase in prescription fill time during 1800–1900 is not related to an increase in demand; the average demand during this hour is 40 prescriptions, compared to average of 70 items per hour during the rest of the day. Prescription fill time only includes the time it takes to get the prescription to the pharmacist for verification, which means a customer could potentially be waiting upwards of 90 minutes for their specific order.

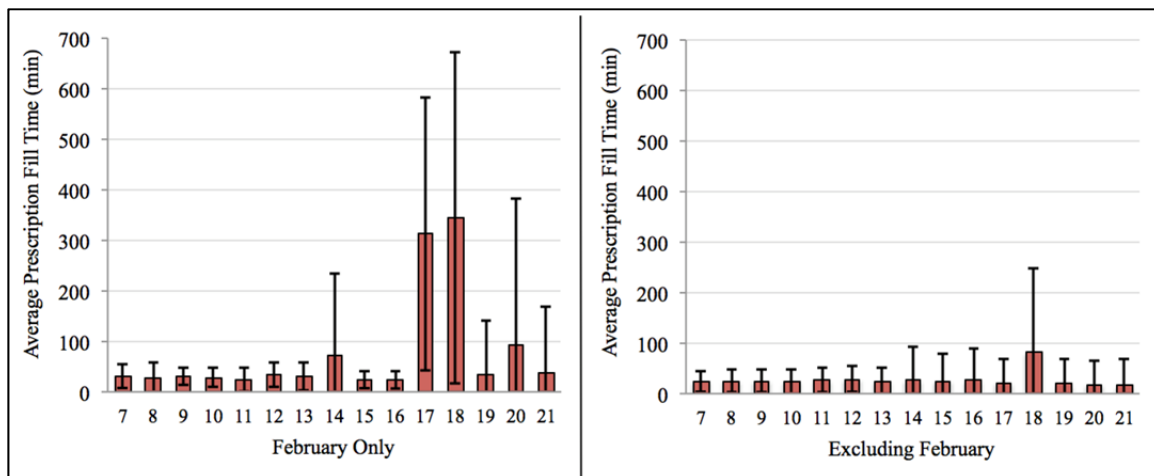


Figure 27. *Average Hourly Prescription Fill Time During Working Hours, Monday, February Only and Excluding February.* The black bars represent standard error of the mean. Though Mondays in February represent a considerable departure from the average, the average prescription fill time in the hour from 1800 to 1900 is significantly higher than the rest of the workday, without a corresponding increase in demand.

This increase in prescription fill time during the latter part of the day is not just limited to Mondays, however. If the entire year is observed, there is an increase in average prescription fill time during the hour from 1800 to 1900, but the demand is almost at a daily low. This increase in prescription fill time is also not attributable to variance in manual fill times; Figure 28 displays the average prescription fill time, excluding February, for weekdays between 0700 and 2200, separated by type of fill. Average manual fill times from 1800 to 1900 are 34.4 ± 98.8 with a corresponding average hourly demand of only 18 items, while average automatic fill times during the same hour are 29.9 ± 79.8 minutes with a corresponding average hourly demand of 13 items. In comparison, for the rest of the working day, an average manual fill takes 26.7 ± 55.2 minutes with an average demand of 37 prescriptions; an average automatic fill is completed in 19.3 ± 39.8 minutes with an average demand of 21.3 prescriptions.

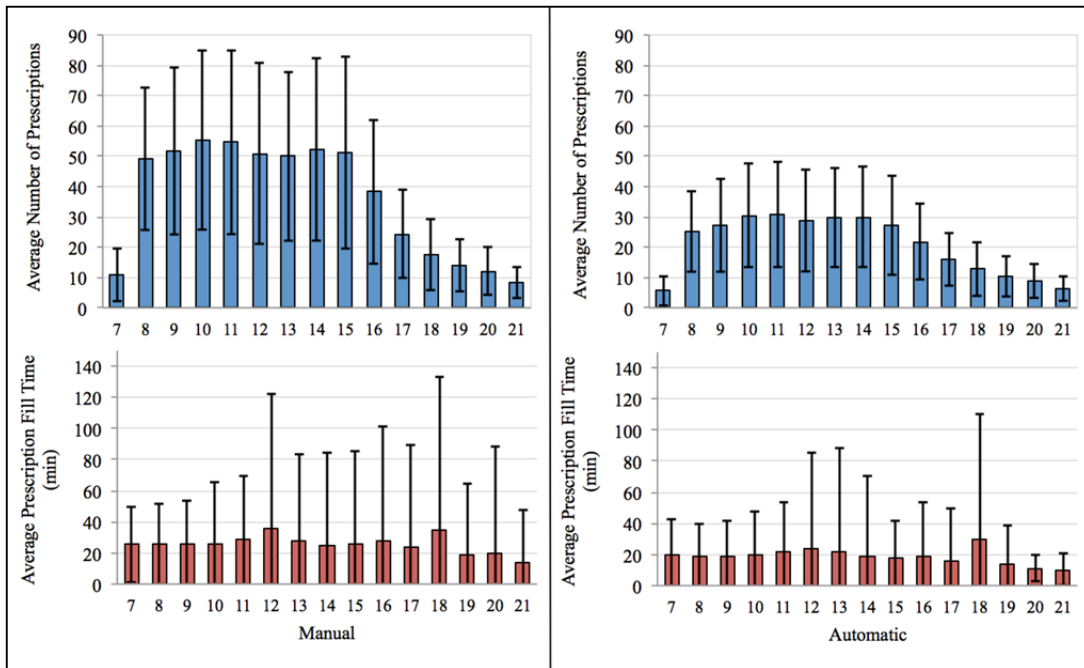


Figure 28. *Average Hourly Prescription Demand and Prescription Fill Time, Working Hours, Monday through Friday, excluding February.* The black bars represent standard error of the mean. Though the demand and average prescription fill time for manual fills is higher than automatic fills for all hours during the work week, both manual and automatic fills experience a delay from 1800 to 1900 without a corresponding increase in prescription demand.

Without more information, it is difficult to determine the source of these delays. The absence of a corresponding increase in demand indicates this increase in prescription fill time is unrelated to an influx of customers into the pharmacy. Both the manual prescription fill times and the automatic prescription fill times increase significantly during this hour; there is a 28.8 percent increase in average hourly prescription fill times for manual fills and a 51.8 percent increase for automatic fills. This evidence suggests the delays are related to workflow management within the pharmacy.

B. PRE-AUTOMATION COMPARED TO POST-AUTOMATION

When evaluating the total time spent filling prescriptions both pre-automation and post-automation, it is important to understand that several technicians are filling prescriptions at the same time; in the post-automation environment, the automation system is also continuously routing prescriptions through the fill process. The total time spent filling prescriptions reflects the amount of time it would take to fill each prescription sequentially, one at a time. In most instances, it is most appropriate to refer to total prescription fill time for the year in the units of days.

During regression analysis, one of the significant indicators of a larger difference between the average daily prescription fill time pre-automation and post-automation is the post-automation proportion of prescriptions filled automatically. Overall, the prescriptions filled automatically account for 37.3 percent of total prescription fills in CY2014, with a maximum of 47.7 percent and a minimum of 11.2 percent. With all other factors held constant, an average automation proportion of 0.37 is related to an increase in the difference of average prescription fill time of 2.98 ± 1.95 (standard error) minutes; if this proportion can be maintained over the course of an entire year, assuming an average daily weekday demand is 1186 prescriptions, this could reduce yearly workload by an average of 636 days alone, compared to pre-automation. Figure 29 illustrates the yearly reduction in weekday workload based on proportion of prescriptions filled through automation.

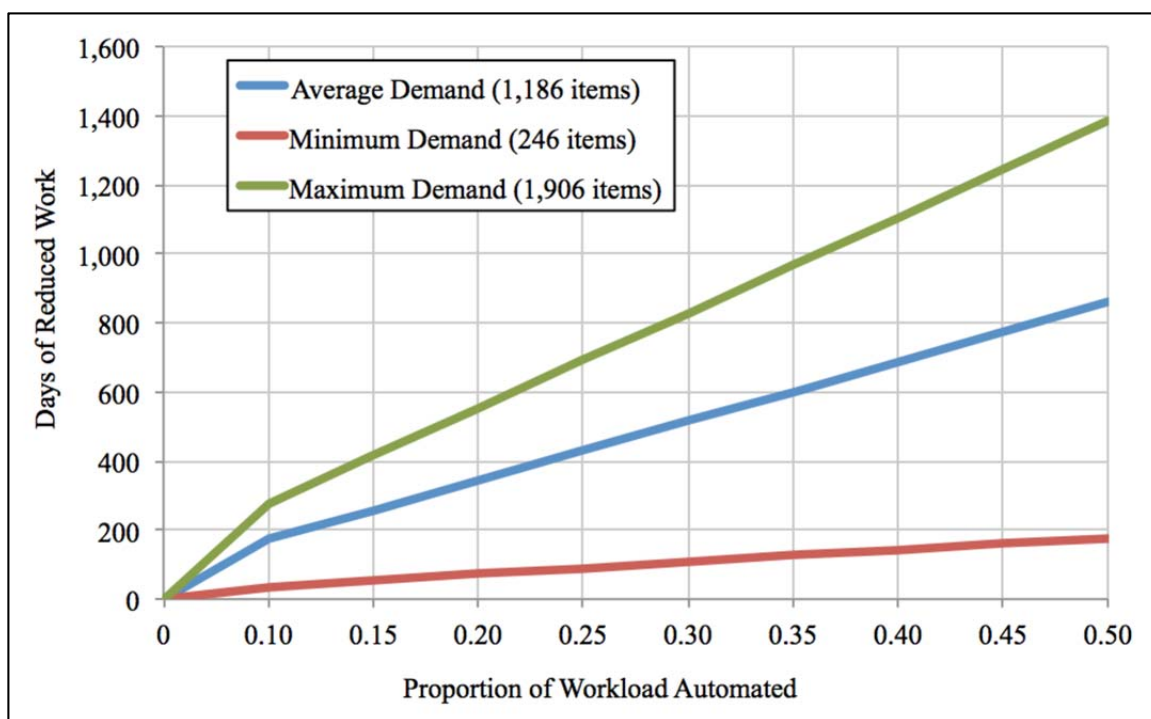


Figure 29. *Estimated Yearly Reduction in Weekday Workload Based on Proportion of Prescriptions Filled Through Automation and Demand.* If the proportion of prescriptions automated can be maintained at 0.37, there is potential to reduce weekday workload within the pharmacy by 636 days, compared to pre-automation. With all other regressors held constant, there is no additional reduction of work in any scenario when the proportion of workload automated is set to zero, causing a non-linear line.

This same type of logic can be applied to the daily workload of each pharmacy technician in NMCSO. Based on the January 2015 schedule, at a minimum, 25 pharmacy technicians are assigned to work in the pharmacy from 0745 to 1615 every weekday, with other additional staff during various parts of the workday; less pharmacy technicians are assigned during non-working hours (B. Detlef, BUMED, personal communication, August 12, 2015). Assuming there are 25 pharmacy technicians working within the pharmacy, if the proportion of prescriptions automated is held constant at 0.37 for an entire day, with an average weekday demand of 1,186 items, the daily workload for each technician can be reduced by 2.34 ± 0.03 hours, compared to pre-automation. When this proportion is maintained at 0.50, the daily workload can be reduced by 3.16 ± 0.02 hours, which is a 0.40 Full Time Equivalent (FTE), assuming an eight-hour workday. Figure 30

illustrates this reduction in daily workload based on proportion of prescriptions automated and number of pharmacy technicians working in the pharmacy.

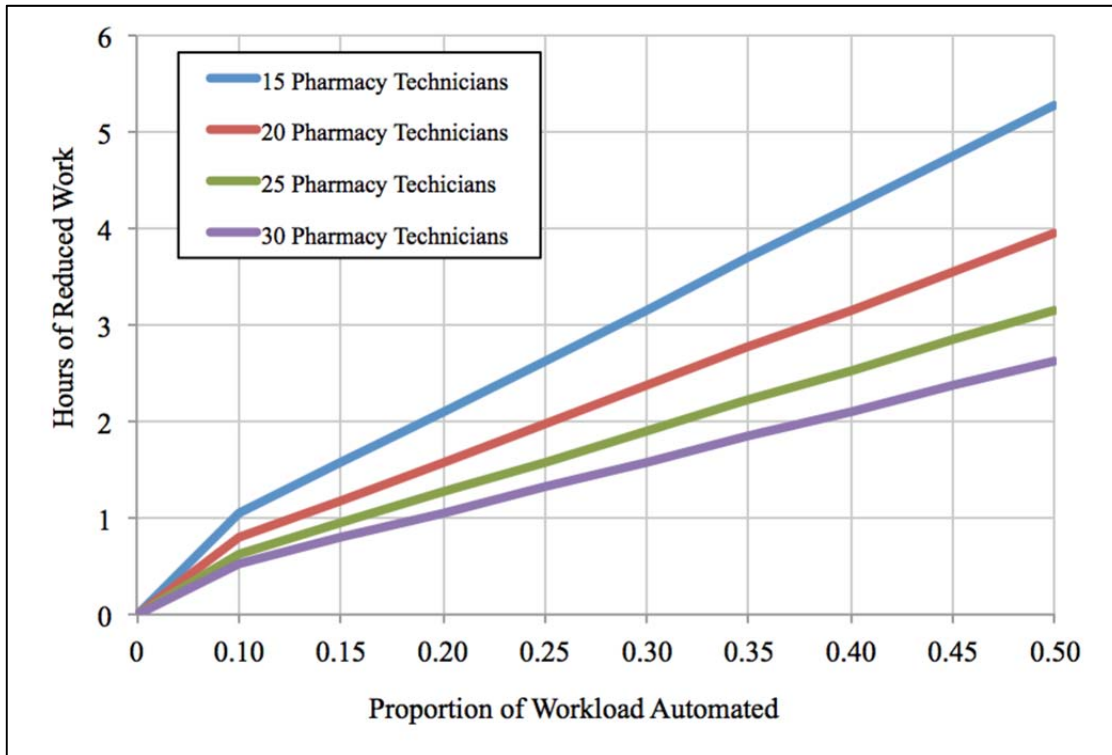


Figure 30. *Estimated Daily Reduction in Weekday Workload Based on Proportion of Prescriptions Filled Through Automation and Number of Pharmacy Technicians.* If the proportion of prescriptions automated can be maintained at 0.37, with ten pharmacy technicians working and an average demand of 1,189 items, there potential to reduce daily workload by 2.34 hours, which is the same as 0.29 FTEs. With all other regressors held constant, there is no additional reduction of work in any scenario when the proportion of workload automated is set to zero, causing a non-linear line.

It is also important to consider the implementation from a cost perspective. The pharmacy automation system at NMSCD carried an individual implementation cost of \$2.4 million of the total \$49 million contract. (B. Detlef, BUMED, personal communication, September 10, 2014). Based on the watchbill from January 2015, most of the pharmacy technicians are of the rank Petty Officer Third Class (E-4), so the base salary for this rank, with over three years of service, will be used at the basis for cost

analysis (B. Detlef, BUMED, personal communication, August 12, 2014); there is a mix of several military ranks, as well as civilians and contractors, which suggests that this estimate is conservative. Appendix F details the conversion of E-4 military salary to hourly wage.

When directly comparing the total time spent filling prescriptions pre-automation and post-automation, recall the yearly demand for each is roughly the same: 364,463 and 364,531 observations, respectively. Pre-automation, the total time spent filling prescriptions is 7,699 days, while the total time spent filling prescriptions post automation is 6,604 days; this is a reduction of 14.2 percent. This reduction in time spent filling prescriptions is associated with \$330,000 reduction in cost, the amount of money it would cost to pay for the equivalent amount of work from E-4 military members established only on base pay. With these calculations, it would take roughly seven years to recoup the cost of implementation at NMCS D based on increased efficiency.

These are extremely conservative estimates. In reality, many other factors contribute to the benefits of implementing a new system. For example, the increased tracking ability due to the barcode scanning of medications could potentially lead to increased efficiency in the stocking and ordering of medications. In addition, wait times in the pharmacy are a major source of complaints for many customers within a medical facility, and the main reason many customers choose to have prescriptions filled at non-military pharmacies. Prescriptions filled at non-military pharmacies are more expensive for the Navy to fill, and the potential decrease in customer wait time within the pharmacy could then be tied to a recapture of costs from non-military pharmacy prescription fills. Decreased wait time also likely leads to better patient satisfaction, which is an intangible benefit of such an upgrade.

C. CONCLUSIONS AND FUTURE WORK

After the implementation of pharmacy automation at NMCS D, there is an increase in efficiency, defined as the total prescription fill time. This efficiency can be quantified as number of reduction total time to fill a prescription, reduction in FTEs, or reduction in equivalent salary of pharmacy technicians. This data is collected after a little

more than one year of implementation; with better training and more emphasis placed on the optimal automation workload, these savings in efficiency will continue to increase.

There is great potential for future study into this subject. With the implementation of the barcode scanning system, more in-depth investigations can be made into the optimal ordering and stocking of frequently filled medications. In addition, this study does not attempt to quantify the impacts of the automation system on prescription accuracy, patient satisfaction, or overall access to care. With additional data, comparisons can be made between changes in the pharmacy to increases or decreases in these areas with all of NMCS D. Most importantly, this study is limited by lack of data, both in duration of post-automation data collection and lack of pre-automation data; with additional post-automation data, a more significant evaluation of possible trends observed within the pharmacy could be conducted, and with pre-automation data, a considerably better comparison could be completed.

APPENDIX A. PROCESSES TRACKED IN PRESCRIPTION DATA

Table 7. *Processes Tracked in Prescription Data.* The prescription data contains the date and time, accurate to the second, of fifteen specific processes during the entire prescription order procedure. Priority High, Priority Urgent, Initial Pending, Suspend, Reschedule to Manual, and Rescheduled to Automatic do not occur with every prescription; these processes tend to happen when there is a complication. Only the eight processes outline in Chapter III are specifically relevant to this study.

Process	Description (date/time)
Scheduled	Entered into the system
Diverted	Divert from an automatic fill to manual fill, reason provided
Priority High	Priority is updated from standard to high
Priority Urgent	Priority is updated from high to urgent
Initial Pending	Initially put into a “pending” status, reason provided
Suspend	Suspended from completion, reason provided
Rescheduled to Manual	Rescheduled from an automatic fill to manual fill
Rescheduled to Automatic	Rescheduled from manual fill to automatic fill
Counted	Count of quantity of medication is complete
Added to Tote	Counting, bottling, capping, and labeling is complete
Verified	Pharmacist verification for errors is complete
Added to Bag	Combined with remaining customer order
Added to Location	Complete order is placed in assigned cubby location
Ready for Pickup	Order is complete and ready for customer pick up
Pickup	Customer picks up completed order.

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APPENDIX B. FREQUENCY OF PRESCRIBED MEDICATIONS

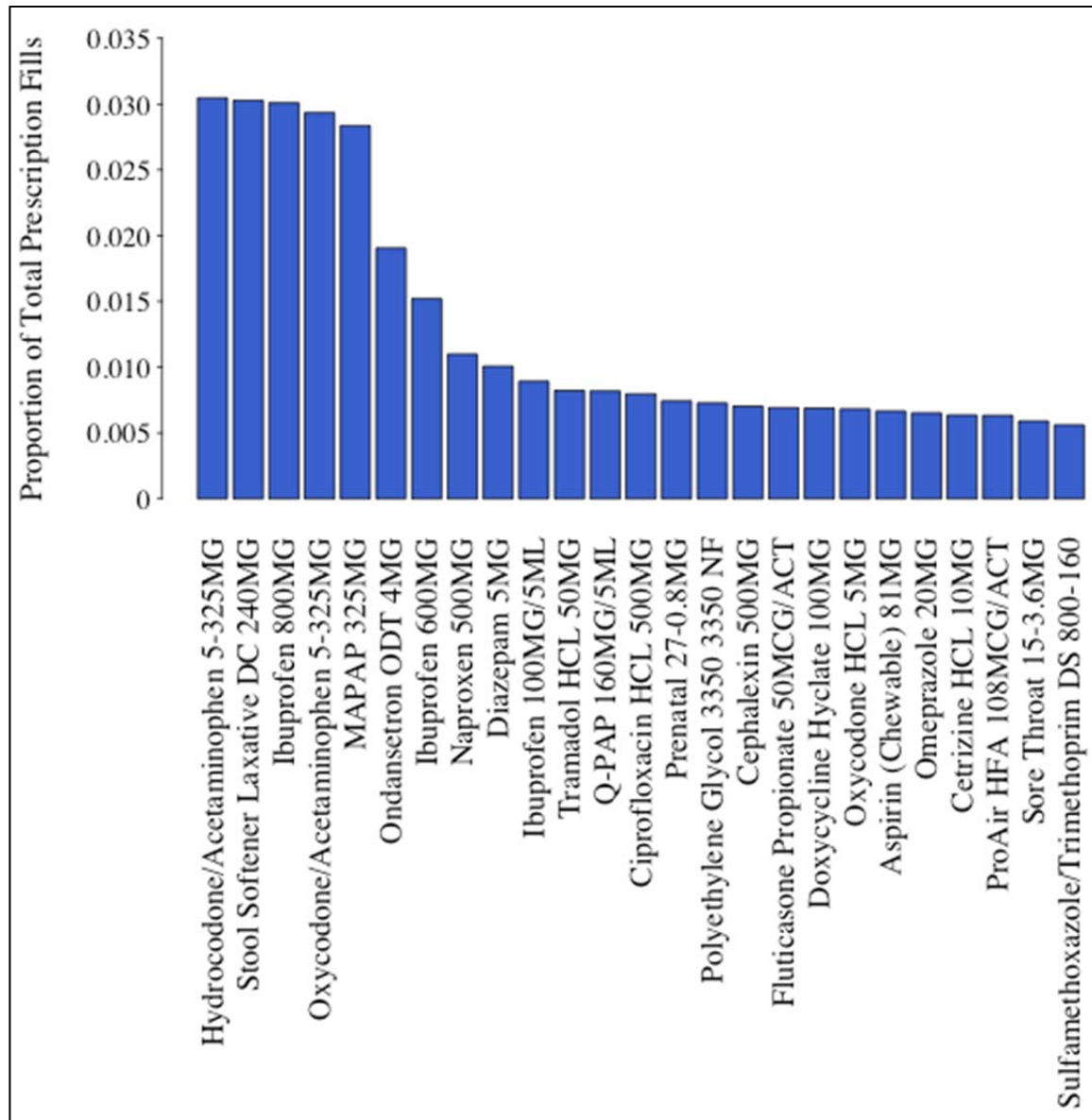


Figure 31. *Most Frequently Prescribed Medications, Post Automation.* The 25 most frequently prescribed medications comprise 31.7 percent of all post-automation prescription fills.

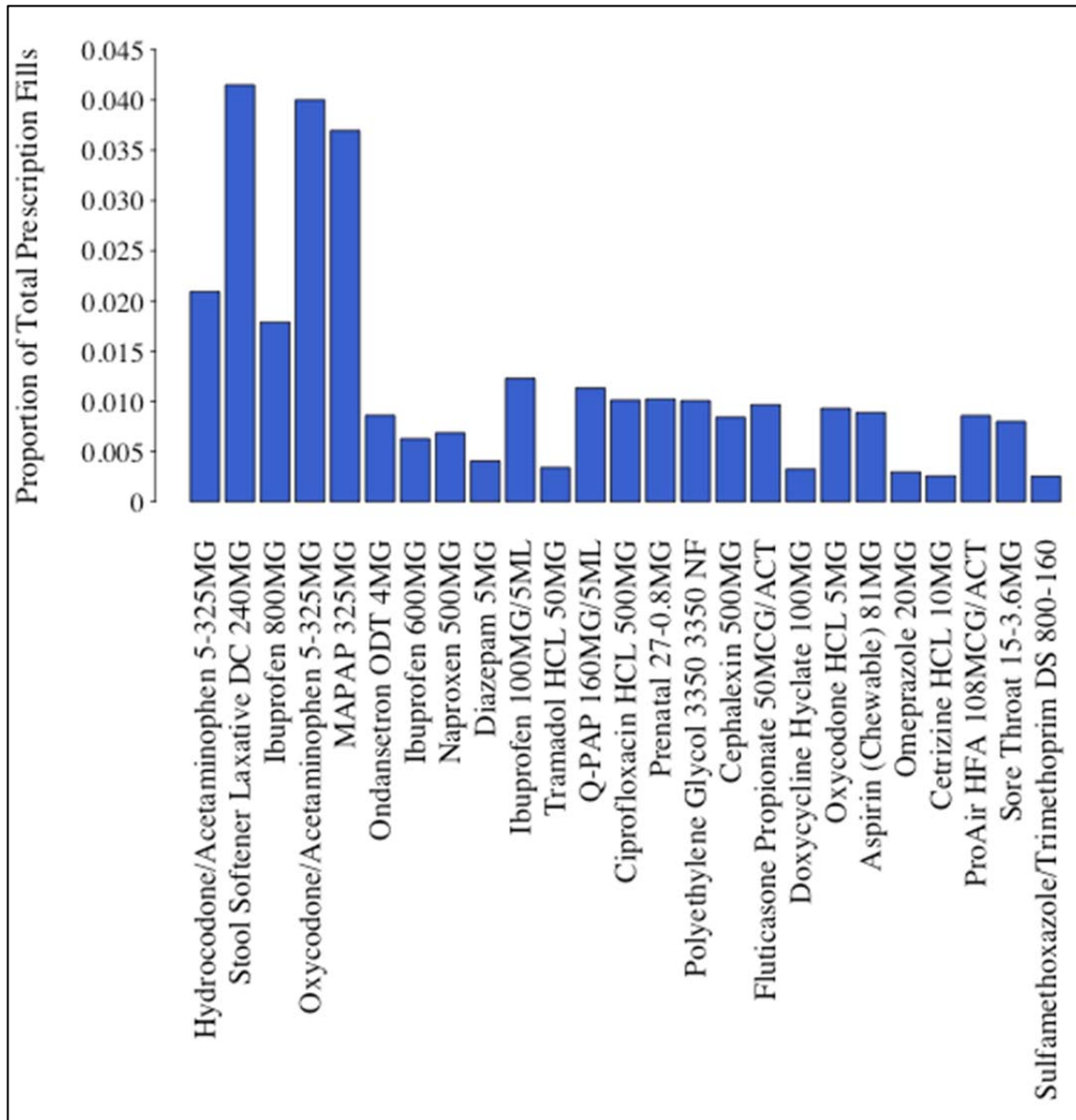


Figure 32. *Most Frequently Prescribed Medications, Pre-Automation.* The 25 most frequently prescribed medications comprise 30.5 percent of all pre-automation prescription fills

APPENDIX C. DIFFERENCE IN AVERAGE FILL TIME IN OBSERVED AND SIMULATED DATA SET, MONTH BY DAY OF THE WEEK.

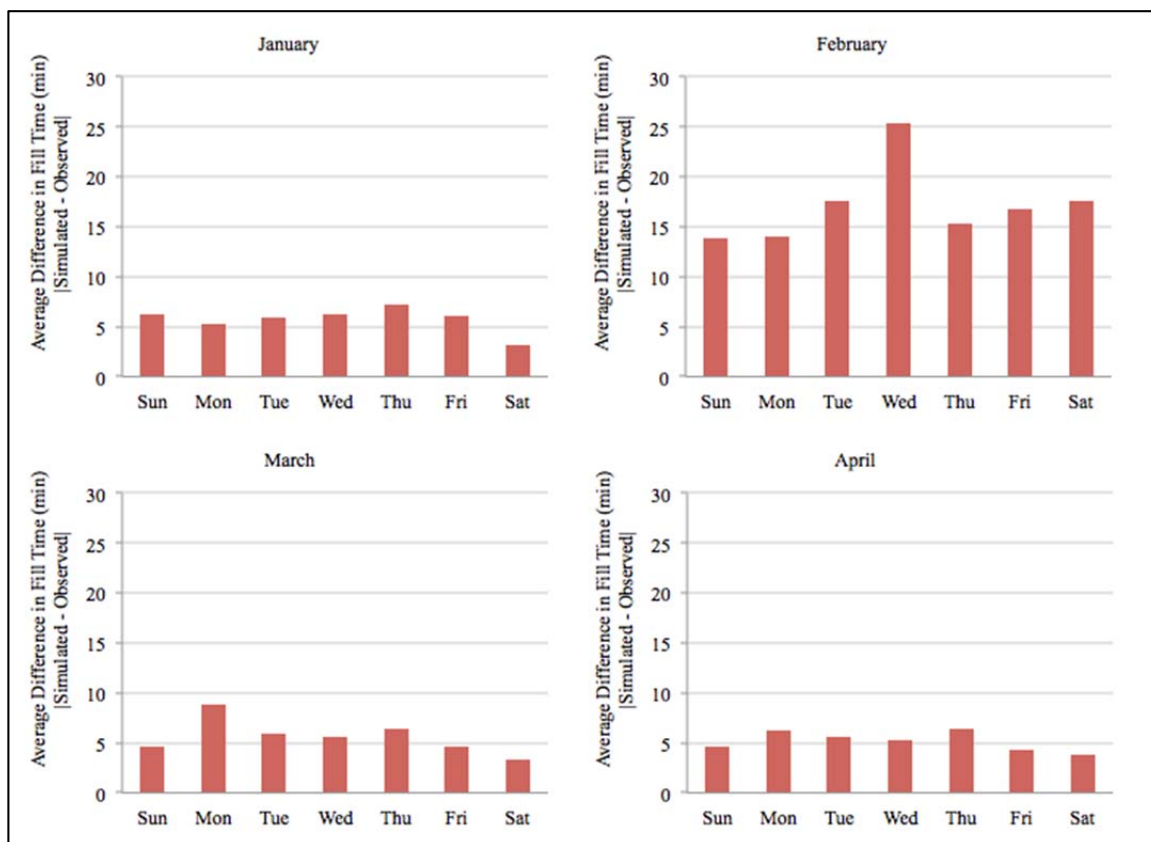


Figure 33. *Month by Day of the Week for the Difference in Average Daily Prescription Fill Time between the Observed and Simulated Automation Data Set, First Quadrimester CY2014.* Other than the month of February, there does not appear to be any significant patterns based on month or day of week

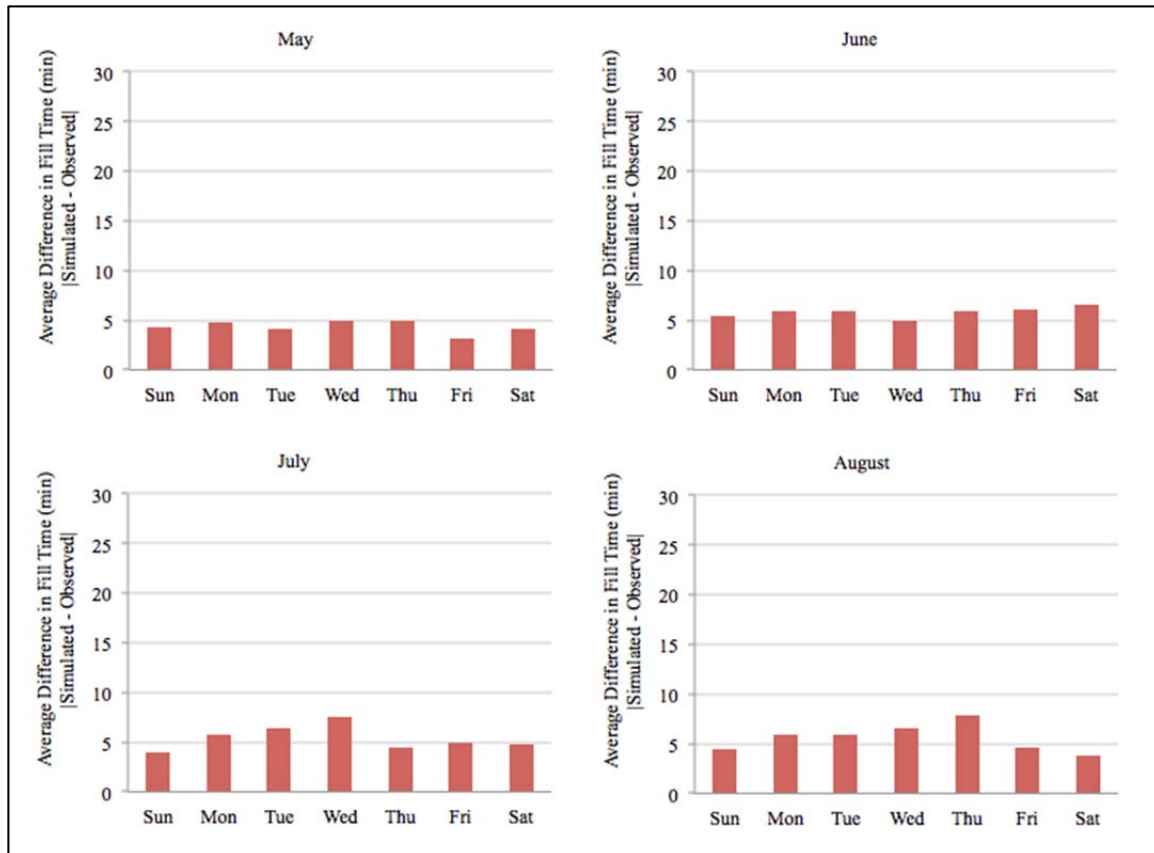


Figure 34. *Month by Day of the Week for the Difference in Average Daily Prescription Fill Time between the Observed and Simulated Automation Data Set, Second Quadrimester CY2014.* There does not appear to be any significant patterns based on month or day of week

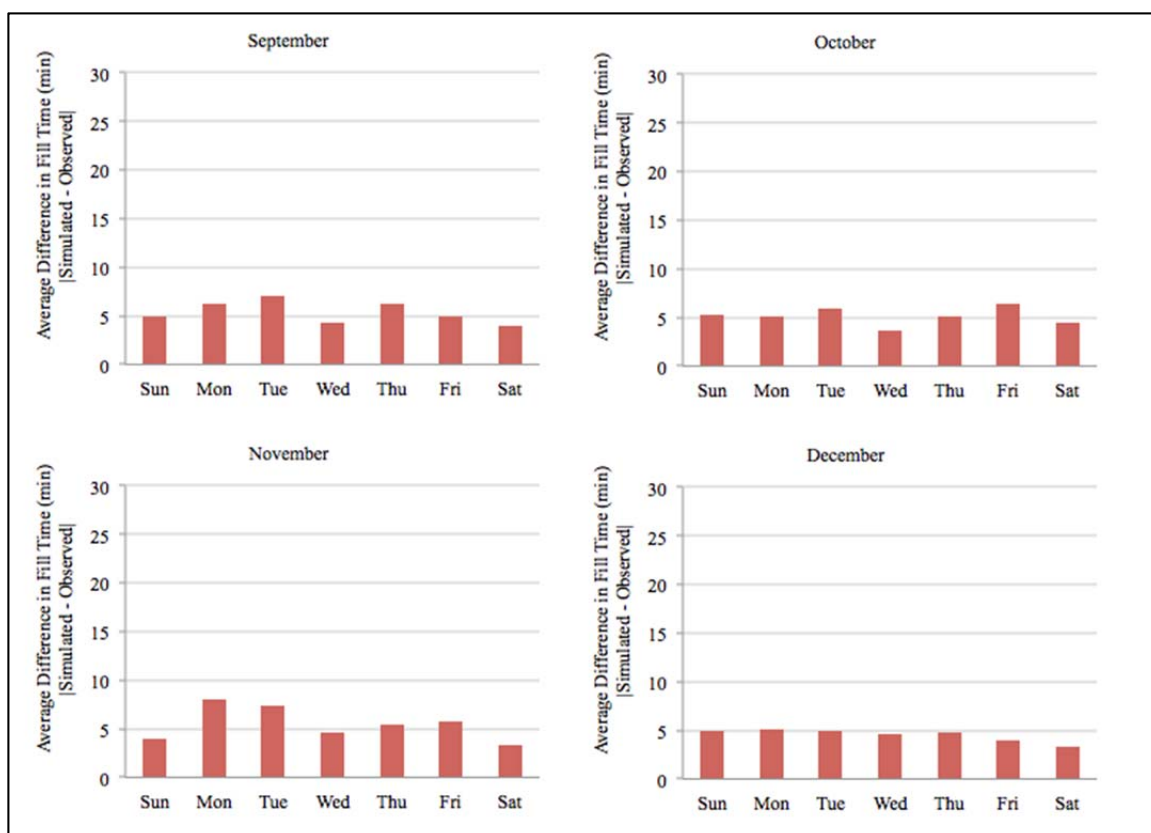


Figure 35. *Month by Day of the Week for the Difference in Average Daily Prescription Fill Time between the Observed and Simulated Automation Data Set, Third Quadrimester CY2014.* There does not appear to be any significant patterns based on month or day of week

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APPENDIX D. REGRESSION DIAGNOSTICS

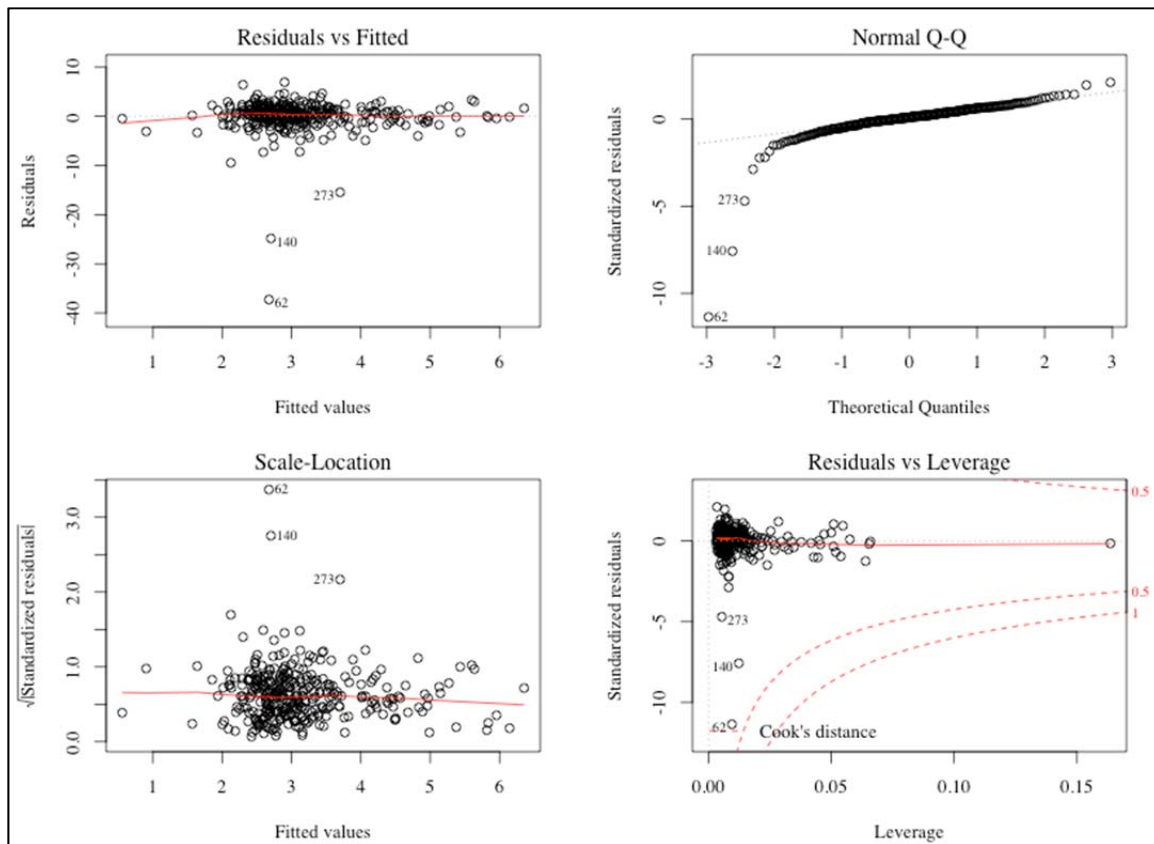


Figure 36. *Regression Diagnostic Plots for Final Linear Regression Model.* The final model is validated using regression diagnostics. The four residual plots indicate that the error terms have constant variance and mean zero, but may not be normally distributed. In addition, none of the outlying observations are found to be influential.

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APPENDIX E. LINEAR FITS OF ELIMINATED VARIABLES

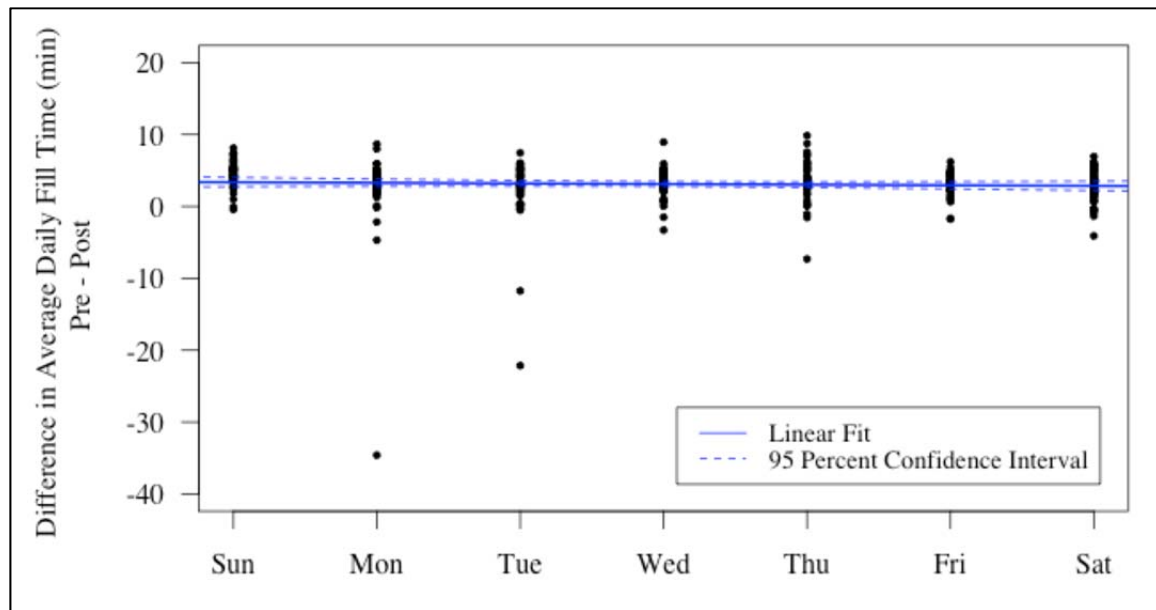


Figure 37. *Difference in Average Daily Prescription Fill Times Based on Day of the Week.* The linear fit reflects a straight line, indicating that day of the week does not impact the difference in average daily prescription fill time.

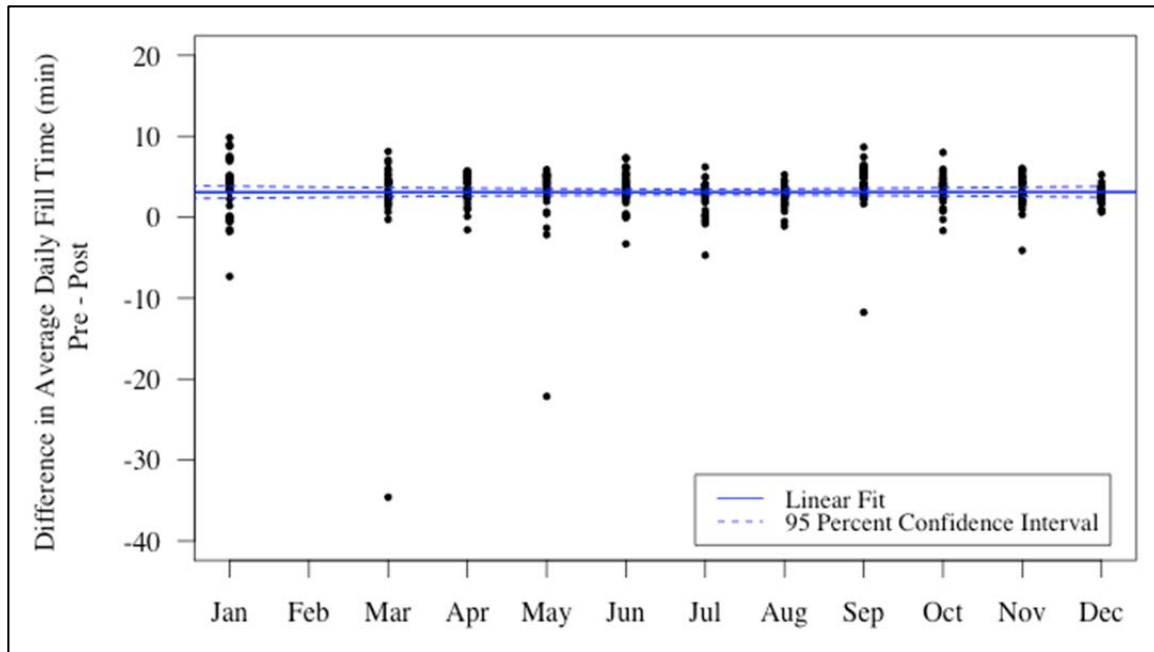


Figure 38. *Difference in Average Daily Prescription Fill Times Based on Month.* The linear fit reflects a straight line, indicating that month does not impact the difference in average daily prescription fill time.

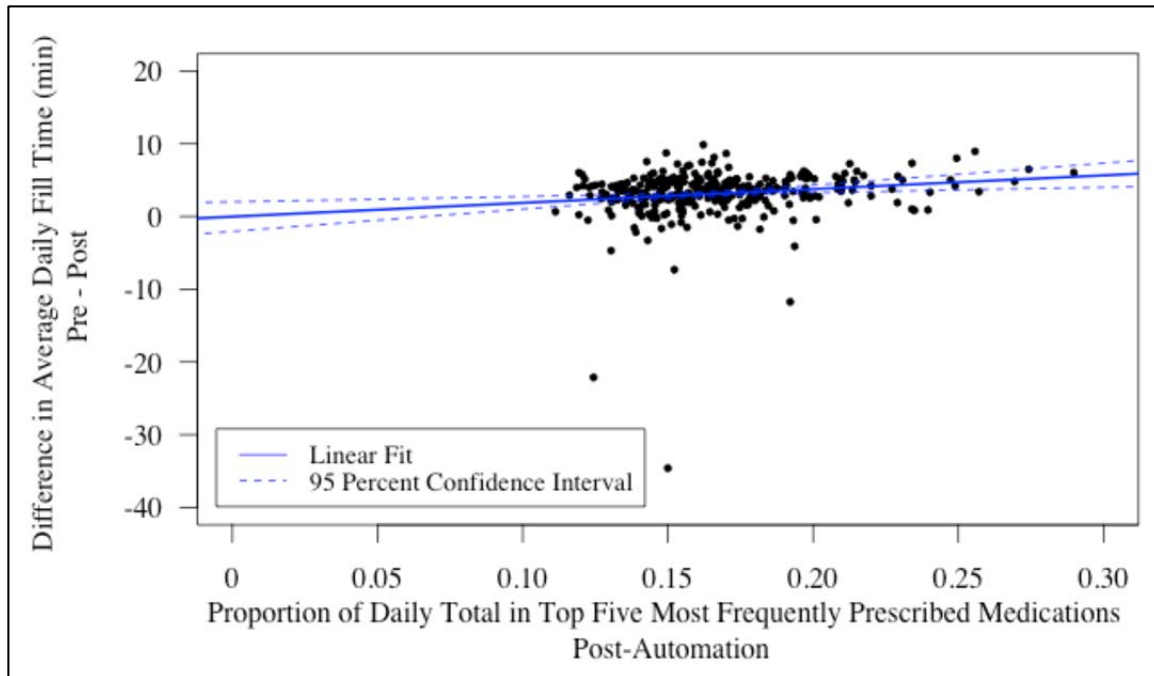


Figure 39. *Difference in Average Daily Prescription Fill Times Based Daily Proportion of Prescriptions that are the Five Most Prescribed Medications, Post-Automation.* The linear fit reflects a slightly increasing trend, indicating that a higher proportion of highly prescribed medications increases the difference in average daily prescription fill time.

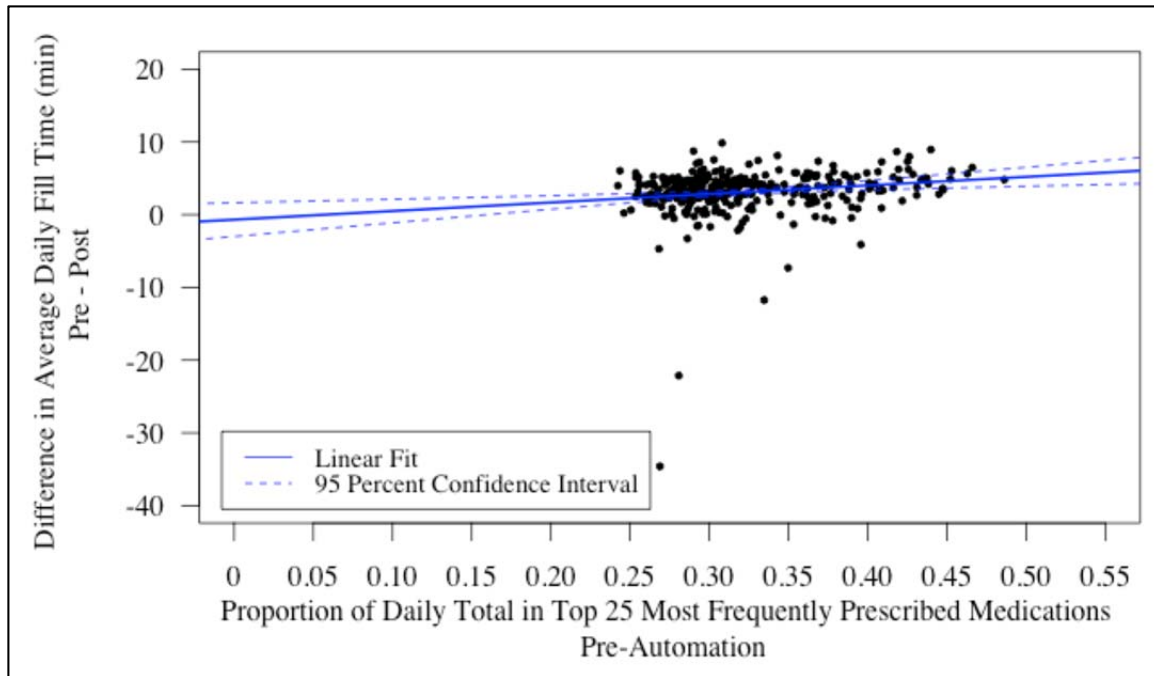


Figure 40. *Difference in Average Daily Prescription Fill Times Based Daily Proportion of Prescriptions that are the Ten Most Prescribed Medications, Pre-Automation.* The linear fit reflects a slightly increasing trend, indicating that a higher proportion of highly prescribed medications increases the difference in average daily prescription fill time.

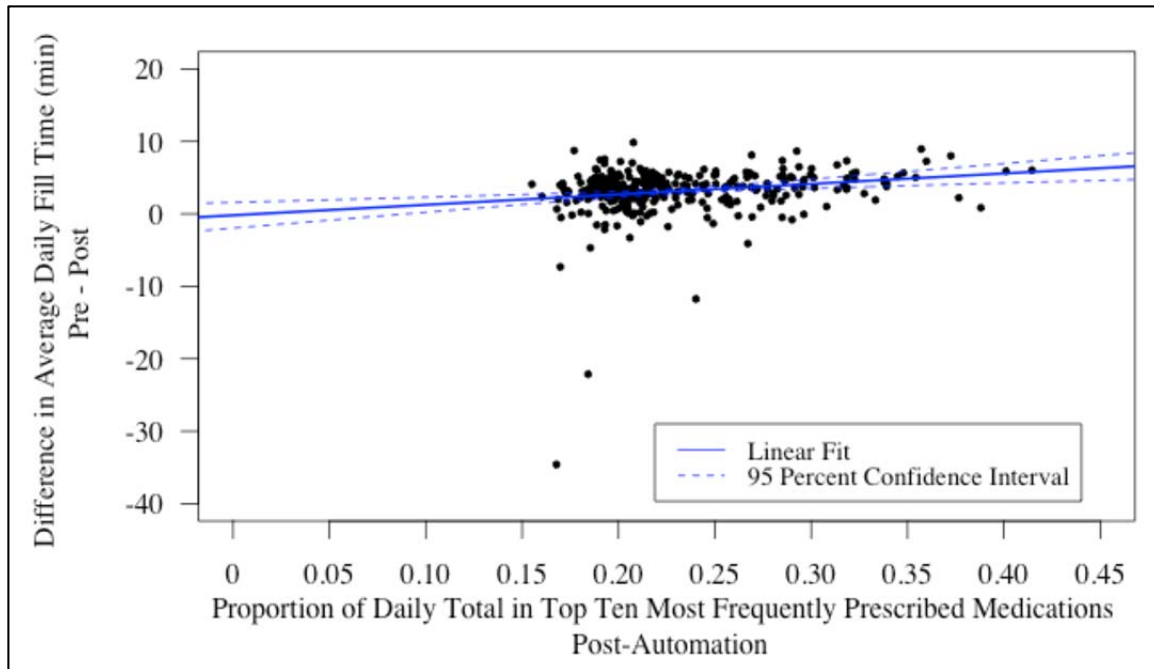


Figure 41. *Difference in Average Daily Prescription Fill Times Based Daily Proportion of Prescriptions that are the Ten Most Prescribed Medications, Post-Automation.* The linear fit reflects a slightly increasing trend, indicating that a higher proportion of highly prescribed medications increases the difference in average daily prescription fill time.

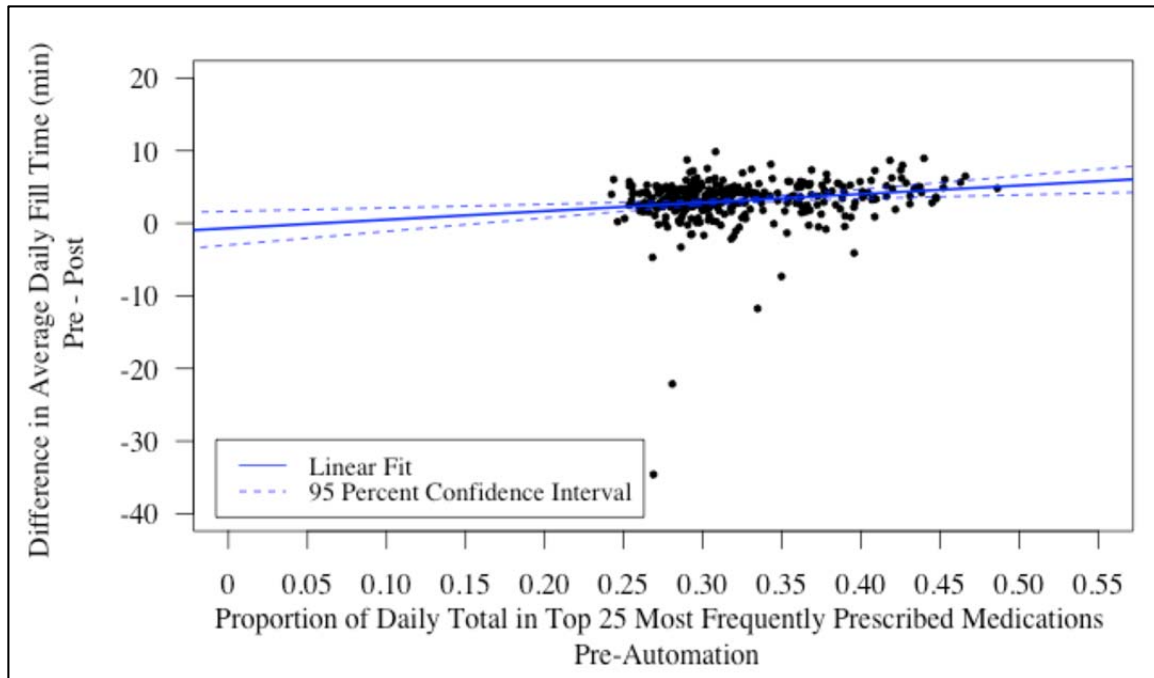


Figure 42. *Difference in Average Daily Prescription Fill Times Based Daily Proportion of Prescriptions that are the 25 Most Prescribed Medications, Pre-Automation.* The linear fit reflects a slightly increasing trend, indicating that a higher proportion of highly prescribed medications increases the difference in average daily prescription fill time.

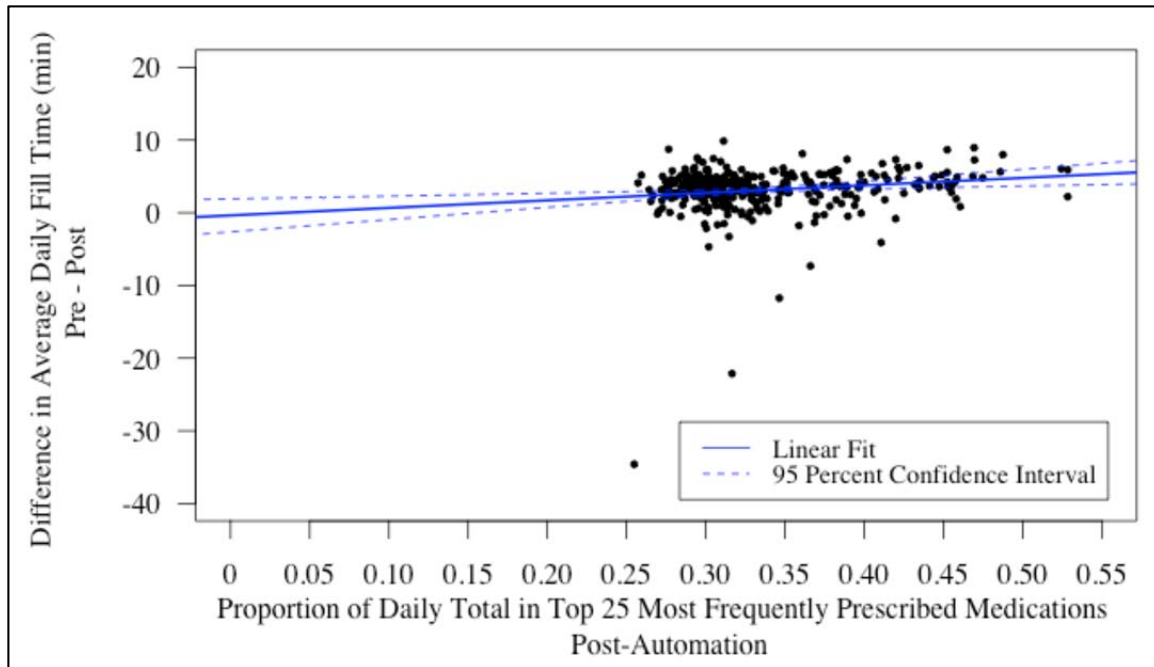


Figure 43. *Difference in Average Daily Prescription Fill Times Based Daily Proportion of Prescriptions that are the 25 Most Prescribed Medications, Post-Automation.* The linear fit reflects a slightly increasing trend, indicating that a higher proportion of highly prescribed medications increases the difference in average daily prescription fill time.

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APPENDIX F. CONVERSION OF MONTHLY EARNINGS TO HOURLY WAGES

Military salary is normally presented in terms of monthly earnings. Equation (8) details the conversion of monthly earnings for an E-4 into hourly wages (Defense Finance and Account Service, 2015).

$$\left(\frac{\$2238.07}{\text{Month}}\right)\left(\frac{12 \text{ Months}}{1 \text{ Year}}\right)\left(\frac{1 \text{ Year}}{261 \text{ Weekdays}}\right)\left(\frac{1 \text{ Weekday}}{8 \text{ Work-Hours}}\right) = \left(\frac{\$12.86}{\text{Hour}}\right) \quad (8)$$

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