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A SIMULATION-BASED EVALUATION OF EFFICIENCY STRATEGIES FOR A PRIMARY CARE CLINIC WITH UNSCHEDULED VISITS

by

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A dissertation submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
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Major Professor: Waldemar Karwowski

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ABSTRACT

In the health care industry, there are strategies to remove inefficiencies from the health delivery process called *efficiency strategies*. This dissertation proposed a simulation model to evaluate the impact of the efficiency strategies on a primary care clinic with unscheduled "walk-in" patient visits. The simulation model captures the complex characteristics of the Orlando Veteran's Affairs Medical Center (VAMC) primary care clinic. This clinic system includes different types of patients, patient paths, and multiple resources that serve them. Added to the problem complexity is the presence of patient no-shows characteristics and unscheduled patient arrivals, a problem which has been until recently, largely neglected. The main objectives of this research were to develop a model that captures the complexities of the Orlando VAMC, evaluate alternative scenarios to work in unscheduled patient visits, and examine the impact of patient flow, appointment scheduling, and capacity management decisions on the performance of the primary care clinic system. The main results show that only a joint policy of appointment scheduling rules and patient flow decisions has a significant impact on the wait time of scheduled patients. It is recommended that in the future the clinic addresses the problem of serving additional walk-in patients from an integrated scheduling and patient flow viewpoint.

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CHAPTER 1 INTRODUCTION

1.1 Background

The health care industry in the United States (US) accounts for 17.4% of the Gross Domestic Product (GDP), one of the highest percentages amongst all countries, and is expected to rise to 19.6% by 2024 (Keehan et al., 2015). The percentage of medically uninsured individuals has declined from 16% in 2010 to 9.1% in 2015, a 43% reduction (Obama, 2016). This decline partly suggests that demand for health care services has increased, and consequently has put more pressure on the health care system where resources are tightly constrained. The area of the health care system which is significantly affected by the increase in new patient demand is the primary care service. According to the Agency for Healthcare Research and Quality (AHRQ), primary care physicians (PCP) account for less than one-third of the country's physicians, and researchers estimate a need for 52,000 additional PCPs by 2025 (Robinson & Reiter, 2007). Until then, patients will continue to experience delayed access to health care services.

Timely access to care is one of six areas that the Institute of Medicine (IOM) declared to be of focus in creating a health care system for the 21st century (Medicine, 2001). However, this area still has room for improvement as evidenced by research reports of excessive waiting times for medical appointments (Rosenthal, 2014). Excessive waiting times are no more apparent in the health care industry than in the Veteran Health Administration (VHA), where controversies over manipulated waiting lists caught national attention (Oppel & Shear, 2014). The demand of patient care for veterans created a heavy burden on the strict performance standards set forth by the administration and may have resulted in the death of some veterans as they waited for medical treatment. In the Veterans Access, Choice, and Accountability Act of 2014, a *Commission on*

Care was formed to examine how to strategically use resources to deliver care to veterans. In the Commission's report of June 30, 2016, it was recommended that a culture of continuous improvement of workflow process be developed and fully funded (Commission on Care Charter, 2016). One source of improvement that researchers have investigated is the appointment scheduling function of health care clinics.

Appointment scheduling became a popular strategy to reduce the waiting time for patients whilst many research studies were conducted on the impact of scheduling rules on the health clinic's operational performance. Murray and Tantau (2000) introduced *open access scheduling*, which accommodates the *same-day patient* or *walk-in patient*, with minimal delayed access to medical appointments. However, this method has had mixed results in implementation, and been proven to be difficult in achieving success in certain clinical settings (Mehrotra, Keehl-Markowitz, & Ayanian, 2008; Rose, Ross, & Horwitz, 2011). As a result of this shortcoming, walk-in services are implemented in addition to certain traditional scheduled appointments, creating a hybrid scheduling approach between traditional scheduling and open access scheduling. This occurs mostly in primary care clinics.

1.1.1 Primary Care Clinics

The major entry-point to the health care system is through primary care services. According to, primary care is defined as "basic and routine health care provided in an office or clinic by a *provider* who takes responsibility for coordinating all aspects of a patient's health care needs". Healthcare literature has found that increase in access to primary care services results in improved services for disadvantaged populations, prevention and early management of health issues, and less wasteful expenditures due to unnecessary specialist care (Denton, 2013).

As the first contact between the health care delivery system and the patient, the provider in a primary care facility is generally referred to as the primary care physician. Also known as a generalist, the PCP provides care for undiagnosed illnesses or general health concerns. A PCP has a defined population of patients to serve, known as the "panel". Historically, the size of a panel has been between 1500 and 3000 patients and the goal of the primary care clinic is to establish a continuous, ongoing patient-PCP relationship (Robinson & Reiter, 2007). There are different types of PCPs, classified according to the type of patients they serve. Family PCP tend to have the largest panel sizes and greater variety of patients. Pediatricians manage complex child patients, and internist typically serve adult patients, thus having a smaller panel size than most family PCPs. In some instances, PCPs can also include nurse practitioners (NPs) and physician assistants (PAs).

Registered nurses (RNs) are central to the primary clinic operations. They may be responsible for triaging patients, particularly if patients walk in without an appointment. RNs also support patients in need of chronic disease management (e.g., medication adherence and education), preventive care, and lifestyle changes such as smoking cessation. Typical duties include taking vital measurements for patients, conducting screening questions, verifying current medications and medical history, and other pre-appointment activities. There may be a single RN to a group of PCPs or one-to-one ratio of RNs to PCPs. In larger health facilities, a staff of nurses can also include licensed practical nurses (LPNs) with more training than RNs, and certified nursing assistant (CNAs) who have the least training.

The support staff of primary care clinics are the first health care personnel that interact with patients, either personally, via phone, or electronically. The front desk members retrieve and maintain documentation of personal information for the clinic visit. They may also perform the billing and payment activities, as well as follow-up appointments, at the end of a clinic visit. Figure 1-1 illustrates the patient flow through a primary clinic.

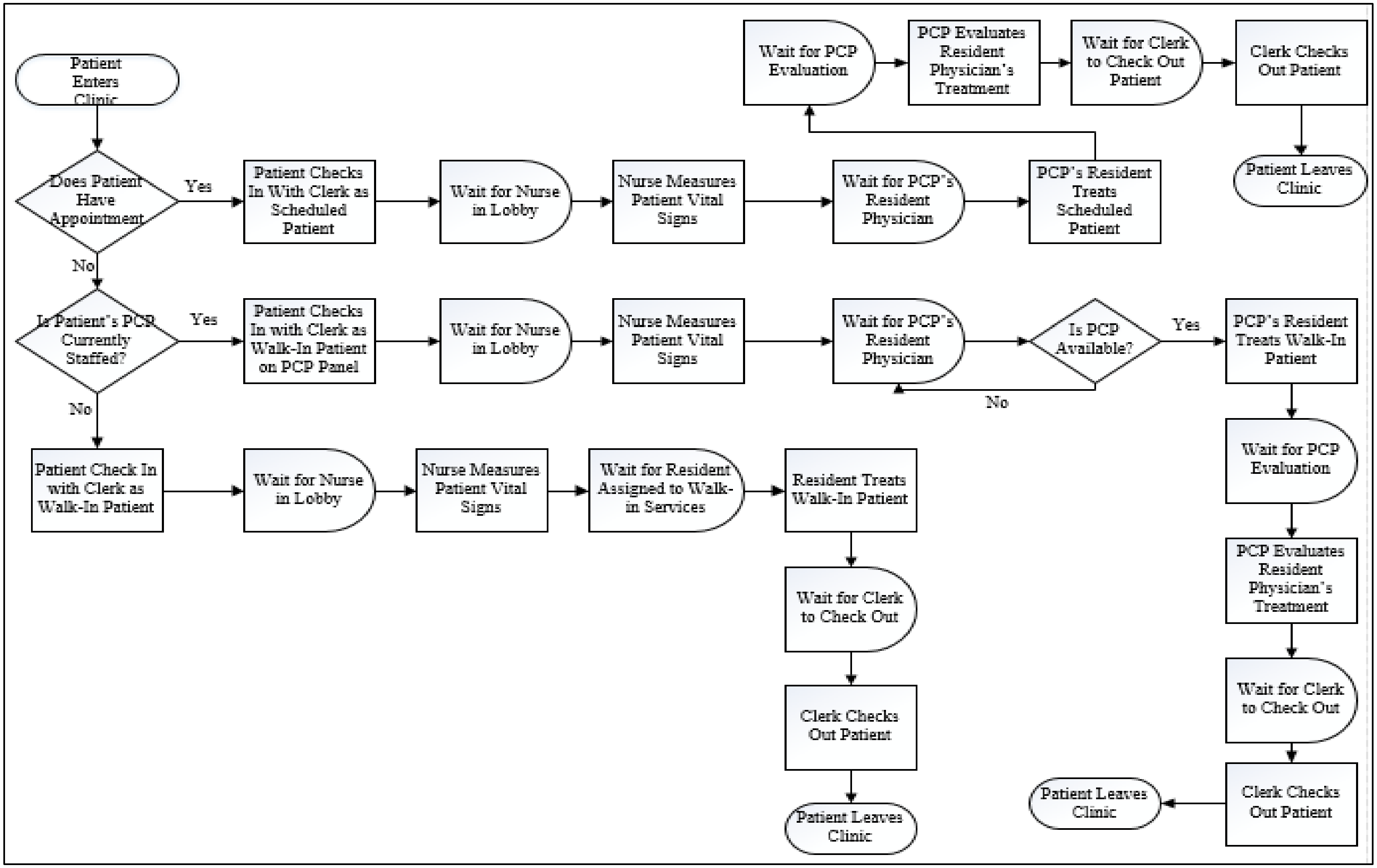

Figure 1-1:Primary Care Patient Flow

1.1.1.1 Orlando Veteran's Affairs Medical Center (VAMC) Primary Care Clinic

At the Orlando VAMC primary care clinic, the pathway that a patient follows when they arrive to the clinic for health services varies by the patient-type classification. As shown in Figure 1-1, scheduled patients "check-in" with a clerk, then wait in a lobby area for the nurse to call them for their vitals check. After this preparatory work, the scheduled patient is ready to see the PCP. However, if the PCP is unavailable the scheduled patient then returns to the lobby to wait for the PCP to become available. On the other hand, unscheduled patients must be confirmed by their PCP when they arrive to the clinic. The clerk must check that the patient's PCP will be able to see them before "checking-in" the patient. The unscheduled patient also waits for a nurse in the lobby area. After the nurse measures the unscheduled patient's vital signs, that patient is able to see a designated resident physician who treats minor health issues. If this resident is unavailable, the unscheduled patient must wait in the lobby until the resident becomes available. For both types of patients, once the final clerk is seen for billing or instructions, they are able to leave the clinic.

In this study, we investigated the patient flow of an academic primary care clinic located in the Orlando VAMC. The primary clinic operates for 510 minutes per day, Monday through Friday. In that timeframe, the clinic is expected to see and treat a certain number of patients, and each patient is expected to wait to be seen for a certain amount of time. By not meeting these expectations, the clinic may be underperforming and management will look for ways to achieve the acceptable level of efficiency at which the clinic must operate. We will discuss a few of the strategies to achieve clinic efficiency in this thesis.

1.1.2 Strategies to Achieve Clinic Efficiency

Clague et al. (1997) were the first to notice greater attention being paid to inefficiencies in delivery of care and proposed "patient processing" as a way to improve clinic efficiency. Clinic efficiency suffers when patients do not show up for their appointments and resources are underutilized, or when appointments are overbooked and congestion leads to overworked physicians (Denton, 2013). A clinic is operating efficiently if the waiting time for patients is minimal, utilization of physicians is high, the expected number of patients treated is reached, and overtime is minimal. Unfortunately, some of these goals conflict with one another (e.g., patient waiting time and physician utilization) and tradeoffs must be evaluated. Fortunately, health care practitioners have worked with researchers from the fields of Industrial Engineering and Operations Research (IEOR) to balance these tradeoffs, and there are several strategies that can improve efficiency at the clinic level. Some of these strategies include: clinic redesign, patient flow analysis, appointment scheduling, planning, and forecasting (Cote, 1999; Shi, Peng, & Erdem, 2014; White, Froehle, & Klassen, 2011). For the purposes of this dissertation, the term *efficiency strategy* refers to management decisions aimed at improving the operations of the clinic. We include appointment scheduling, capacity management, and patient flow design decisions in this study.

1.1.2.1 Appointment Scheduling

Effective appointment scheduling is defined as a method of matching demand with capacity so that resources are better utilized and patient waiting times are minimized (Cayirli & Veral, 2003). Traditionally, pen and paper methods were used to maintain appointment times for physicians and their patients. This often resulted in fully booked schedules, which were set multiple weeks in advance, and rarely changed. With technological advances, scheduling systems have become dynamic, constantly changing as patients book their preferred appointment times and make changes as necessary. However, because the demand for appointment time increased, other appointment strategies were investigated to accommodate the long pre-appointment waiting time that patients were experiencing. In the early 2000s, Murray and Tantau introduced the concept of *advanced access* or *open access* scheduling. The concept is the opposite of traditional scheduling, in that appointment slots are left open for the same-day appointment requests. The effectiveness of open access scheduling has had mixed reviews as researchers have determined that the impact of this scheduling strategy is dependent on different environmental factors such as the patient no-show rate (Kopach et al., 2007). Other strategies to improve the efficiency of clinic operations include varying the length of appointment intervals.

1.1.2.2 Capacity Management

In health care systems, *capacity* refers to the number of hospital beds that are staffed for inpatient use (Leiyu Shi & Douglas A. Singh, 2012). Capacity planning, as a strategy, can be used to determine how many patients the hospital is able to treat at one time. Capacity can also be measured in terms of the number of staff that has been scheduled and the number of patients each staff personnel can care for. Managing capacity can be *fixed*, which may be a specific number of patients a physician or nurse can treat at one time. Capacity can also be *flexible*, where extra staff such as “floating nurses” may be used to adjust to fluctuations in patient demand (N. Kortbeek, Braaksma, Burger, Bakker, & Boucherie, 2015). Other approaches, similar to that of extra staffing, are staffing of NPs, PAs, or advanced medical staff.

1.1.2.3 Patient Flow Design

Patient flow analysis is another effective strategy in improving clinic performance. Patient flow analysis points out inefficiencies, such as bottleneck operations and possible areas of improvement. For example, many studies using patient flow analysis have been conducted in Emergency Departments (ED) because the time a patient spends waiting for emergency care is critical. By studying the flow of different patient types, such as urgent versus non-urgent, researchers have developed a "split-flow" approach to improve performance of ED operations (Konrad et al., 2013). This strategic approach to improve clinic performance has also been applied to other areas of the health care system, specifically in the primary care area.

1.1.3 Methods of Evaluating Efficiency Strategies in Primary Care Clinics

In primary care services the patient waiting time is a key performance measure of clinic efficiency and one of the key barriers to primary care access (Hefner, Wexler, & McAlearney, 2015). As a way of studying and improving the performance of outpatient clinics, researchers and practitioners opt to use several methods of analysis. Many research studies have used different analytical methods such as mathematical programming and queueing theory to evaluate appointment scheduling and staffing. Some used simulation studies to assess the impact of environmental factors on appointment scheduling performance or compare alternative appointment scheduling designs. Case studies are also used to gather empirical information to be used in quantitative modeling. We investigate the related quantitative modeling methodologies in CHAPTER 2.

1.2 Research Gap

According to Liu and Ziya (2014), there are few published research studies that investigate the waiting time to gain access through patient appointments, known as *indirect wait time*. Most of these studies look at how scheduling rules can impact the performance of the scheduling system. An efficient scheduling system allows short direct waiting time for unscheduled patients, while having minimal impact on the waiting time of scheduled patients (Gupta & Denton, 2008). In these studies, there is a decision to schedule or not to schedule a walk-in patient. In primary care clinic similar to that of the Orlando VAMC, this constraint is relaxed as the clinic provides walk-in services so that any walk-in patient is seen by a healthcare provider. There are no studies to our knowledge that investigate how scheduling rules impact the clinic's performance when walk-in patients are included.

Also, it is uncommon to find studies investigating multiple efficiency strategies and their joint impact on clinic efficiency, particularly, capacity management and appointment scheduling (Denton, 2013). To our knowledge, there are a very few studies that incorporate the effects of three different strategies on clinic efficiency: appointment scheduling, capacity management, and patient flow analysis (Baril, Gascon, & Cartier, 2014; Santibáñez, Chow, French, Puterman, & Tyldesley, 2009; White et al., 2011). However, none of these studies address the impact on primary care clinics providing walk-in services. The presence of extra patients, and the uncertainty of when those patients will present themselves has a major impact on the patients who are already scheduled. Therefore, we intend to address the gap in evaluating the impact of multiple strategies to improve clinic efficiency in the presence of walk-in patients.

1.3 Research Objectives

This study addresses the gap in the current use of appointment scheduling, capacity management, and patient flow design in primary care clinics to improve clinic efficiency. By evaluating the impact of these efficiency strategies for managing walk-in patients on the clinic efficiency measures, this research captures their joint effects and provides managerial insight into improving clinic operations. While methods to capture or model the effects of appointment scheduling, capacity management, and patient flow decision range from analytical modeling to simulation modeling, this research leverages the advantages of discrete event simulation modeling to build a simulation model of a VA academic primary care clinic. To measure the joint effects of appointment scheduling, capacity management, and patient flow decisions, this research uses an experimental design of simulated models. This research further uses the results of the experimental design to estimate the clinic efficiency measures. Our evaluation step provides insights or benefits for primary clinic managers and improvement specialist with information that could help direct their clinic efficiency efforts.

1.4 Research Questions

The main research question to be studied in this investigation is: How can primary care managers schedule more walk-in patients without negatively impacting scheduled patients in primary care clinics? Because patient waiting time is an important barometer of clinic efficiency, it is important to evaluate the impact of management's strategic decisions on clinic efficiency. The secondary questions to support the primary research question are:

(1) *How does the interaction of appointment scheduling, capacity management, and patient flow decisions jointly affect the efficiency of the clinic?* The question seeks to determine the

relationship between joint decisions in appointment scheduling, capacity management, and patient flow, and clinic efficiency measures: the waiting time of scheduled and walk-in patients, the number of walk-in patient seen, and the length of overtime. Based on the arguments in the literature on the impact of scheduling and capacity on patient flow, we hypothesize that patient flow will not significantly affect waiting time of scheduled or walk-in patients, nor will it significantly affect the number of walk-in patients seen or the length of overtime.

(2) *What effect does appointment scheduling and capacity management decisions have on clinic efficiency?* The response to this question will provide insight into which strategy is more effective in improving any one of the efficiency measures. By varying the tactical levels of each strategy, the results will prove that both strategies significantly affect each efficiency measure: waiting time for scheduled and walk-in patients, number of walk-in patients seen, and length of overtime.

(3) *What effect does appointment scheduling and patient flow design decisions have on clinic efficiency?* The response to this question will also provide insight into the joint influence of appointment scheduling and patient flow decisions on clinic efficiency. Existing literature argue that scheduling and patient flow design joint affect the waiting time of patients, and we assume that the there is a significant joint effect on the clinic efficiency measures: waiting time of scheduled and walk-in patients, the number of walk-in patients seen, and the length of overtime.

(4) *What effect does capacity management and patient flow design decisions have on clinic efficiency?* As with the previous supporting questions, the purpose of this question is to understand how capacity management and patient flow strategies affect clinic efficiency

measures. Existing literature argue that capacity management and patient flow decisions jointly affect the waiting time of patients, and we assume that there is a significant joint effect on the clinic efficiency measures: waiting time of scheduled and walk-in patients, the number of walk-in patients seen, and the length of overtime.

1.5 Research Limitations

The scope of this research investigation is limited to primary care clinics and VA operations. The data collected in the study is also limited to expert opinion as observational data was not approved by the Orlando VAMC management. The application of results from this study would be limited to primary care clinics with operations and policies similar to that of the Orlando VAMC. However, due to the tight constraints of the VA, the application of this research to private healthcare practices would require relaxation of certain constraints such as appointment slot length.

1.6 Research Contributions

This research investigation produces three contributions to the body of knowledge. First, this study is the first to evaluate appointment scheduling, capacity management, and patient flow decisions together in a single study, applied specifically to a primary care clinic setting with walk-in services. Second, this study is the first to provide predictive models for clinic efficiency measures, based on making joint appointment scheduling, capacity management, and patient flow decisions. Third, this study is the first to analyze the impact of appointment scheduling rules on clinic efficiency in a VA primary care clinic setting. This research also extends the applicability of discrete event simulation modeling for studying alternative designs in healthcare service operations.

1.7 Organization of Document

The rest of this dissertation is organized as follows. CHAPTER 2 investigates the body of related literature on modeling in healthcare, pertaining to appointment scheduling, capacity management, and patient flow analysis in the presence of walk-ins and scheduled patients. CHAPTER 3 introduces the simulation modeling methodology we developed to understand the dynamics between walk-in patients, scheduled appointments, and primary care clinic performance. CHAPTER 4 provides an experimental design to test the impact of strategies on clinic performance measures. CHAPTER 5 concludes the research study, including suggestions for future research.

CHAPTER 2 REVIEW OF LITERATURE RELATED TO SIMULATION MODELING & ANALYSIS IN HEALTHCARE

What is the healthcare system? A definition for *systems* proposed by Kast and Rosenzweig (1974) states that: "a system is defined as an organized or complex whole; or an assemblage or combination of things or parts forming a complex or unitary whole" (Hitchins, 2008). Other research studies follow Schmidt and Taylor (1970), which defines a system as a collection of entities, e.g., people or machines that act and interact together toward the accomplishment of some logical end (Law, 2007). From a systems perspective, the healthcare system encompasses four basic components; financing systems, insurance systems, payment systems, and delivery systems (Leiyu Shi & Douglas A Singh, 2012). Financing includes employers and government programs such as Medicaid. Insurance companies participate in both payment of health services, and insurance services. Delivery is the component most patients directly encounter; physician, hospitals, and health centers. The sub-system that this research focuses on is the healthcare delivery system.

Studying and analyzing healthcare delivery operations is a topic of interest for many researchers in Industrial Engineering/Operations Research (IE/OR) (Gupta & Denton, 2008). The healthcare industry faces challenges that are central to methods of IE/OR that reduce costs, utilize resources efficiently, increase the number of visits for patients, and reduce the amount of time patients spend in the clinic or hospital facility. A popular method of addressing such challenges is creating a model representation of the healthcare system of study. A model allows researchers and practitioners to measure the performance of the clinic or hospital with an aim of improving healthcare processes or establishing some standard of operation. A model also allows for investigative research, as there are many prohibitive policies to testing research hypotheses. For example, if the oncology wing of a hospital is interested in the impact of adding an operating (OR) suite, it would be unwise and costly to build the OR suite and then study its effect on patient cases or nursing staff. When interested in the relationships and interactions between people, machines, physical space, and technology, modeling provides an experimental tool for researchers and practitioners to estimate changes and their impact on healthcare systems.

Modeling can be conducted not only using a physical model, but a mathematical (theoretical) model as well (Law, 2007). As stated above, if it is possible to build an OR suite in an oncology wing without disrupting the flow and, more importantly, health of patients, then the resulting estimate of the impact on patients from this change is completely valid. Realistically, however, this is not the case. On the other hand, mathematical models provide quantitative relationships and logic that can be controlled, thus allowing a reasonable estimate of the impact on patients by the OR suite. It is for this reason that this study uses a mathematical model to analyze healthcare delivery.

2.1 Analytical Solutions vs. Simulation Models

There are some mathematical models that are simple enough to provide straightforward relationships between components of a system. For example, the area of a triangle is modeled mathematically as; one-half of the base length of the triangle, multiplied by the height of the triangle. The solution to the model is a *closed-form*, or an exact solution. The closed-form solution is an advantage for models with analytic solutions. However, the tradeoff for exact solutions is difficulty in handling complex systems, where there are many relationships between several components of the system. One example of increasing difficulty in modeling systems is observed in *queueing models.* Queueing models represent systems where people, machines, or objects join a line, called a *queue*, to receive services from other people, machines, or objects. Most evident is entering a banking institution to join a queue for teller services. Therefore, a queueing system is defined as a system consisting of one or more servers, an arrival process, and a service process, along with additional assumptions about how the system works (Solberg, 2008). When there a fewer servers and fewer arrivals in the queuing system, the queueing models are easily computed. The approach has advantages: it uses spreadsheet data transfer, few required data elements, and easy calculations in some cases. However, in health care system environments, where the entities are patients, the system may not reach a steady state and the results of queueing theory application cannot be used (Brahimi & Worthington, 1991). Additionally, as the number of servers, stations, or types of arrivals increase, the queueing system becomes more complex and the models no longer result in closed-form solutions. In fact, queuing models become intractable as the number of stations or the size of the queuing network increases (Osorio & Bierlaire, 2009).

An alternative to analytical models with exact solutions is simulation models with not-so-exact estimates. Centeno and Díaz (2015) provide a definition of *simulation* from Robert E. Shannon: "*the process of designing and building a model of a real system, conducting experiments to understand the behavior the system, and evaluating various strategies for the operation of that system*." Simulation models describe the state of a system at a single point in time (static) or as time changes. The latter is known as dynamic modeling, and is very popular for many applications from manufacturing, transportation, and public services to pandemics and outbreaks. Dynamic simulation models are advantageous in being able to capture complex relationships that are obstacles for analytical models. Thus modeling of healthcare systems with dynamic simulation models provides an opportunity to investigate complex healthcare delivery processes that, otherwise, would be difficult to study.

In Section 2.2, research studies in healthcare are discussed to gauge the wide application of simulation modeling. Section 2.3 follows, where a general overview of how patient flows through healthcare facilities are modeled with a simulation. Section 2.4 reviews simulation studies that describe capacity management issues in healthcare. Section 2.5 gives the literature describing the use of simulation modeling to address appointment scheduling problems is examined. Lastly, Section 2.6 evaluates the use of simulation modeling to analyze the impact of appointment scheduling, capacity management, and patient flow on the efficiency of primary care clinic operations. More specifically, the purpose of this review of literature related to simulation modeling in healthcare is to investigate the relationship between these strategies for clinic efficiency and the uncertain impact of walk-in patients.

The keywords that were used to conduct the literary search are *healthcare appointment scheduling*, *capacity management*, *patient flow*, *discrete-event simulation in healthcare, walk-in patients*, *clinic efficiency*, *primary care, and walk-in patients*. The literature for this review are retrieved from research databases such as Compendex, Web of Science, ABI/INFORM Complete, Google Scholar, Springer Link, and Academic Search Premier.

2.2 Simulation Modeling in Healthcare

Researchers in healthcare pursue models that can optimize the systems of healthcare for safety, quality, and efficiency (Gaba, 2007). The human body presents many complexities, particularly when being treated for illness, that can be difficult to predict or plan ahead for. In many cases, when “simulation” is the topic of discussion in health-related circles, the training aspect of simulation is often the focus. Like flight simulators in the aerospace industry, human simulators train clinicians through different “what-if” scenarios. In the same manner, the analytical ability of simulation modeling allows healthcare managers to also test “what-if” scenarios and gain a better understanding of the health system. To support the clinical effort of physicians and staff, managers use these “what-if” scenarios to ensure the operation of delivering healthcare service meets the organization’s objectives. Discrete-event simulation (DES) is a dynamic simulation modeling technique that aids decision makers with a data-driven tool to explore operational changes prior to implementation (Hamrock, Parks, Scheulen, & Bradbury, 2013). Agent-based simulation (ABS) modeling also aids decision makes in the same manner, however, this novel method focuses on the interactions between individual people, machines, and their environments (Barnes, Golden, & Price, 2013).

2.2.1 Discrete Event Simulation

In health systems research studies, DES modeling imitates the healthcare delivery system over time by capturing the states of change at distinct points in time. When a new patient is admitted to a hospital floor, or an ambulance arrives at the emergency department, DES models take a snapshot of the healthcare delivery system’s state. As time passes, the model aggregates these snapshots to calculate and measure statistics that describe the system. Examples of DES modeling cover a wide range of applications. Norouzzadeh, Riebling, Carter, Conigliaro, and Doerfler (2015) apply DES modeling to an internal outpatient clinic practice and measure resource utilization, capacity, and turnaround time. B. Kim et al. (2013) research alternative system designs to avoid trial-and-error changes to a mental health clinic. Eswaran, Lowery, McVay, Dollins, and Lenin (2015) capture the length of time patients stay in an obstetrics and gynecology clinic, and estimate improvements to reduce such length of stay measures. Quality improvement efforts benefit from using DES modeling by testing the impact of proposed changes on patient flow, staffing, and current policies (Rutberg, Wenczel, Devaney, Goldlust, & Day, 2015). Overall, DES modeling applies, but is not limited to managing bed and patient capacity, improving patient flow by finding bottleneck processes, managing appointment scheduling policies, studying ancillary services such as laboratory and testing services, and staffing of medical personnel. This research study uses DES modeling to address implementation of strategies for clinic efficiency.

2.2.2 Agent-Based Simulation

While discrete-event simulation models the behavior of systems over time, agent-based simulations (ABS) model the behavior of individual people, or *agents*. ABS is commonly used to model individual decision-making, or the behavior of social groups and organizations (Macal & North, 2014). In healthcare delivery system research, ABS helps researchers reduce the number of delays in a hospital. For example, delays are caused by late starts for morning surgeries in the OR. As outpatients (patients not hospitalized) enter the hospital and become inpatients, there are a series of paths the patients follow before their scheduled time for surgery. These paths include several different hospital personnel; anesthetist, registered nurse, surgeon, and patient care technicians. Pearce, Hosseini, Taaffe, Huynh, and Harris (2010) treats each healthcare worker and patients as individual agents, capable of making independent decisions on what task to start in their pathway. The research results show the impact of implementing a signaling process to coordinate hospital staff to treat high acuity patient on those requiring blood work upon arrival to the preoperative room. Laskowski and Mukhi (2008) develop an ABS model to compare staffing strategies in an emergency department. In the study, the model tracks patient waiting time and throughput in a singular emergency department and uses the data to establish diversion policies for incoming ambulances. The study further extends the methodology to multiple emergency departments to improve ambulance diversion policies between departments.

To address the problem statement in Section 1.2.1, we frame the literature discussion with research studies using DES modeling. This review of literature does not attempt to cover the entire range of simulation research studies and applications to healthcare delivery. For breadth in DES modeling, reference is made to comprehensive literature reviews and surveys such as; Jun, Jacobson, and Swisher (1999), Günal and Pidd (2010), Mielczarek and Uziałko-Mydlikowska (2010), and Bhattacharjee and Ray (2014). For breath in ABS modeling, reviews such as Isern, Sánchez, and Moreno (2010) and tutorials like Macal and North (2014) are referred to.

2.3 Patient Flow Literature

Several pathways to health service access exist, depending on the health facility. Access modalities to outpatient services can range from *appointment-only* to *walk-in* clinics. For example, specialized outpatient centers such as an oncology or ophthalmology department may accept appointments, referrals, and urgent/emergency requests; but not allow walk-in patients. On the other hand, EDs do not take appointments; but some primary clinics allow both appointments and walk-ins. Regarding Outpatient Clinic (OPC) services, we classify the literature by clinic modality: scheduled, unscheduled, and combined scheduled and unscheduled arrivals.

For system that are modeled using queueing models, there are several aspects of patient flow that are necessary for modeling the structure of the clinic: the arrival distribution of patients, the possible branching events, and the timing of services distribution. With such methodology for patient flow modeling, the network structure represents the number of nodes in a queueing system. The structure helps in determining if the model is a single or a multi-server model, or if the system is a closed or an open queueing system. The arrival distribution describes the time between patient arrivals to the clinic. Depending on the clinic modality, the literature mostly describes the arrival process as homogenous or non-homogenous Poisson processes (Bhattacharjee & Ray, 2014). If the patient flow does not follow a serial queueing system, then the probabilities of branching from node to node should also be addressed. Lastly, the service time distribution describes the amount of time a server (nurse, physician, or non-medical staff) provides the required or requested service.

2.3.1 Scheduled Arrivals

Because of the cost to home-bound patients who may not need extensive care, most hospitals outsource some health treatments to outpatient services. Outpatients are patients who receive medical treatment without being admitted into a hospital for care. These outpatient facilities are categorized by the type of evaluated health diagnosis (e.g., oncological, ophthalmological, or orthopedic). Because these clinics provide specialized care, they do not service the general surrounding population and can thus use appointments to control patient arrivals.

For clinics with appointment-only policies, simulation modeling studies are used to find the bottlenecks in patient flow, explore changes in operational design to improve clinic efficiency, and predict the impact of such changes. Pan, Zhang, Kon, Wai, and Ang (2015) used a discrete-event simulation to model the flow of patients in an ophthalmology clinic. They investigated different improvement strategies using a combination of DES results, and designed experiments and found that amending their services could have a significant impact on the patients' time in the clinic.

Similarly, Al-Araidah, Boran, and Wahsheh (2012) also investigated various improvement alternatives using DES and scenario analysis. They found that several scenarios would reduce waiting time and visit length without the need to invest in new resources.

Rohleder, Lewkonia, Bischak, Duffy, and Hendijani (2011) successfully used DES to find improvement strategies regarding staffing levels and scheduling patients. The orthopedic clinic that Rohleder et al. (2011) modeled served multiple patient types with multiple provider resources and 20-30 different patient pathways. The authors focused on early/late patient arrivals, thus approximating the inter-arrival time distribution as a Johnson SU distribution. Although an appointment/referral only clinic, some walk-in patients were allowed; however, very few. The authors randomly distributed these arrivals over the clinic hours of operation. The service times had varying distributions based on collected data. After validating the model, improvement strategies were found and data collected after implementation showed that significant reduction in patient waiting times was achieved.

Baril et al. (2014) also studied an orthopedic clinic where one patient type was served by multiple health providers under multiple patient trajectories. The inter-arrival data was collected from the appointment schedules; however, the authors considered physician lateness and walk-in inter-arrival times as fixed parameters, which they later conceded that this assumption “does not reflect completely the reality” (Baril et al., 2014).

In most cases, specialists (physicians of specialized care) operate on an appointment-only schedule. In such outpatient care settings, the planned capacity for specialists fail due to uncertain patient behavior for scheduled patient arrivals. These failures are described as appointment no-show, cancellation, or lateness (punctuality).

2.3.2 Unscheduled Arrivals

When a person falls unexpectedly ill an immediate care is sought, EDs provide emergency treatment and stabilization of the critical patient. In contrast to specialized care, EDs do not require an appointment to accept patients. This means that most EDs operate 24 hours daily, and do not turn patients away due to Federal laws. Although emergency services include ambulance arrivals, most ED patients arrive unscheduled. Unscheduled patient arrivals make planning decisions difficult by presenting uncertain medical issues and disrupting patient flow with possible reneging behavior while waiting. Chetouane, Barker, and Oropeza (2012) assumed exponential inter-arrival times throughout the day, along with variable intra-daily arrival rates. Ultimately, EDs aim to reduce the patient waiting time by using simulation to find areas of improvement in their clinic operations {(Love, Murphy, Lietz, & Jordan, 2012); (Konrad et al., 2013);(Chetouane et al., 2012)}.

2.3.3 Scheduled and Unscheduled Arrivals

There are some outpatient clinics that allow both scheduled and unscheduled arrivals. Primary and family care clinics are the main facilities that have this unique characteristic. We refer to unscheduled patient arrivals as walk-in patients, and we exclude arrivals from EDs or referrals from other outpatient departments from this modality or classification.

The majority of primary care studies omit unscheduled visits from modeling analysis. However, there are some studies that include both scheduled and unscheduled patient arrivals in their patient flow studies {e.g., (Alexopoulos, Goldsman, Fontanesi, Kopald, & Wilson, 2008); (Cayirli & Gunes, 2013)}. A major assumption about unscheduled patient arrivals is that they are random in nature and can thus be characterized as a homogenous Poisson process. Cayirli, Veral, and Rosen (2008) found that patient waiting time and provider utilization were affected primarily by no-show and walk-in probabilities. The arrival pattern of unpunctual patients was modeled as a Normal distribution and the inter-arrival times of walk-in patients were assumed to follow an exponential distribution (Cayirli et al., 2008). Alexopoulos et al. (2008) contested this notion by noting that unscheduled arrivals violate three basic assumptions of a homogenous Poisson process: (1) arrivals occur one at a time, (2) arrival rates remain constant throughout the day, and (3) arrivals are independent of one another. There are multiple factors that could influence the arrival pattern of unscheduled patients such as public transportation, coincidental lunch schedules, traffic jams, etc.

Shi et al. (2014) is the closest study to this research, and they too use a constant exponential rate of two hours for their walk-in patient inter-arrival time. In contrast, it is of interest to explore the impact of modeling a nonstationary Poisson process on a primary care clinic performance.

2.4 Capacity Management Literature

Capacity determines the number of patients that a healthcare system can treat, perhaps in a given day or hour. Capacity management solutions in healthcare aim to reserve the correct allocation of resources to provide services to these patients. Due to the variability in patient demand, as well as potential variability in staffing (if classified as capacity), managing capacity is a complex problem. There are several approaches to scheduling examination rooms or equipment for capacity. Santibáñez et al. (2009) use simulation to discover that pooling resources in a facility with multiple medical providers reduces patient wait time by 70%. Berg et al. (2009) finds that the maximum number of patients that can be served in a colonoscopy clinic depends on the fixed ratio number of examination rooms to endoscopic physicians. However, the study also demonstrates diminishing benefits from pooling as the capacity is constrained.

Another approach, similar to pooling, is to manage capacity by using flexible staff. Particularly for primary care clinics, primary care physicians are encouraged to maintain continuity with patients under their care. Balasubramanian, Banerjee, Denton, Naessens, and Stahl (2010) investigate the amount of workload for primary care physicians that should be dedicated for prescheduled patients versus urgent (unscheduled) patients. The study does not use simulation, but rather an analytical mathematical model to determine that higher flexibility amongst primary care physicians decreases patient wait time by 44%. Capacity management also applies to appointments and the number of time slots per physician, that are dedicated to scheduled patients. The management approaches are typically handled by appointment scheduling systems.

2.5 Appointment Scheduling Literature

There are several performance measures used in the research literature to evaluate appointment systems (Cayirli & Veral, 2003). Those measures are based on cost (idle time of doctors), time (percentage of patients seen within some period, say, minutes, of arrival), and congestion (mean number of patients in a queue). Simulation modeling is an appropriate tool that can capture many of these performance measures in a single model. We examine the studies that use simulation to evaluate the performance of appointment systems, either established or proposed.

Patient flow and clinic visit efficiency are affected by appointment scheduling (Shi et al., 2014). The ability of a scheduling system to keep waiting time and costs minimal is sensitive to patient behavior, including unscheduled patient arrivals (Cayirli, Veral, & Rosen, 2006). When both scheduled and unscheduled patient arrivals are present in a primary care system, there are two main decisions made by practitioners; how should access to appointment time slots be given to patients (access); and where in the clinic session should these patients be slotted (scheduling) (Cayirli & Gunes, 2013). The classification of the following studies will follow these two decisions.

2.5.1 Access Rules

Appointment slots are characterized by the size of the block (time slot) and the interval length. Cayirli and Veral (2003) included a review of research studies based on different combinations of block and interval length. Those investigations range from individual-block and fixed interval length to variable block sizes and variable interval lengths. The traditional practice in appointment scheduling is to fill the physicians' schedules with appointments well in advance. In so doing, the physicians would rarely be idle, not costing the clinic, and patient throughput is fixed. However, as demand for service increased and waiting time for an appointment became unsatisfactory, clinics started noticing a significant number of scheduled patients not showing up. Overbooking (OB), a concept from other reservation/appointment-based service industries, was adopted to ensure that appointment slots did not go unused if a scheduled patient did not show up. However, the strategy had negative effects such as clinic overtime and longer patient waiting times, if not properly executed. Researchers found a correlation between the length of time leading up to a patient's appointment and the probability of not showing up.

In 2000, Tantau and Murray developed the concept of same-day appointments to reduce this no-show probability. Open Access (OA), as it is referred to in the health scheduling literature, also has negative effects since it is difficult to plan capacity under such short notice; and patients can also experience longer waiting times than under traditional scheduling. We note the similar impact on scheduling between same-day requests for an appointment and unscheduled patient arrivals. Schedulers are faced with deciding to increase the block size, which is done by overbooking two or more patients into a single time slot when a patient "no-show" is likely to happen, or reserve empty slots in anticipation of unscheduled patient arrivals.

Lee and Yih (2010) conducted a simulation study to evaluate the performance of different OA scheduling configurations. Under these configurations, the effects of demand variability and no-show rates on patient waiting time and clinic utilization were determined to find the best policy for a certain clinical environment. The follow-up study used Discrete Event Simulation (DES) to compare OA and OB scheduling methods under various clinic environments, resulting in proposed guidelines for choosing a scheduling method (Lee, Min, Ryu, & Yih, 2013).

Some studies aim to determine the optimal number of appointments in a clinic session (S. Kim & Giachetti, 2006); (Muthuraman & Lawley, 2008). S. Kim and Giachetti (2006) studied the use of probability distributions of no-show and walk-ins to determine the optimal number of patients to book. In their case, the number of no-shows was higher than walk-ins; which happens to be the opposite environment in this research study. The results helped plan clinic capacity levels to meet demand and maximize total expected profit. However, difficulty was found as the daily capacity of resources for the clinic session become more fixed, as is the case in our study. Finding an optimal scheduling solution is beyond the scope of this research study.

Cayirli and Gunes (2013) investigated the daily capacity problem under seasonal arrivals of walk-in patients to understand if accounting for seasonality improves access rules. Using hypothetical data, an experimental design was used to compare the impact of different types of seasonality (monthly, intra-week, and intra-day) on the performance of the appointment schedule. A separate simulation-optimization model was then used to investigate where certain blocks should be overbooked. The authors found that while adjusting access rules for seasonal walk-ins is important, appointment (scheduling) rules must also be considered to find the best performing appointment system.

2.5.2 Scheduling Rules

Scheduling rules refer to the decision of how to assign appointment slots to patients. There are several factors that impact this decision-making (e.g., no-shows, punctuality, variance of service time, and patient classification). Since the 1970s, patient classification has been studied as a way of improving clinic performance. Scheduling low-variance patients at the beginning of the clinic session was found to outperform other sequencing approaches (Klassen & Rohleder, 1996).

Peng, Qu, and Shi (2014) proposed a discrete event simulation and genetic algorithm approach to find the best scheduling template for an advanced access clinic experiencing walk-in patients. Using sensitivity analysis, they found that the optimal solution varies under different scenarios.

The work of Peng et al. (2014) closely resembles that of Cayirli and Gunes (2013), modeling a primary care clinic experiencing walk-in arrivals, to analyze the impact of scheduling rules on the clinic performance. The use of discrete-event simulation overlaps these studies and with that used in this research, but unlike these authors’ study, we investigate an actual primary care clinic that also has multiple patient types and servers. Possible gaps in the clinic modeling and analysis literature, specifically with computer simulation, can be found in Table 2-1.

Table 2-1: Selected Literature Review

Author(Year)	Clinical Setting	Multiple Patient Types	Walk-in Arrival	Patient waiting time	Patient Flow Analysis	Scheduling Decisions	Method	Research Problem
Balasubramanian (2010)	PC	X		X		X	Integer Programming	Number of appointment slots to allocate to physicians
White (2011)	ORTH	X		X	X	X	DES	Finds optimal scheduling rule for costs
Shi (2014)	PC	X	X	X	X		DES	Studies the impact of factors on patient flow
Baril (2014)	ORTH	X		X	X	X	DES	Studies relationships between patient flow,

Author(Year)	Clinical Setting	Multiple Patient Types	Walk-in Arrival	Patient waiting time	Patient Flow Analysis	Scheduling Decisions	Method	Research Problem
								resource capacity, and scheduling
Bard (2014)	PRIMARY CARE			X	X	X	DES	Manages early and late arrivals
Bobbie (2016)	PRIMARY CARE	X	X	X	X	X	X	Studies the impact of patient flow, appointment scheduling, and capacity management on clinic performance

2.6 Analyzing the Impact of Appointment Scheduling, Capacity Management, and Patient Flow on Clinic Efficiency

Santibáñez et al. (2009) simultaneously analyzed the impact of scheduling and capacity allocation on patient waiting time and resource utilization. Using DES and scenario analysis, they found that clinic start time has a significant impact on patient waiting time, and double-booking "add-on" patients to the end of the schedule also causes a significant reduction in patient waiting time. This study incorporated scheduling, patient flow, and resource allocation factors in the scenario analysis. However, walk-in patients could not be addressed as the study took place in an oncology clinic.

White et al. (2011) investigated the impact of scheduling policies, patient trajectories, and capacity decisions on clinic performance. Using discrete-event simulation, their findings suggest that scheduling lower-variance, shorter appointments earlier in the clinic session results in less overall patient waiting time. Additionally, if higher-variance and longer appointment slots are scheduled later in the day, physician utilization is not reduced and clinic overtime does not increase. These two types of appointments are similar to new and established patients that occur in our clinic study. Closely related to the study by Baril et al. (2014), the authors' research is applied in an orthopedic clinic; but it makes no mention of walk-in patients.

2.6.1 Impact of Walk-In Patients on Primary Care Clinic

Bard, Shu, Morrice, Poursani, and Leykum (2014) applied their research to a primary care clinic and used DES and experimental design to understand the relationship between scheduling rules and patient punctuality (patient flow) in order to improve the patient experience. Unlike Shi et al. (2014), the authors analyzed different scheduling rules and their impact of clinic performance of patient waiting time. However, walk-in patients had appointment slots reserved at the end of the session, and an arrival distribution was not described or addressed.

There are few studies that specifically address the impact of urgent patients on non-urgent patients (Chen & Robinson, 2014; Dobson, Hasija, & Pinker, 2011; Nikky Kortbeek et al., 2014; Peng et al., 2014). However, these studies used mathematical modeling approaches to find optimal templates for OA scheduling. As discussed Section 2.1, due to the complexity of the VA primary clinic, we limit the scope of our methodology to simulation methods.

2.6.2 Conclusion of Primary Clinic Modeling Literature

Many studies focus on improving or studying scheduling strategies of primary care clinics. The prevalent source of uncertainty has been patient no-show and scheduling methods to mitigate the impact of no-show patients. However, the impact of a related source of uncertainty, unscheduled patient arrivals, has been largely neglected. Under design of clinic operations, if these patient arrivals are neglected, particularly in scheduling efforts, there is the potential to have significant patient waiting time increase, which can cause several problems in the clinic environment. This research overlaps with studies cited above in that extensive use of simulation is used to evaluate scheduling rules and policies in order to improve clinic efficiency. The paper published by Shi et al. (2014) is the study closest to our research question. However, the authors' research fell short of investigating the impact of scheduling walk-in patients on the waiting time of scheduled patients. To fill the gap in research, we use a simulation-based methodology to investigate this impact on clinic efficiency.

CHAPTER 3 SIMULATION ANALYSIS OF A PRIMARY CARE CLINIC WITH UNSCHEDULED PATIENT VISISTS

In the general healthcare industry, there are increasing trends of long waiting times and poor use of resources (e.g., physicians, nurses, and examination rooms). The United States (US) Department of Veterans Affairs operates the country's largest integrated health system, the Veterans Health Administration (VHA), which includes 150 medical centers and 1400 community-based outpatient clinics and serves over 8.3 million veterans every year (Williams et al., 2016). The long waits for healthcare services that are experienced by the patients of the VHA are like those of the private healthcare sector. It is the long wait times, and resulting social impacts that motivate this research study. The purpose of this study is to gain insight into the impact of choosing an appointment scheduling policy on a primary care clinic's ability to service walk-in patients. A simulation model is used to obtain this insight, which provides mitigating solutions and inspiration to the VHA and the less restrictive private sector.

3.1 Current Primary Care Clinic Operations

The Orlando Veterans Affairs Medical Center (VAMC) provides many patient care services including primary care, ophthalmology, physical therapy, and podiatry to name a few. Health services are primarily organized by a team-based approach, where a patient is served by a team of health professionals (e.g., physician, pharmacist, social worker, nurse, clerk and scheduler). The simulation model of this study is based on the Orlando VAMC primary care clinics. The clinics are operated by primary care physicians (PCPs), nurses, and clinic staff (clerks). The clinics use an appointment system to provide fixed amounts of time for patients and their PCPs. The clinics allow PCPs to work in their schedules patients who have not scheduled an appointment to be seen.

According to past studies, the average panel size of a private sector primary care clinic is 2300 patients (Altschuler, Margolius, Bodenheimer, & Grumbach, 2012) with the average patient requesting 3 appointments per year. Depending on the number of physicians that are full-time employees, the number of available appointment slots per day may be small, causing long waits for an appointment. In these types of situations, the delay, described as the time from the appointment request to the actual appointment day, is called an *indirect wait*. It is known that the negative impacts of indirect waits affect the health of patients and the operations of the clinic. The health of a patient with a chronic illness may quickly deteriorate while that patient is waiting for their appointment day. In response, that patient may seek care at a facility outside the clinic network of the original primary care clinic, resulting in a patient no-show (if appointment is not cancelled) and less effective use of the physician's time.

The VA has implemented the "Veterans Choice Program" where any appointment beyond 30 days of the physician-determined or veteran-requested appointment time, can be served outside the VA health network (Gellad, 2016). Despite the Choice Program, some medical centers provide "walk-in services" which allow patients a same-day appointment with their PCP or alternative medical professional. Ideally, this strategy is one alternative strategy to reduce the impact of long indirect waiting time. However, this action opens the door for potential crowding of walk-in patients seeking service, or longer direct waiting time for patient with appointment times.

Ultimately, we want to examine the impact of appointment scheduling policies on the clinic's performance of treating walk-in patients. We also want to understand how walk-in patients impact the clinic performance measures on scheduled patients. It is important to acknowledge possible tradeoffs and present guidelines if possible. We believe that reduction in the length of appointment time will have a significant impact on the clinic performance measures when walk-in patients are present.

3.1.1 Patient Descriptions

The Orlando VAMC clinic we studied serves multiple types of patients, categorized by the status of their appointment. Patients can be classified as a scheduled or unscheduled (*walk-in*) patient. Scheduled patients who are arriving for their first appointment with their PCP are further designated as "new", and patients with prior appointment history are designated as "returning". We describe the patient flow of each type of patient through a primary care clinic at the Orlando VAMC. The patient flow is depicted below as a process flow chart in Figure 3-1.

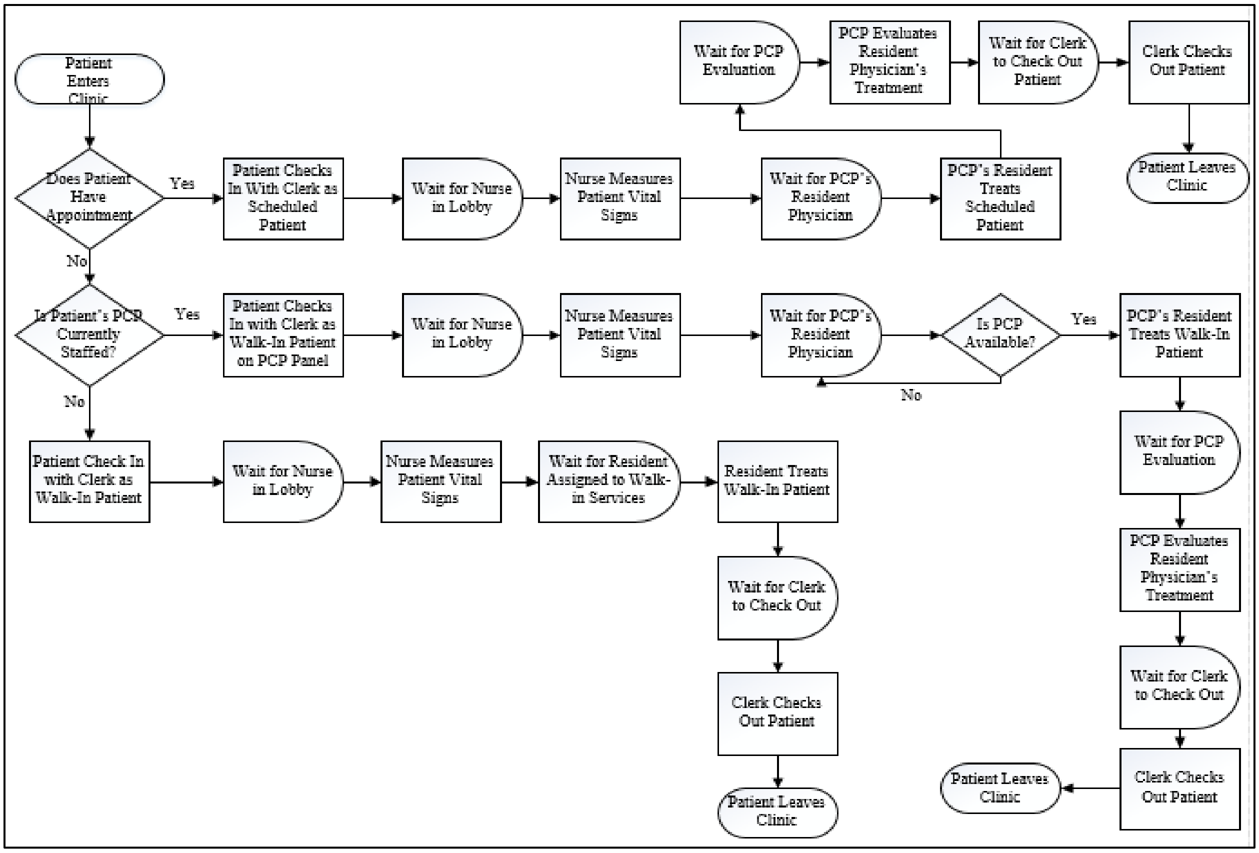

Figure 3-1:Orlando VAMC primary care clinic patient flow

3.1.1.1 Scheduled Patients

Scheduled patients call the clinic ahead of their appointment date. They may also be referred from another outpatient department or clinic for an appointment time. There is a wide range of reasons for which they make their medical appointment, covering any illness or symptom that is non-life threatening or a non-emergency. If the urgency of seeing a physician is high, a primary care clinic may schedule the patient for a same-day appointment. The clinic can also book the patient with an appointment slot that is already filled, a scheduling policy known as double-booking. As illustrated in Figure 3-1, once it is determined that an arriving patient has a scheduled appointment, they can be immediately checked in by the clinic clerk. Scheduled patients can be classified as either *new patient* or *returning patient*.

3.1.1.2 New Patients

A new patient enters the clinic facility and encounters a registration process that is necessary to receive personal information from the patient to establish a record of medical treatment. In addition to personal identification information, the patient may provide health history and insurance information. The clinic personnel that the new patient needs to see to accomplish these tasks is the clinic clerk or receptionist. All patients who enter the clinic facility must go through this process, or initial step; however, it may take a bit longer for new patients due to the nature of the new information that is needed before the patient can be treated.

3.1.1.3 Returning Patients

Returning patients also encounter the same process; however, the time they spend at the clerk's station is less significant due to the patient's history already established or, that needs an update. After the registration process, returning patients (as well as new patients) wait for some clinic personnel to take their vital signs such as pulse, body weight, height, and temperature. For the clinic in this study, a registered nurse (RN) is assigned to each primary care physician. Thus, the patient's RN will take the vital signs.

After the patient's vital signs have been recorded, the patient waits to be served by the next clinic personnel scheduled for that appointment. In some clinics, the patient is instructed to wait in the examination room. However, the clinic in this study instructs the patients to wait in the lobby waiting area. Once the patient's physician is ready, the PCP treats the patient for the health concern that is presented via the scheduling process prior to the clinic visit. After the PCP treats the scheduled patient (new or returning) the patient must go through a “check-out” process where billing, medication instructions, or possible follow-up scheduling occurs. At this point in the process, the patient must be served by a clinic clerk.

3.1.1.4 Walk-in Patients

Patients that do not call in, or are not referred, and are not given an appointment time, but arrive at the clinic without notice, are classified as walk-in patients. Like scheduled patients, the walk-in patient goes through a registration process; however, they create a significant delay in service due to the uncertainty of the patient’s reason for the visit. The difference in the patient flow is shown in Figure 3-1. As an example, a scheduled patient can call in expressing pain in their hip and the clinic has an opportunity to schedule an appropriate appointment time, as well as look at the medical history before the patient arrives at the clinic. However, if a walk-in patient arrives, there are a series of questions and procedures that must be completed to determine how and when the patient should be seen by their provider. A walk-in patient is confronted by one of two issues: the time the patient arrives for a PCP creates a conflict in the current scheduling of appointments (e.g., the PCP schedule is full) or the PCP of the presenting patient is not available for the clinic session. A patient on a PCP panel who walks into the clinic without an appointment is designated as a *Walk-in Patient-PCP*.

After registration, the walk-in patient waits for a nurse to provide the measuring of vital signs. After the nurse takes the vital signs, the patient must then wait for a physician to treat them. This waiting period is usually done in the waiting area (clinic lobby). The VAMC clinic used for this study categorizes walk-in patients who are not on a physician's patient panel as a *Walk-in Patient-No PCP*.

3.1.1.5 Walk-In Patients on a Physician Panel

Walk-in patient presenting themselves may be on a physician panel, which means that the patient has been assigned to a physician (*Walk-in Patient-PCP*). If this physician is working (or seeing patients) when the patient walks in, the physician must treat the patient by finding some time in the day's appointment schedule. On the other hand, if the walk-in patient presents themselves on a day when their PCP is not available, or not seeing patients, the walk-in patient (*Walk-in Patient-No PCP*) is served by a resident (student physician) who is able to treat minor health concerns.

Overall, both scheduled and walk-in patients all have different patient flow routes through the clinic. However, all patients are similarly served by a receptionist clerk, a nurse, and a primary care physician or medical resident (student physician) who medically treats the patient before payment is received and the patient exits the clinic facility. After treatment, all patients are then processed by the clinic clerk for billing, medication instructions, or follow-up scheduling.

3.2 Simulation Model of Primary Care Clinic

A number of researchers have used simulation techniques to study and analyze the operating behavior of outpatient clinics, including primary care facilities. Chand, Moskowitz, Norris, Shade, and Willis (2009) conducted a study using simulation to identify sources of variability and find areas of improvement. Findlay and Grant (2011) analyzed operational policies of a military-based clinic and use alternative designs to identify procedural changes that could improve system performance. Both studies employed discrete event simulation to model the primary care clinics.

A DES model is concerned with modeling a system as it evolves over distinct points in time. According to Law (2007), such a system is defined to be a collection of entities that act and interact together toward the accomplishment of some end. A typical example is a primary care clinic system of interacting PCPs, nurses, residents, and clerks operates on an 8-hour shift, opening with first appointments in the morning, and closing with final appointments in the afternoon. In the Orlando VAMC, two primary care clinics (Hero and Patriot) operate from 8AM to 4:30 PM, Monday through Friday. We note that our modeling approach to the Orlando VAMC primary care clinic (Patriot) is likened to that of Shi et al. (2014) due to the similarities of the clinic operations among VA primary care clinics used in both studies. However, our model differs from Shi et al. (2014) by the appointment scheduling method(s) that are investigated. Our model also differs in respect to the presence of resident physicians treating walk-in patients.

3.2.1 Data Collection

To begin the study of the primary care clinic, we met with clinic supervisors to discuss the basic operations of the Patriot clinic. The Patriot clinic serves as a primary care clinic focused on the treatment of veteran patients by their PCPs, a group of 6 faculty physicians. For three days, this physician group serves as the main doctors treating patients on their patient panels. The remaining two days are used as "teaching" days where the primary doctors that treat patients are 1st and 2nd year resident physicians. The patient flow graph in Figure 3-2 is a flowchart and description of the primary care clinic system (conceptual model), at the time of the first patient's arrival. The patient flowchart is essentially the same for teaching and non-teaching days, thus for modeling purposes; and it also depicts the sequences of operations in both types of clinic sessions. Figure 3-2 shows two process steps for treating patients, "Faculty Doctor Evaluates Treatment" and "Patient Sees

Resident Doctor". Because of their different roles, we make a distinction between PCPs and Resident Physicians.

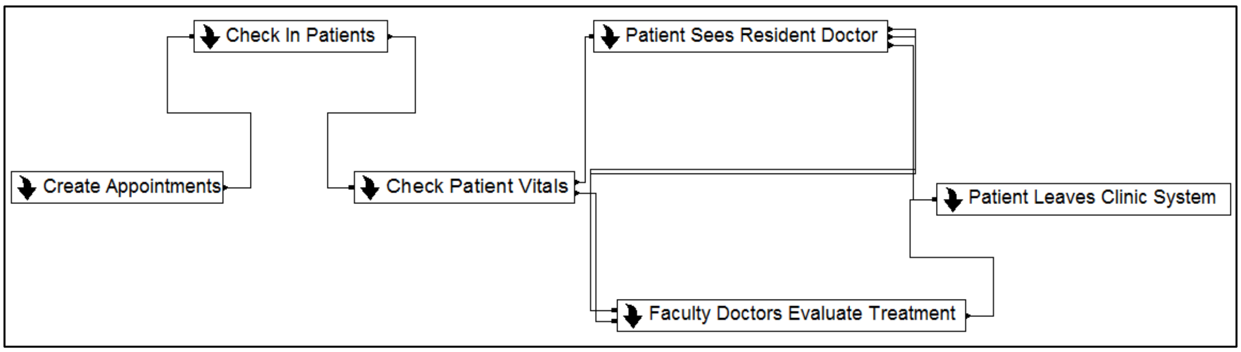

Figure 3-2: Process Flow of Primary Care Clinic

3.2.1.1 Clinic Process Steps

When patients enter a queue, they must wait until the employee that they need to see is available. When that employee is available, they conceptually attach themselves to that employee, thus preventing any other patient from using the same employee. Once the patient is finished with the employee (e.g., completed registration with a clinic clerk), that employee is released and made available to any other patient in need of their services. The length of time it takes the patient to retrieve, use, and release an employee is known as the processing time. For this simulation model, if an employee is not being retrieved, used, and released, the employee is either idle or not able to operate, e.g., a physician taking a lunch break. However, in the real world, the employee may take on other task related to their job during this "idle" time from servicing a patient.

Figure 3-2 shows two process steps for treating patients: “Faculty Doctor Evaluates Treatment” and “Patient Sees Resident Doctor”. Because of their different roles, we make a distinction between PCPs and Resident Physicians. Table 3-1 shows the process steps and the estimated time for each operation, based on the expert knowledge of primary care staff.

Table 3-1: Clinic Process Data

Process Steps	**Clinic Employee**	**Number Available**	**Estimated Duration per Patient**
Checking Patients In	Clinic Clerk	2	New/Returning: 5-10 min Walk-in: 20 min
Checking Patient Vital Signs	Registered Nurse	6	New/Returning: 5-10 min Walk-in: 20 min
Treating Patients	Faculty Physicians	6	All patients: 10-15 min
	Intern Physicians	4	New: 60 min; Returning: 30 min; Walk-in: 30 min
	Resident Physicians	4	New: 50 min; Returning: 20 min; Walk-in: 20 min
Checking In/Checking Out Patients	Clinic Clerks	2	All patients: 5-10 min.

An important performance metric for measuring how well the clinic system is operating is the amount of additional time the clinic must remain open to service untreated patients, which is referred to as *length of overtime*. We will discuss the performance measures in Section 3.2.4.

3.2.1.2 Clinic Employees

Faculty Primary Care Physician(s) (PCPs): The main task or operation of the PCPs is to treat the health concerns of the patient. These concerns may be understood and acknowledged beforehand via the appointment scheduling process, or may be presented at the time of registration if the patient walked in without an appointment. This processing time for treating patients is defined as the amount of time the patient is with the physician employee who is conducting the examination/consultation.

Student/Resident Physician(s): When the PCP is ready to see, or treat, an incoming patient, the patient will first be treated by a resident physician. For the clinic of this study, there are 8 resident physicians that are assigned to the 6 faculty physicians. When the resident physician has treated the patient, the faculty physician evaluates the patient's treatment before the patient can be released, or the appointment is completed. There are two main groups of residents that are categorized by the number of years in the residency program, *interns* who are 1st year residents, and *residents* 2nd year, and 3rd year student physicians.

Nurse(s): Nurses are employees who conduct the assessment of vital signs, and their processing time is defined as the amount of time the patient spends with them. We measure this time as the time between being called by the nurse and the time the patient returns to wait for the next employee. This data is also shown in Table 3-1.

Clerk(s): Clerks are employees who check patients in, and their processing time is defined as the amount of time the patient spends with them. We measure this time as the time between the initial patient-clerk encounter and the patient leaving for the waiting area, with the results listed as shown in Table 3-1.

Figure 3-3 shows the work schedule for staff, which is used as input into our foundational simulation model. The simulation model is based on our stated model assumptions in Section 3.2.2.

Physician Appointment Schedule

	Morning Session								Break		Afternoon Session						
Minutes in Clinic Session	0-30	30-60	60-90	90-120	120-150	150-180	180-210	210-240	240-270	270-300	300-330	330-360	360-390	390-420	420-450	450-480	480-510
Appointment Slot #		1	2	3	4 - 5		6	7	LUNCH	LUNCH	8	9	10 - 11		12	13	14
Patient Arrival	1	2	3	4		5	6			7	8	9		10	11	12	

Figure 3-3: Physician Appointment Schedule

Resident Appointment Schedule

	Morning Session								Break		Afternoon Session						
Minutes in Clinic Session	0-30	30-60	60-90	90-120	120-150	150-180	180-210	210-240	240-270	270-300	300-330	330-360	360-390	390-420	420-450	450-480	480-510
1st Year Resident (1)		1		1	1		1				1		1		1		1
2nd Year Resident (2)		2	2	2	2		2	2			2	2	2		2	2	2

Figure 3-4: Resident Schedule

3.2.2 Model Assumptions

Generally, the relationships between entities and resources in DES modeling are complex, making it quite difficult to obtain exact formulas to describe those relationships. Thus, we make several assumptions based on the logic of the conceptual model depicted in Figure 3-2. We assume:

(1) The scheduled patient arrives to the clinic 30 minutes ahead of their appointment time

(2) A *Walk-in Panel* patient is randomly assigned to a faculty PCP

(3) Breaks for employees are scheduled. However, in the case of an employee seeing a patient when a scheduled break is to commence, the employee will finish servicing the patient before taking the scheduled break. Return from break remains fixed.

(4) There are no batch arrivals (i.e., multiple patients arriving simultaneously)

(5) Patients waiting for Faculty physicians are served on first-come-first-serve basis

3.2.3 Building Model

The Arena™ Simulation software, which is a general-purpose simulator, was used for modeling the clinic system of this research. Arena™ uses a process-oriented approach to mimic the behavior and characteristics of system entities. The building blocks of the software are called *modules* (Create, Decide, Process, Assign, and Dispose) and together they provide the logical building blocks for modeling the dynamics of a system (Kelton, 2008). These modules are called "flowchart" models because they represent the process flow of entities. A second type of module are the *Data modules*. These modules represent the characteristics of entities, resources, employee schedules, and queueing behavior. Unlike flowchart modules, data modules are not visibly seen in any animated or process view of the model but are working in the "background" of the model.

Using Arena™, a simulation model was built to represent and mimic the operations of the Patriot VA primary care clinic with walk-in services. The main entities in the model are patients, followed by clinic resources or employees (physicians, nurse, clerks, etc.), and process steps (treatment or consultation). Figure 3-1 provides the conceptual model of operations and process sequences, beginning with the arrival of patients to the clinic system.

The patients in a primary care clinic mainly arrive to the facility per their appointment time. The patients are advised to arrive 30 minutes prior to their appointment time to allow time for nurse assessments and ensure that the patient is punctual for their appointment with the PCP. The only other type of arrival is an unscheduled arrival, a patient that is seeking the consultation of a provider without an appointment. We discuss both types of arrivals and explain how the data is used for our simulation model.

3.2.3.1 Incorporating Patient Arrivals

Scheduled Patient Arrival: This type of patient arrival is described by the schedule of the provider with whom the patient has an appointment. As an example, if a doctor has a 10:00 AM appointment, the patient is scheduled to arrive at 9:30 AM. Scheduled patients routinely visit the clinic for follow-up appointments. These types of patients are classified as *Return Patients*, whereas patients who visit for the first time are classified as *New Patients*. At the Patriot clinic, New Patients are allotted 1 hour of consultation time, compared to 30 minutes for Return Patients.

In our Arena® simulation model of the Patriot Clinic, the patients are represented by *entities* that follow a sequenced pathway through the clinic (e.g. registration-vital checks-treatment-check-out pathway). We create *entities* according to certain rules that govern the model. In our case, appointment slots or intervals were created as *entities* so that an appointment could be created every 30 minutes. We also used this logic to dictate when the last appointment could be created. Once our appointment slot *entities* are created, patient characteristics such as "appointment time" can be assigned to each *entity*, helping the *entity* follow a specified path. For scheduled patients, characteristics (referred to as attributes in DES simulation modeling terminology) such a *clerk registration time, nurse assessment time*, and *physician treatment time* were used to assign processing times to each entity. Patients without an appointment are introduced in the same manner; however, the uncertainty in how often they arrive must be accounted for.

Unscheduled Patient Arrival: This type of patient arrival is described as the event of an arrival for a patient that does not have an appointment scheduled, and is seeking a PCP's consultation. We define this arrival process by the number of unscheduled patients expected over the course of a clinic day, e.g., an average of 8 walk-ins per day; so, for 8-clinic hours there is an average of 1 unscheduled patient per one hour. The data from the clinic of study indicate that there are 10 walk-in patients per day, with 2 of those patients belonging to a PCP's patient panel (*Walk-in patient-PCP).* In the same manner as creating scheduled patients, we use a Create module to produce 10 walk-in patients during the 8-hour clinic session. The random arrivals of walk-in patients are best described as Poisson arrivals. The Poisson distribution is a discrete probability distribution that gives the probability of a given number of events that happen in a fixed amount of time, provided a known average rate of occurrence and independent arrivals between patients.

3.2.3.2 Sorting Appointments by Physician Schedule

Although scheduled appointments are created every 30 minutes, it is important to note not all appointment intervals are 30 minutes. Another important note is that clerks, nurses, and physicians have dedicated break times (particularly for lunch). Therefore, not all the generated appointment slot entities are used, nor are they converted into new or returning patients time slots. We use a series of Decision modules (of Arena™) to specify which appointment slot entities are discarded, which ones are converted to new patients, and which ones are converted to returning patients. Once the correct entities are reassigned as scheduled patients, the series of processing steps that guide each newly formed patient entity commences.

3.2.3.3 Establishing Processing Times

The processing times, indicated by employee resource and patient type are shown in Table 3-2. We use the Triangular (min, mod, max) distribution to establish the processing times for clerks, nurses, residents, and doctors. When access to empirical data is limited, according to Kelton (2008), the triangular distribution is an ad-hoc method of data input that is usually used for "activities", compared to the exponential distribution which is used for inter-arrival times. Table 3-2 lists the mode (min, mod, max) for each type of patient and clinic resource.

Table 3-2: Probability Distribution for Clinic Operations

Process Step	Clinic Employee	Number Available	Probability Distribution Used (minutes)
Checking Patients In	Clinic Clerk	2	New/Returning Patients: TRIA (3,5,7) Walk-In: TRIA (15,20,25)
Checking Patient Vital Signs	Registered Nurse	6	All patients: TRIA (10,15,20)
Treating Patients	Faculty Physicians	6	All patients: TRIA (10,12,15)
	Intern Physicians	4	All patients: Resident physician time + 10
	Resident Physicians	4	New patient: TRIA (30,40,45) Returning patient: TRIA (10,15,20) Walk-in patient: TRIA (10,15,20)
Checking In/Checking Out Patients	Clinic Clerks	2	All patients: TRIA (3,5,7)

3.2.3.4 Completing the Model Logic

The clinic operates on an 8-hour operating schedule. Thus, the model stops execution after 480 minutes to signify the closing of the clinic. However, this does not happen in the real clinic. The Patriot clinic stops accepting patients one hour prior to the scheduled closing time. Therefore, a mechanism that stops creating available appointment slot entities 7 hours into the clinic session day, is needed. We use a *global variable* to establish when the model stops creating appointment slot entities. For example, the variable *SlotsPerArrival* can represent the number of appointment slots created per entity, and be set to “1” to create the appointment slots entities. At the desired time of completion, the model needs to create a new entity called *CutOff Entity* and assign the variable *SlotPerArrival* a new value of “0” to stop any more appointment slot entities.

Also of importance is the complete treatment of all current patients at the time of closing. The clinic cannot stop treating patients at the time of close and resume treatment at a later time (highly unlikely). Therefore, we use another variable, “work in progress” (*WIP),* to keep track of the number of active patients in the clinic at any point in time. When the variable *WIP* reaches “0”, and the last patient arrival has been accounted for at 450 minutes, the model can terminate. Figure 3-5, shows the interface for setting the Run Setup parameters in Arena™.

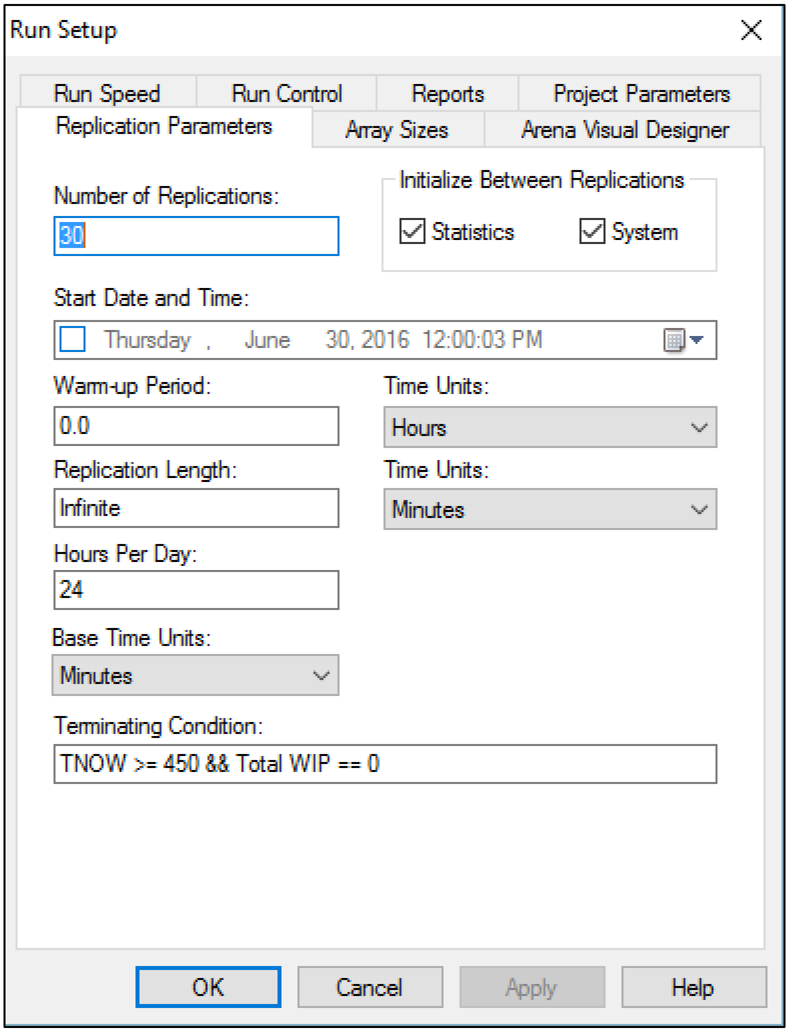

Figure 3-5: Run Setup Configuration

3.2.4 Model Output

With the final logical configuration of the model, the simulated primary clinic process is ready to be run. However, there should be specific system parameters under which the run is designed. We run the length of the simulated clinic system under the two conditions as specified in Figure 3-5. We assume that each clinic session is independent of each other, thus performance measures can be based on daily metrics.

3.2.4.1 Clinic Performance Measures

In addition to the clinic system throughput, we are interested in addressing issues of clinic efficiency when non-scheduled patient visits are present. Therefore, it is of great importance to determine how the clinic performance is measured. According to Shi et al. (2014), clinic visit efficiency is measured by the patient waiting time and the utilization rates of medical staff resources. Therefore, we use four performance-related variables to measure the operating efficiency of the clinic: average waiting time of scheduled patients, average waiting time of walk-in patients, average number of walk-in patients seen and average duration of overtime hours.

In the simulation model, we use a flowchart module called *Record* to count the number of patients that complete their visit. We also use this module to tally the total amount of time the patient entity spent inside the simulated clinic system. Every *Process* module has a queue, where a "counter" tallies the average waiting time for all entities that pass through its logic. The counters are used to tally the total waiting time for patients, both scheduled and non-scheduled. Table 3-3 presents an output of the waiting time of patients that are seen on a typical day for the teaching clinic session.

Table 3-3: Primary Clinic Performance Measures

Performance Measure	Average (min.)	Half Width (min.)	Minimum Average (min.)	Maximum Average (min.)
Patient Waiting Time (Scheduled Patients)	21.4035	1.90	13.2516	39.1048
Patient Waiting Time (Walk-in Patients)	18.7599	3.48	2.9617	49.5268
Number of Walk-in Patients Treated	11.86	1.54	4	21
Average Duration of Overtime	46.37	30.8	0	104.55

shows the expected output for the clinic system based on the performance measures described for this study. As discussed in Section 3.1, each student physician is assigned a certain number of patient appointments, contingent on their years of residency. After the patients are treated, the assigned faculty doctors evaluate the treated patients before the patients exit the clinic through the check-out process. The results in Table 3-3 show that scheduled patients wait slightly longer than walk-in patients, however the clinic can treat 12 additional patients through the walk-in service. The average overtime spent is 46 minutes, or a total clinic operating time of 526 minutes.

3.2.5 Model Verification

The final step in creating a usable simulation model is to validate the output of the simulation. As stated earlier, each "run" of the model represents a single sample of estimated measurements collected by the simulation model counters. To test the validity of our simulation output, we simulate or primary clinic model for 30 replications, i.e. 30 clinic sessions. The results in Figure 3-6 show the faculty PCPs themselves treat a daily average of two walk-in patients who arrive during the clinic session. Walk-in patients on the PCP's patient panel number 8 unscheduled patients who are treated by residents. As stated earlier, there are 4 first year residents who see 1 new patient and 3 return patients, and 4 second year residents who see 1 new patients and 5 return patients. The resulting output from the simulation, listed in Figure 3-6, indicates 38 scheduled patients were seen with an additional 12 walk-in patients.

Number Out	Average	Half Width	Minimum Average	Maximum Average
Cut Off Entity	1.0000	0.00	1.0000	1.0000
Entity 1	149.00	1.59	141.00	156.00
New Patient	8.0000	0.00	8.0000	8.0000
Return Patient	32.0000	0.00	32.0000	32.0000
Scheduled Patient	37.9000	0.58	34.0000	40.0000
Walk In	11.8667	1.58	4.0000	21.0000
Walk In Doctors Panel	1.9667	0.44	0.00	5.0000

Figure 3-6: Number of Patients Treated

With random input going into the model, the results are comparable to a purely deterministic model with no random input. Collectively, the clinic system can see 12 additional patients that do not have a scheduled appointment. Considering the chance that a scheduled patient does not show up for their appointment is 6%, according to expert data, the clinic still treats 38 of the 40 scheduled patients. Before comparing alternative clinic operations, we presented the results to the primary clinic management for their verification. The model assumptions and results were affirmed to be accurate according to the expert knowledge at the VA Patriot clinic.

3.3 Alternative Clinic Designs

Our model can be used to measure the impact of walk-in patients on the clinic performance measures of the Patriot primary care clinic. By understanding the effect of uncertainty associated with walk-in patient arrivals, we can compare alternative clinic designs to mitigate the negative effect.

We begin by altering our base model from Section 3.2 so that no walk-in patients arrive to the primary care clinic. The results are shown in Table 3-4.

Table 3-4: Primary Clinic Performance Measures (without walk-in patients)

Performance Measure	**Average (min.)**	**Half Width (min.)**	**Minimum Average (min.)**	**Maximum Average (min.)**
Patient Waiting Time (Scheduled Patients)	14.2478	1.28	8.1805	26.4352
Average Duration of Overtime	0	0	0	0

In Table 3-4, the results show an average waiting time for patients to be roughly 14 minutes. This is quite a difference from the average of 21 minutes when walk-in patients are present. It is also important to note, particularly from a financial and efficiency point of view, that there are no overtime hours experienced when walk-in patients are not present. These results imply that the clinic operates quite efficiently with some variation in processing times causing wait time for patients. By adding walk-in services, waiting time increases by 50% and overtime hours begin to appear, which has a financial impact as well. We are interested in what insight can be gained from comparing scheduling rules, e.g. reduced appointment intervals, or open appointment slots. Particularly, we want to examine the impact of the scheduling rules on the performance measures of the clinic.

3.3.1 Alternative Comparison

In order to investigate the impact of scheduling rules on the primary clinic performance measures of this study, we compare two specific rules for appointment scheduling; advanced access scheduling (Open Access) and scheduling reduced appointment lengths. As discussed in CHAPTER 1 and CHAPTER 2, advance scheduling creates open appointment slots for patients that seek same-day or urgent treatment. On the other hand, reducing the length of appointments allows for more patients to be scheduled during the clinic session. We discuss each alternative in the following sections and present the results of each simulation model.

3.3.1.1 Advanced Scheduling

In order to create open appointment slots for each PCP-student physician schedule, we assumed that all scheduled patients are allotted the same amount of time, i.e., new patients are allotted 30 minutes rather than 60 minutes. In doing so, 2 additional appointment slots are created without an assigned patient. These slots (one during the morning shift and one during the afternoon shift) are available to potential walk-in patients. The results of this alternative clinic design are displayed in Table 3-5.

Table 3-5:Clinic Performance Measures (Advance Scheduling)

Performance Measure	**Average (min.)**	**Half Width (min.)**	**Minimum Average (min.)**	**Maximum Average (min.)**
Patient Waiting Time (Scheduled Patients)	22.4620	2.03	10.9893	38.7428
Patient Waiting Time (Walk-in Patients)	21.0089	3.60	8.2484	58.4454
Number of Walk-in Patients Treated	12.9667	1.38	6	21
Average Duration of Overtime	52.25	29.45	0	102.62

The results show that there is a 16% increase in waiting time of walk-in patients when using an advanced scheduling method. This is probably due to the increase in the number of walk-in patients that are treated due to the extra appointment slots. A similar increase of 17% is seen in the average duration of overtime, also due in part to the increase in number of walk-in patients treated. It appears that advanced scheduling does not significantly impact the waiting time of scheduled patients, as compared to that of walk-in patients.

3.3.1.2 Reduced Appointment Length

Although the VAMC has strict adherence to policies regarding changes in operating procedures, the flexibility of simulation modeling can be used to test difficult to implement changes, and illustrate the potential benefits gained from such changes. To perform the logic of changing the appointment scheduling rule, the Create module is used to reflect appointment slot entities being created every 24 minutes, rather than every 30 minutes. In this manner, more appointments are generated for scheduled patient, which is reflected in the number of scheduled patients "Number Out" in Figure 3-7. However, an increase in the number of scheduled patients results in busier employees (particularly physicians) and longer waiting times for all patients. The results from instituting a reduced appointment length schedule are shown in Table 3-6.

Table 3-6: Primary Care Performance Measures (Reduced Appointment Length)

Performance Measure	Average (min.)	Half Width (min.)	Minimum Average (min.)	Maximum Average (min.)
Patient Waiting Time (Scheduled Patients)	30.7699	3.84	19.5605	65.7813
Patient Waiting Time (Walk-in Patients)	28.0961	7.03	2.9290	83.2858
Number of Walk-in Patients Treated	12.2	1.36	5	21
Average Duration of Overtime	26.2054	28.77	0	125.80

Number Out	Average	Half Width	Minimum Average	Maximum Average
Cut Off Entity	1.0000	0.00	1.0000	1.0000
Entity 1	173.13	1.41	167.00	182.00
New Patient	8.0000	0.00	8.0000	8.0000
Return Patient	38.0000	0.00	38.0000	38.0000
Scheduled Patient	43.6667	0.64	39.0000	46.0000
Walk In	12.2000	1.36	5.0000	21.0000
Walk In Doctors Panel	2.2667	0.48	0.00	7.0000

Figure 3-7: Number of Patients Treated (Reduced Appointment Length)

The waiting time for scheduled appointments increases by 43% under a reduced appointment length design, whereas the waiting time for walk-in patients increase by 55% under such scheduling. Although more patients are seen, the higher volume of patient means increases in waiting time for all patients. The results of the waiting times for the reduced appointment time length are shown in Figure 3-7.

3.4 Conclusion

The discussion in this chapter has focused in the impact of walk-in patients on the performance of a primary care clinic, and the impact of appointment scheduling rules in the performance of the clinic when walk-in patients are present. We demonstrated the ability of a simulation model to capture the impact of walk-in patients on the performance of a VA primary care clinic, finding that waiting time for scheduled patients can increase by 50%, as well as the need for the clinic to incur overtime penalties. One strategy to increase the operating efficiency of the clinic is the use of appointment scheduling. We used our base model, which is a validated model of a VAMC, as a starting point to compare alternative clinic designs.

On the one hand, the reduction in the length of standard appointments results in an increase in the number of patients treated by the clinic. The tradeoff is the amount of time waiting for services by all patients, scheduled and walking in. On the other hand, using an advanced scheduling method, where a given number of appointment slots remain open for walk-in or urgent patients, does not have a significant impact on the waiting time of scheduled patients. The tradeoff with advanced access scheduling is the increase in overtime penalties.

This chapter details the simulation method that was used to investigate the impact of scheduling strategies (policies) on primary care clinic services when walk-in patients are present. The model in this chapter addresses the primary research question of the impact of scheduling rules on clinic performance. Realistically, operating decisions are not made in isolation. Therefore, we must examine the impact of joint policies on clinic performance.

Our aim for CHAPTER 4 is to find a viable solution; using a scenario-based, experimental design methodology, that will reduce the increase in waiting time experienced by patients who have scheduled an appointment with their primary care physician.

CHAPTER 4 SCENARIO ANALYSIS OF A PRIMARY CARE CLINIC MODEL

Although a computer simulation model of the clinic aids in comparing alternative system designs and determining which decision has the best impact on clinic performance, it is important to understand which factors, attributes, or characteristics of the system affect the performance of the primary care clinic. The purpose of this scenario analysis is to analyze the effect of scheduling decision rules, capacity management decision rules, and patient flow decision rules to gain a better understanding of the impact of these managerial decisions on the clinic performance measures. Previous results have shown that carefully adjusting the appointment scheduling policy can reduce the patient length of stay by as much as 8.5% (Bard et al., 2014). In the long run, this extra time can be of much benefit to physicians, particularly those with high workloads or large panel sizes. There are also research study results that support the insight of using patient flow design to improve clinic performance. First, we discuss benchmark scheduling rules to understand how appointment schedule designs impact the clinic performance. The same is done for capacity management and patient flow analysis. Second, we use an experimental design method to conduct several experiments using the computer simulation model from CHAPTER 3. Using this method, we can examine several characteristics of the clinic operations to determine which clinic parameters significantly impact the clinic performance measures. The results of this examination provide further insight into strategic decision making, specifically that of joint decisions being made. The approach followed, and discussed in this chapter, closely follows the works of Bard et al. (2014), Shi et al. (2014), and White et al. (2011), where the joint impact of appointment scheduling, capacity management, and patient flow decisions on clinic performance is investigated. In Section

4.1 we briefly discuss the strategies for clinic efficiency. Section 4.2 follows with the scenario analysis methodology, which includes a summary of the experimental design method. Section 4.3 discusses the analysis of data produced from the experimental runs and the results thereof, and Section 4.4 provides the results of the regression analysis used to build the models for estimating the primary clinic performance measures.

4.1 Benchmark Efficiency Strategies for Clinic Efficiency

4.1.1 Scheduling Decisions

There has been much research on scheduling rules, particularly for appointment scheduling systems for multi-server clinic facilities. We point the interested reader to Cayirli et al. (2006) for a full review of appointment scheduling research. We are interested in some of the benchmark scheduling rules for outpatient scheduling. Per Millhiser, Veral, and Valenti (2012), the rules are as follows:

1. IBFI (Individual block/fixed interval): Every patient scheduled has a unique appointment time, an equal interval length of time
2. 2BEG (2 at the beginning): An extension of the IBFI rule, with 2 patients in the first-time slot (time 0) and no appointment scheduled in the last time slot (Bailey-Welch Rule)
3. 2BFI (2 block/fixed interval): 2 patients are assigned to a time slot; however, the time slot is twice as large as IBFI and remains fixed for each pair of patients

4. OFFSET (Individual block/variable interval): The offset rule is shares the common form of individual appointment slots for a patient, however the slot lengths allow for varying amounts of time.
5. DOME: Time intervals are larger in the middle and smaller at the beginning of the session
6. Half DOME: Time slots begin small and increase throughout the clinic session (variant of 2BFI and DOME rules)

4.1.1.1 Advanced Scheduling and Overbooking

A somewhat recent appointment scheduling strategy is advanced scheduling. Traditional scheduling of appointments fills all slots for a clinic session up to the beginning of the session when it is then closed to incoming requests. In contrast, advanced scheduling leaves open-time slots in a session in anticipation of having requests for the same-day appointment.. Also, advantageous when the no-show rate is high, advanced scheduling has been adopted by many outpatient clinics. However, the uncertainty in daily appointments and the potential loss of scheduled time due to no-shows is a weakness of advanced scheduling. Therefore, some researchers investigate optimal policy selection and when to use advanced scheduling, sometimes based on environmental factors such as physician availability, patient punctuality, walk-ins, and no-shows.

Another popular scheduling strategy is to overbook time slots in anticipation of a patient not showing up for their appointment time. In some cases, particularly when the no-show rate is high, overbooking has proven to be a practical approach. However, when the no-show rate is low, the extra demand increases the overall patient waiting time as physician utilization goes up. Shi et al.

(2014) investigated the impact of several models, and the input factors, on clinic performance. One of such factors was the amount of double-booking (overbooking). Other factors included no-show rate, new patient rate, walk-in rate, and other patient flow factors. Although closely related, the study by Shi et al. (2014) did not investigate other schedule rules that could be applied, particularly the benchmark rules discussed above. And Bard et al. (2014) also did not investigate the relationship between scheduling rules and patient flow. However, as a contribution this area of research, we investigate the impact of open access and a reduced IBFI scheduling strategies on primary care clinic performance.

4.1.2 Capacity Management Decisions

The allocation of clinic resources is often referred to as *capacity* in the context of capacity management problems. Particularly, in health care systems, *capacity* can refer to several types of resources. For instance, in Balasubramanian et al. (2013), capacity refers to appointment slots; whereas in the study by Choi and Wilhelm (2014), capacity refers to the time allotted to special bookings of operating rooms. In this study, capacity is defined as the number of available time slots that can be scheduled for a physician in a clinic session. (Keep in mind this does not include walk-ins patient time slots that are serviced.) The capacity is based on the number of providers (faculty, residents, or NP and PA for non-academic settings) that are available.

4.1.3 Patient Flow Decisions

One of the most common performance measures of any health care facility is that of patient waiting time. The metric is also a good indicator of the ability of patients to navigate through the health care facility in a reasonable amount of time. Patient flow decisions are geared towards helping improve the cycle time (time spent in the facility) and thereby eliminating wasteful steps in the patients' path. (Thompson, Day, & Garfinkel, 2013) discuss the benefits of improving patient flow, including decreasing the number of stages or stations where patients must stop and wait, and performing stages in parallel.

4.2 Simulated Experiments

4.2.1 Factors of Interest

Experimental design approach is often used to investigate the effects of certain input parameters on an outcome of interest. In the case of this research, our outcomes of interest are the waiting time of patients, both scheduled and non-scheduled, the number of non-scheduled patients treated by the clinic providers, and the length of time over the schedule period until the clinic closes. Chapter 3 discussed the validation of the simulation model by replicating the current conditions of the primary care clinic. We selected *high*, *medium* and *low* levels of the following clinic parameters to discover the effect of these factors on the clinic performance measures, as previously discussed. The *medium* level represents the base case or configuration of the Orlando VAMC current operations. Below are the factor-effects that we examined:

1. Patient flow decision: There are multiple patient flows in the clinic of study. The main point of deviation occurs at the end of the process flow where faculty physicians evaluate the treatment of the interns and residents. However, if a patient is unscheduled and is treated by the designated resident, there is no evaluation made. The assumption is that treatment at this stage is minor and does not require faculty approval, or the relative time the faculty physician would spend evaluating

this treatment is insignificant. Therefore, we conducted experiments at two levels: a high level where the faculty spends significant time evaluating resident treatment, and a low level where this evaluation period is insignificant.

2. Appointment scheduling decision: As discussed in Section 4.1.1, scheduling rules are intended to organize the flow of patients seeking healthcare services. Designated time slots are assigned to specific patients. The main decision we are inquiring about is determining the length of the appointment time slots. Therefore, we examined the clinic system under the high level condition, where there is an increase in the number of appointment slots. This was achieved by reducing the length of each appointment. Under the low level condition, we created time slots of equal length for new and returning patients and two empty appointment slots (open access or advanced scheduling strategy).
3. Capacity Management decision: The bottleneck of resource allocation (capacity) in the clinic is found among the physicians as they spend the most time with patients. To examine the impact of decisions regarding capacity, we simulate the clinic system under two approaches: more interns (1^{st} year residents) than 2^{nd} and 3^{rd} year residents representing the low level setting, while a reversal of this proportion (more 2^{nd} and 3^{rd} year residents than 1^{st} year residents) represents the high level setting. The current setting in the clinic is assumed to be an equal balance of the type of residents available. Due to experience, residents typically work faster than interns. As so, we desire to measure the impact of this increase in capacity. Although we acknowledge that there may be constraints in implementing this strategy, a similar strategy would be to implement nurse practitioners or physician

assistants, which may be more realistic. See Section 3.2.1.2 for the resident physician schedule.

4. In contrast to the above qualitative factors, we included the patient no-show rate as it is an important system characteristic for many types of clinic systems. We observed a high level (10%), where more appointment slots become available, and a low level (2%), where the schedule becomes more constrained.
5. An important component of this research is the environmental setting of unscheduled visits to the primary care clinic. We modeled the clinic system at a high level of 35 minutes for the "walk-in arrival time", and a low level of 48 minutes.

The decision factors of this experimental design are listed in Table 4-1.

Table 4-1: Decision Factors for Scenario Analysis

Decision Factors	**High Level (+1)**	**Low Level (-1)**
No-Show Rate	10%	2%
Walk-In Rate	14/day	10/day
Capacity	Five 2nd and 3rd Year Residents and Three 1st Year Residents	Five 1st year Residents and Three 2nd and 3rd Year Residents
Scheduling	Reduced IBFI	Open Access
Patient Flow	Significant Evaluation	Insignificant Evaluation

4.2.2 Response Variables

- Average Scheduled Patient Wait Time (SPWT) - The waiting time for patients who have made an appointment with their primary care physician. This aspect of the clinic performance is measured by the average time spent in a queue for each service by each scheduled patient.
- Average Walk-In Patient Wait Time (WPWT) – The waiting time for patients who have not made an appointment with their primary care physician. This aspect of clinic performance is measured by the average time spent waiting in a queue for service by each walk-in patient.

- Walk-In Patients Seen (WIPS) – This aspect of clinic performance is measured by the number of patients that do not have an appointment, but are seen and treated by a faculty physician or resident physician.
- Overtime Hours (OVT) – This aspect of the clinic performance is measured by the difference in time of when the clinic closes (last patient exits the system) and when the clinic is scheduled to close (operating hours 8:00 AM – 4:30 PM, or 510 minutes).

4.2.3 Experimental Design

Factorial designs are a class of experimental designs that are used to increase the "volume" of information that can come from an experiment (Mendenhall & Sincich, 2006). Depending on the number of levels for each factor, we must determine if a full factorial design is applicable, or if a fractional factorial design must be used. In our case, there are 5 factors to investigate, with each potentially having two levels. This results in a 2^5 factorial design with 32 different design configurations. By analyzing these factors, we built a mathematical prediction model to estimate the performance measures of the primary care clinic simulation. The full model is provided in Equation 4-1, up to second order and three interaction terms.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_1 x_2 + \beta_7 x_1 x_3 + \beta_8 x_1 x_4 + \beta_9 x_1 x_5 + \beta_{10} x_2 x_3 + \beta_{11} x_2 x_4 + \beta_{12} x_2 x_5 + \beta_{13} x_3 x_4 + \beta_{14} x_3 x_5 + \beta_{15} x_4 x_5 + \beta_{16} x_1 x_2 x_3 + \beta_{17} x_1 x_2 x_4 + \beta_{18} x_1 x_2 x_5 + \beta_{19} x_1 x_3 x_4 + \beta_{20} x_1 x_3 x_5 + \beta_{21} x_1 x_4 x_5 + \beta_{22} x_2 x_3 x_4 + \beta_{23} x_2 x_3 x_5 + \beta_{24} x_2 x_4 x_5 + \beta_{25} x_3 x_4 x_5 + \beta_{26} {x_1}^2 + \beta_{27} {x_2}^2 + \varepsilon \qquad (4\text{-}1)$$

where X_1 is the no-show rate,

X_2 is the walk-in rate,

X_3 is the scheduling policy (1 = Reduced IBFI, -1 = Open Access)

X_4 is the capacity policy (1 = 5 Residents/3 Intern, -1 = 3 Resident/ 5 Interns)

X_5 is the patient flow policy (1 = Significant time with Faculty Evaluation,

-1 = Insignificant time with Faculty Evaluation).

To test for curvature in the model, we included center points in our design. Below in Table 4-2, we illustrate the 56 (32 runs plus 24 center runs) different treatments of the random order in which the simulations were run.

Table 4-2: 5-Factor Factorial Design with Center Runs

Case	Run Order	No Show	Walk In	Schedule	Capacity	Flow
9	1	Low	Low	Low	High	Low
49	2	Base	Base	Low	Low	Low
11	3	Low	High	Low	High	Low
5	4	Low	Low	High	Low	Low
26	5	High	Low	Low	High	High
25	6	Low	Low	Low	High	High
36	7	Base	Base	High	High	Low
2	8	High	Low	Low	Low	Low
14	9	High	Low	High	High	Low
27	10	Low	High	Low	High	High
34	11	Base	Base	High	Low	Low
30	12	High	Low	High	High	High

Case	Run Order	No Show	Walk In	Schedule	Capacity	Flow
22	13	High	Low	High	Low	High
51	14	Base	Base	Low	High	Low
48	15	Base	Base	High	High	High
28	16	High	High	Low	High	High
47	17	Base	Base	Low	High	High
4	18	High	High	Low	Low	Low
12	19	High	High	Low	High	Low
1	20	Low	Low	Low	Low	Low
24	21	High	High	High	Low	High
15	22	Low	High	High	High	Low
21	23	Low	Low	High	Low	High
42	24	Base	Base	High	Low	Low
7	25	Low	High	High	Low	Low
6	26	High	Low	High	Low	Low

Case	Run Order	No Show	Walk In	Schedule	Capacity	Flow
35	27	Base	Base	Low	High	Low
18	28	High	Low	Low	Low	High
39	29	Base	Base	Low	High	High
29	30	Low	Low	High	High	High
17	31	Low	Low	Low	Low	High
19	32	Low	High	Low	Low	High
33	33	Base	Base	Low	Low	Low
23	34	Low	High	High	Low	High
56	35	Base	Base	High	High	High
37	36	Base	Base	Low	Low	High
20	37	High	High	Low	Low	High
43	38	Base	Base	Low	High	Low
55	39	Base	Base	Low	High	High
50	40	Base	Base	High	Low	Low

Case	Run Order	No Show	Walk In	Schedule	Capacity	Flow
32	41	High	High	High	High	High
40	42	Base	Base	High	High	High
8	43	High	High	High	Low	Low
52	44	Base	Base	High	High	Low
54	45	Base	Base	High	Low	High
53	46	Base	Base	Low	Low	High
45	47	Base	Base	Low	Low	High
13	48	Low	Low	High	High	Low
38	49	Base	Base	High	Low	High
44	50	Base	Base	High	High	Low
41	51	Base	Base	Low	Low	Low
31	52	Low	High	High	High	High
3	53	Low	High	Low	Low	Low
16	54	High	High	High	High	Low

Case	Run Order	No Show	Walk In	Schedule	Capacity	Flow
10	55	High	Low	Low	High	Low
46	56	Base	Base	High	Low	High

Each model was executed to measure five performance metrics: the waiting time for scheduled patients, the waiting time for non-scheduled patients, the number of scheduled patients seen or treated (throughput), the number of non-scheduled patients seen or treated, and the length of overtime. For example, the results for Case 7, when the no-show rate is 2%, the walk-in rate is 3Base minutes, the capacity is favorable to 2nd/3rd year residents, the appointment intervals are reduced, and there is relatively little time spent evaluating treatments The performance measure of interest are as follows: scheduled patients wait an average of 39 minutes, walk-in patients wait an average of 37 minutes, 43 scheduled patients are seen or treated, 15 walk-in patients are seen or treated, and overtime totals 96 minutes.

4.3 Factor Analysis

The data from this experimental design needs to be analyzed before building a linear model to describe the relationship between the scheduling, capacity, and flow factors; and the clinic performance measures: average scheduled patient waiting time, average walk in patient waiting time, total number of walk in patient seen, and average length of overtime hours.

4.3.1 Factor Screening

There is a total of 5 factors that are controlled at two levels, resulting in a total of 32 treatments (simulation models). Ultimately, we wanted to determine which factors have a statistically significant effect on the response (clinic performance measures). Because we included center points in our design to test for possible curvature, there could be more than 6 coefficient effects for our model. These additional effects include interaction effects between the original 5 factors, and possible second order terms. As depicted in Figure 4-1, we tested our design responses for possible second order effects by the following test; H_0: $B_{14} = 0$, H_A: $B_{14} \neq 0$.

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	25	3231.67	129.267	32.43	0.000
No Show	1	13.30	13.297	3.34	0.078
Walk In	1	43.37	43.368	10.88	0.003
Schedule	1	446.78	446.779	112.10	0.000
Capacity	1	5.23	5.226	1.31	0.261
Flow	1	135.09	135.092	33.89	0.000
No Show*No Show	1	0.42	0.417	0.10	0.748
No Show*Walk In	1	9.12	9.117	2.29	0.141
No Show*Schedule	1	0.72	0.725	0.18	0.673
No Show*Capacity	1	0.44	0.441	0.11	0.742
No Show*Flow	1	0.15	0.148	0.04	0.849
Walk In*Schedule	1	0.15	0.153	0.04	0.846
Walk In*Capacity	1	0.96	0.960	0.24	0.627
Walk In*Flow	1	0.03	0.033	0.01	0.928
Schedule*Capacity	1	6.24	6.241	1.57	0.220
Schedule*Flow	1	25.48	25.478	6.39	0.017
Capacity*Flow	1	3.32	3.320	0.83	0.369
No Show*Walk In*Capacity	1	0.05	0.050	0.01	0.911
No Show*Walk In*Flow	1	4.94	4.938	1.24	0.275
No Show*Schedule*Capacity	1	2.10	2.098	0.53	0.474
No Show*Schedule*Flow	1	0.90	0.896	0.22	0.639
No Show*Capacity*Flow	1	0.12	0.122	0.03	0.862
Walk In*Schedule*Capacity	1	0.29	0.290	0.07	0.789
Walk In*Schedule*Flow	1	0.00	0.002	0.00	0.985
Walk In*Capacity*Flow	1	0.26	0.259	0.07	0.800
Schedule*Capacity*Flow	1	7.73	7.734	1.94	0.174
Error	30	119.57	3.986		
Lack-of-Fit	14	77.86	5.561	2.13	0.074
Pure Error	16	41.71	2.607		
Total	55	3351.24			

Figure 4-1: ANOVA Table Testing Curvature

As shown in Figure 4-1, the F-value for testing B_3 (no show*no show) is 0.10, and the p-value is 0.78. This means we do not have enough evidence to reject H_0, resulting in no curvature.

We are therefore left with only the main effects and interaction effects to screen for. We conducted normality test for each response to determine which factors were statically significant. The precision, or confidence, is an alpha value of 0.05, or 95% confidence. Figure 4-2 shows the normal probability plot for the response “average waiting time for walk in patients”.

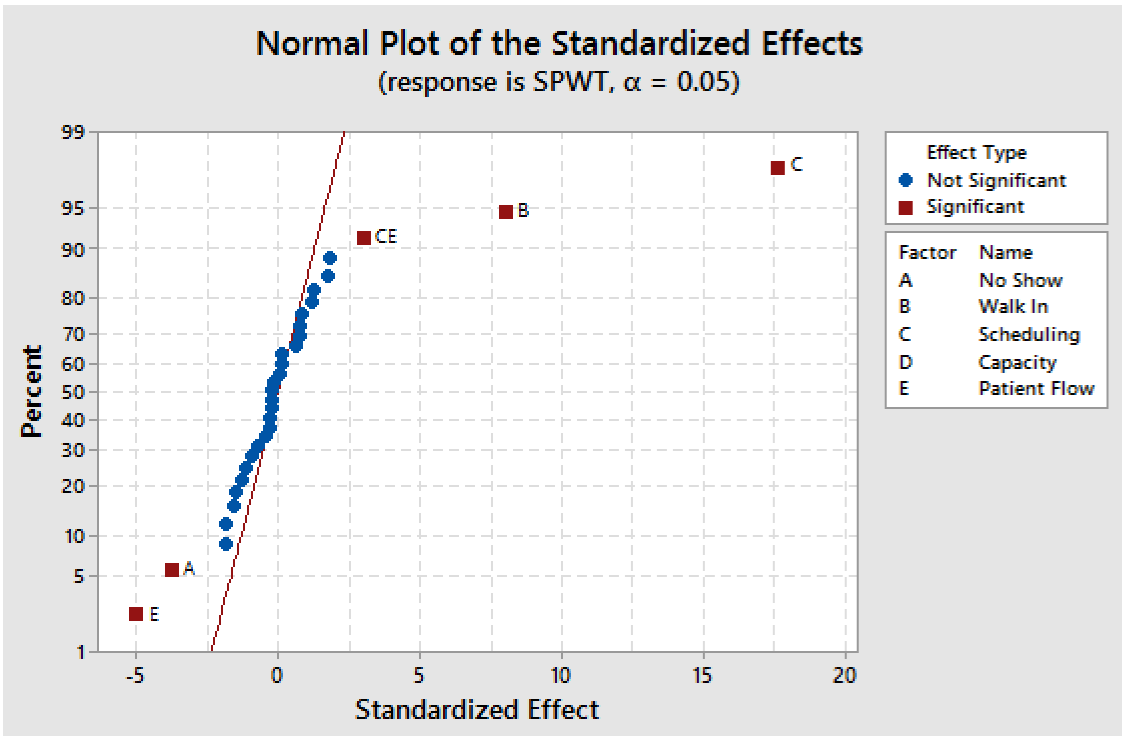

Figure 4-2: Normal Probability Plot for Average Scheduled Patient Wait Time

From Figure 4-2, we can see the significant factors are only the main effect; no show (A), walk in (B), scheduling (C), and patient flow (E). Capacity (E) is not a significant factor in the average scheduled patient waiting time.

The same probability plot is conducted for the remaining performance measures and the significant factors are listed in Table 4-3.

Table 4-3: Screening for Significant Factors

Clinic Performance Measure	**Significant Factors**
Average Scheduled Patient Wait Time	A, B, C, E, CE
Average Walk In Patient Wait Time	A, B, D, AB
Total Number of Walk In Patients Seen	B, C, D, CD, BDE
Average Overtime Hours	A, B, C, D, E, AB, BC, CD, BCD, BCE, CDE

The linear multiple regression models that need to be formulated are listed in Table 4-4 by the following equations:

Table 4-4: Reduced Regression Models

Clinic Performance Measure	**Regression Model**
Average Waiting Time for Scheduled Patients	$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_5 x_5 + \beta_{14} x_3 x_5 + \varepsilon$ (4-2)
Average Wait Time for Walk In Patients	$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_4 x_4 + \beta_6 x_1 x_2 + \varepsilon$ (4-3)
Total Number of Walk In Patients Seen	$y = \beta_0 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_{13} x_3 x_4 + \beta_{24} x_2 x_4 x_5 + \varepsilon$ (4-4)
Average Length in Overtime	$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_1 x_2 + \beta_{10} x_2 x_3 + \beta_{13} x_3 x_4 + \beta_{22} x_2 x_3 x_4 + \beta_{23} x_2 x_3 x_5 + \beta_{25} x_3 x_4 x_5 + \varepsilon$ (4-5)

4.4 Regression Analysis

In this section, the models in the above table are fit to a regression line to be used as a predictive model for scheduled and walk-in patient wait times, the number of walk-in patients seen, and the length of overtime. However, before that can be done, we tested the models for unequal variances and non-normal errors. These are important *analysis of variance* (ANOVA) assumptions that must hold if we are to use multiple regression to fit our simulated response variables to linear models.

4.4.1 Checking Assumptions

To use these models, we first check the following assumptions about ε, the random error component:

i. The probability distribution of ε is normal
ii. The random errors are independently distributed
iii. The E (ε) = 0
iv. Var (ε) is constant

4.4.1.1 Residual Analysis

We conducted a residual analysis to check the regression modeling assumption. First, we checked for an unspecified model. In so doing, we tracked for a curvilinear relationship between the residuals for the fitted models and the respective independent variables. In this case, we only have two quantitative independent variables; thus, there is only one pair of scatter plots for each clinic performance measure.

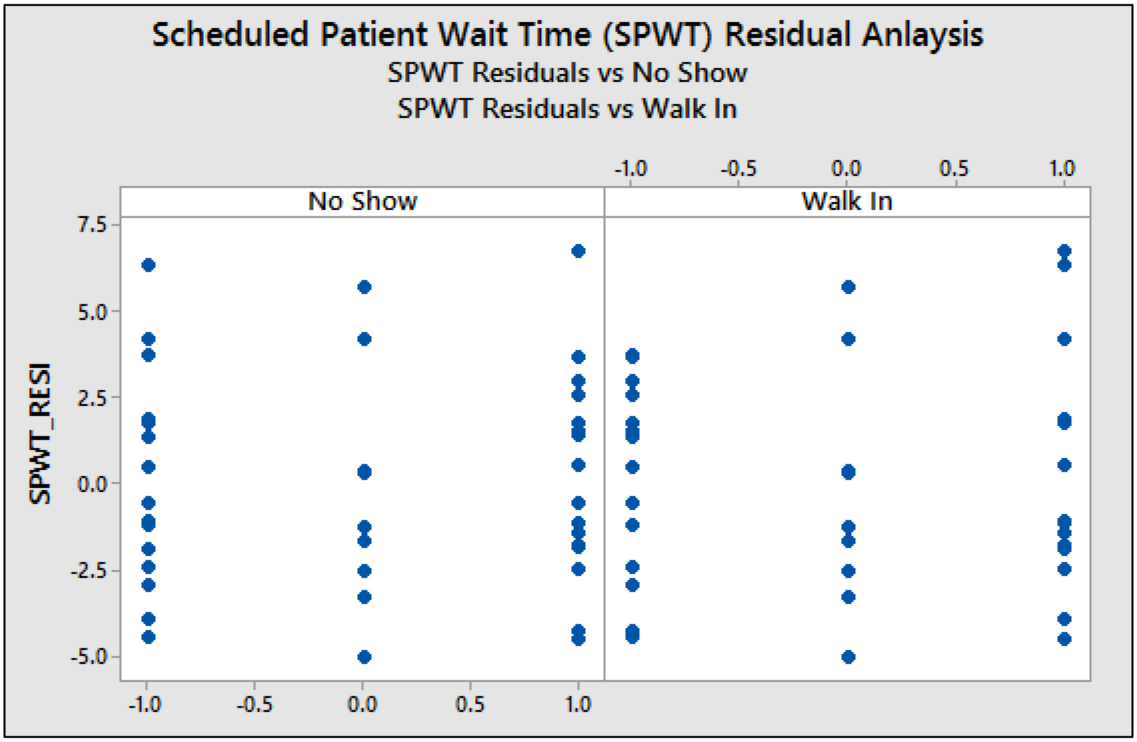

Figure 4-3: Check for Curvilinear Trend – Average Scheduled Patient Wait Time

Next, we checked for unequal variances, or heteroscedasticity. Here we plotted the residuals against the predicted values ($\hat{y}$). In this test, when there is a trend of increasing residuals as $\hat{y}$ increases, a *variance-stabilizing transformation* is applied to "thin" the residuals toward a constant value. This transformation was applied to the response *y*. Below is the residual versus fitted ($\hat{y}$) plot.

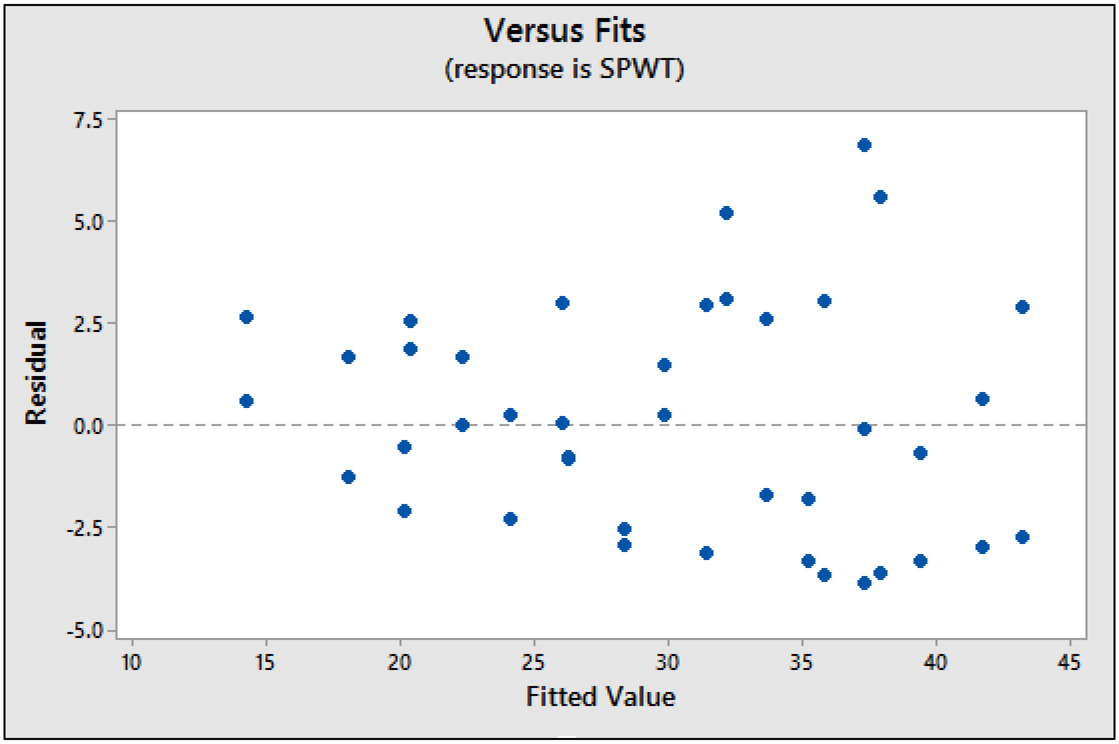

Figure 4-4: Check for Unequal Variances - Average Scheduled Patient Wait Time

As the results indicate, no trend was detected, and the homogeneity assumption holds true; therefore, there was no need to transform the response, which is the average scheduled patient wait time.

Table 4-5: Check for Unequal Variance

$(\hat{y})$	Heteroscedasticity
Average Walk In Patient Waiting Time	False, no trend
Total Number of Walk In Patients Seen	False, no trend
Average Overtime Length	False, no trend

From our residual analysis about the unequal variance of each model, we found that this assumption also holds true.

Next, we checked the assumption for normality amongst the error terms. We constructed a normal probability graph and compared with the residuals. We also conducted one of the formal statistical test for normality, the Anderson-Darling test. Depicted in Figure 4-5 are the results for the model for the Average Scheduled Patient Wait Time.

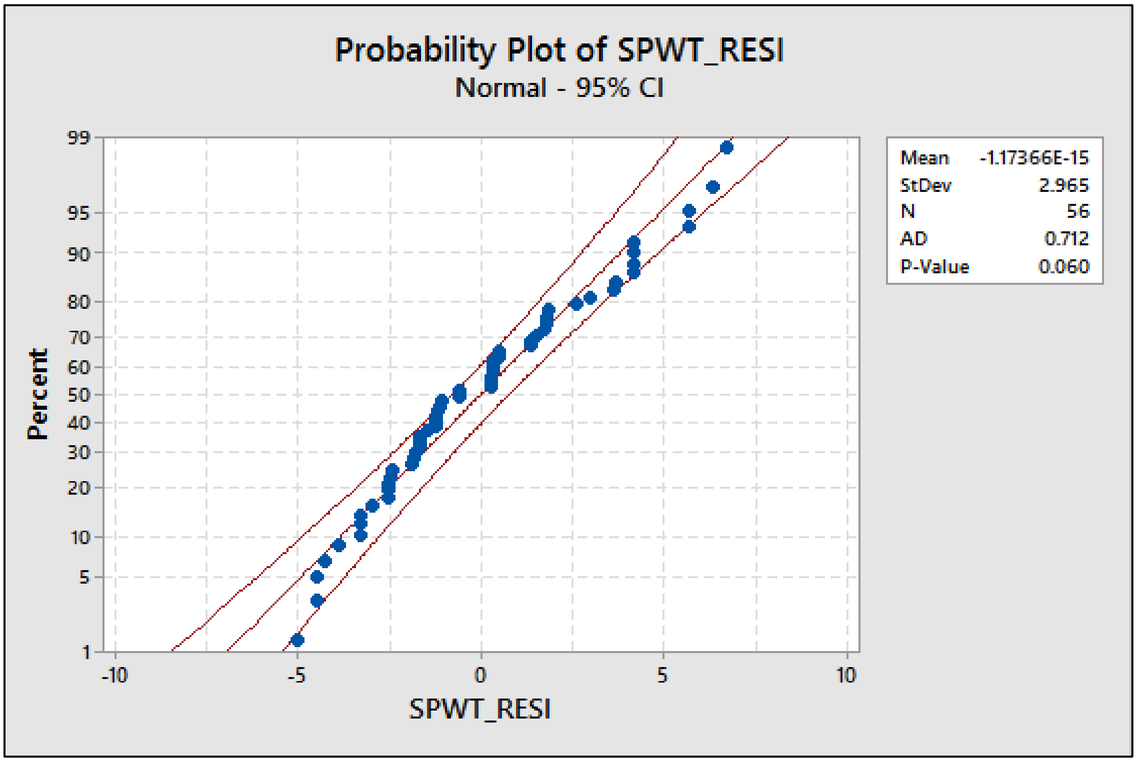

Figure 4-5: Check for Normality - Average Scheduled Patient Wait Time

Per the Anderson-Darling (AD) test, the residuals exhibit normal probability and the hypothesis is confirmed with a p-value of 0.060 and confidence of 95%. Table 4-6 shows the results for the remaining models.

Table 4-6: Check for Normality Assumption

$(\hat{y})$	**AD test: p-value**
Average Walk In Patient Wait Time	0.312
Total Number of Walk In Patients Seen	0.229
Average Overtime Length	0.025

According to the p-values for all four regression models, the test for normality holds true and with 95% confidence, and the errors are normally distributed. We do not expect a possible discrepancy with the conclusion for "Average Overtime Length". The p-value should be greater than or equal to 0.05, but in this case the p-value is 0.025. The data shows two observations that are considered outliers, so we checked the influence of those outliers by looking at their Cook's Distance value. The observations (8 and 27) have Cook's Distance values of 0.1819 and 0.2041, respectively, which implies there is an insignificant influence on the model by this outlier. Had their values been above 0.5, it could be concluded that those observations were influential and be removed from the model. Thus, we retain the observations in this model and proceed with our residual analysis of the four performance measures.

However, due to the nature of the Average Overtime Length values, having positive and negative values, applying a transformation proves to be difficult. A shift of the values so that all value are positive results in the same p-value for the AD test. Therefore, we note the possibility of a Type I error.

Lastly, we checked for correlated errors in our models. We note that if the residuals tend to have the same sign as the observations are taken in time, there may be correlations which would violate the independent error assumption. We used a plot of the residuals for each model according to the order in which the experiments were run. The result for Average Scheduled Patient Wait Time (SPWT) is shown in Figure 4-6.

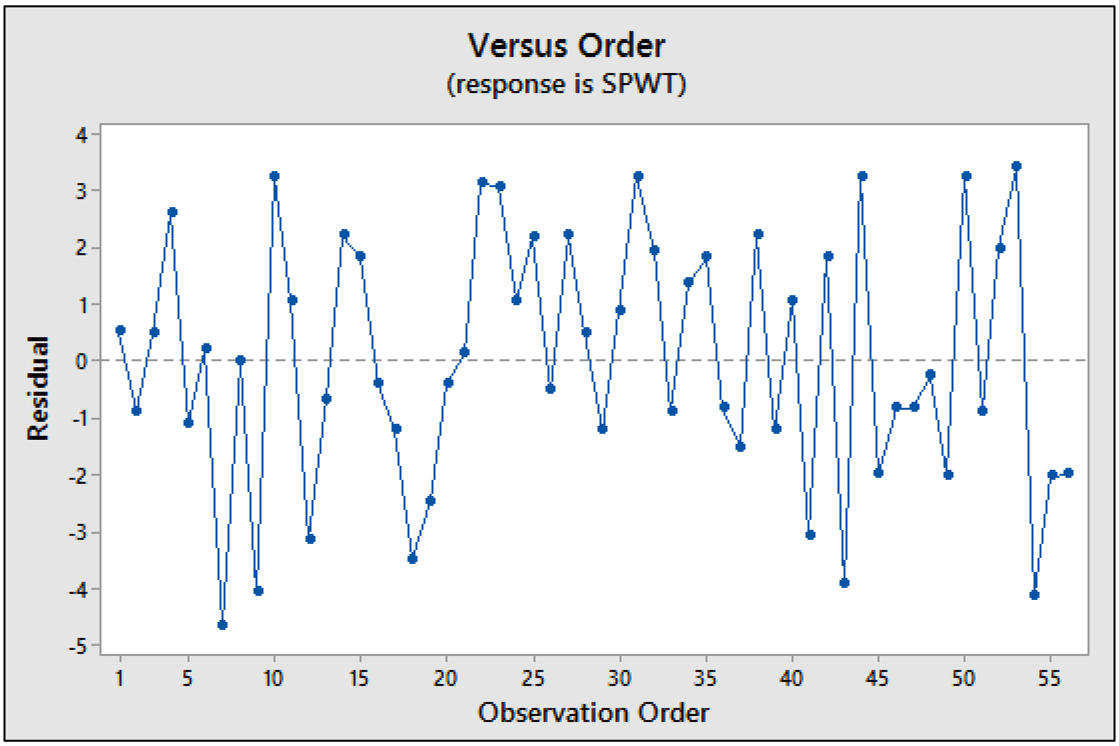

Figure 4-6: Check for Independent Errors

The observed data tend to increase and decrease randomly; however, there are a few runs of negative and positive residuals. To determine a conclusive hypothesis about the correlation of residuals, we used the Durbin-Watson test to detect correlation.

The Durbin-Watson test measures ρ, the correlation between two adjacent observations. The test follows:

$$H_0: \rho = 0 \text{ and } H_A: \rho > 0$$

The test static is d, where $d = \frac{\sum_{i=2}^{n}(e_i - e_{i-1})^2}{\sum_{i=1}^{n} e_i^2}$

If $d < d_L$, Reject the null hypothesis

If $d > d_U$, Do not reject the null hypothesis

If $d_L < d < d_U$, Test is inconclusive

As an example, the model for Average Overtime Length has k=5 regressors (independent variables). With a sample size of 56 runs, the d_L= 1.34 and the d_U = 1.77. Therefore, the residuals for the Average SPWT were not correlated with one another; the d statistic is above the d_U. The results for the remaining models are shown in Table 4-7.

Table 4-7: Check for Correlated Errors

($\hat{y}$)	Durbin-Watson (alpha = 0.05): d-value (d_L/d_U)
Average Scheduled Patient Wait Time	1.93 (1.33/1.81) k=6
Average Walk In Patient Wait Time	2.17 (1.38/1.77) k=5
Total Number of Walk In Patients Seen	1.82 (1.33/1.81) k=6
Average Overtime Length	2.18 (1.03/2.10) k=12

Because of the Durbin-Watson test, the assumption of random error also holds true for the regression models that were fitted. The next section covers the cross-validation models.

4.4.2 Regression models

We provided the resulting Betas, also known as predictor variables, for each of the independent variables in the regression models. The results, along with their corresponding p-values, are listed in Table 4-10 through Table 4-11. Accompanying each table is the formulated model for each clinic performance measure, Eq. 4-6 through Eq. 4-9.

Table 4-8: Average Scheduled Patient Wait Time Model Summary

Term	Coefficient	p-value
Constant	29.847	0.000
No Show Rate	-1.898	0.000
Walk In Rate	4.008	0.000
Scheduling	-6.683	0.000
Patient Flow	1.906	0.000
Scheduling- Patient Flow Interaction	1.133	0.005
Coefficient of Determination	R-sq = 89.22%	R-sq (ad) = 88.14%

$$Predicted\ Average\ Scheduled\ Patient\ Waiting\ Time\ (minutes)$$

$$= 29.847 - 1.898x_1 + 4.008x_2 - 6.683x_3 + 1.906x_5 + 1.133x_3x_5 + \varepsilon \qquad (4\text{-}6)$$

Table 4-9: Average Walk In Patient Wait Time Model Summary

Term	Coefficient	p-value
Constant	24.701	0.000
No Show Rate	-1.683	0.007
Walk In Rate	4.007	0.000
Capacity Type	-1.746	0.000
No Show Rate-Walk In Rate	-1.413	0.022
Coefficient of Determination	R-sq = 58.80%	R-sq (ad) = 55.57%

$$Predicted\ Walk\ In\ Patient\ Wait\ Time\ \text{(minutes)}$$

$$= 24.701 - 1.683x_1 + 4.007x_2 - 1.746x_4 - 1.413x_1x_2 + \varepsilon \quad (4\text{-}7)$$

Table 4-10: Number of Walk In Patients Seen Model Summary

Term	Coefficient	p-value
Constant	15.064	0.000
Walk In Rate	1.921	0.000
Scheduling	-0.454	0.002
Capacity	-0.347	0.015
Scheduling-Capacity Interaction	0.523	0.000
Walk In- Capacity- Patient Flow Interaction	-0.404	0.030
Coefficient of Determination	R-sq = 74.90%	R-sq (ad) = 72.39%

$$Predicted\ Total\ Number\ of\ Walk\ In\ Patients\ Seen$$

$$= 15.064 + 1.921x_2 - 0.454x_3 - 0.347x_4 + 0.523x_3x_4 - 0.404x_2x_4x_5 + \varepsilon \qquad (4\text{-}8)$$

Table 4-11: Average Length of Overtime Model Summary

Term	Coefficient	p-value
Constant	40.37	0.000
No Show Rate	-10.36	0.028
Walk In Rate	14.85	0.000
Scheduling	-14.20	0.000
Capacity	-5.69	0.005
Patient Flow Type	18.40	0.000
No Show-Walk In Interaction	-6.55	0.013
Walk In-Scheduling Interaction	-6.48	0.014
Scheduling-Capacity Interaction	8.53	0.000
Walk In-Scheduling-Capacity Interaction	5.28	0.043
Walk In-Scheduling-Patient Flow	-5.64	0.031
Scheduling-Capacity-Patient Flow	-7.60	0.000
Coefficient of Determination	R-sq = 85.80%	R-sq (ad) = 82.24

$$Predicted\ Average\ Length\ of\ Overtime$$

$$= 40.37 - 10.36x_1 + 14.85x_2 - 14.20x_3 - 5.69x_4 + 18.40x_5 - 6.55x_1x_2 - 6.48x_2x_3 + 8.53x_3x_4 + 5.28x_2x_3x_4 - 5.64x_2x_3x_5 - 7.60x_3x_4x_5 + \varepsilon \quad (4\text{-}9)$$

4.4.3 Analysis of Results

We have been able to build four models to estimate clinic performance measures of the clinic operations in this study. Along with the final models, there is a measure of determination or strength of our models. The "R-squared" values in Table 4-10 through Table 4-11 show a consistently high value for model strength; 60% and above. These percentages represent the amount of variability that is covered or included in the model. The highest, 89.22%, is the scheduled patient waiting time model. In the real system, this performance measure would be greatly constrained as the clinic would not want to increase the estimated waiting time for patients who have scheduled an appointment, wanting to avoid a long wait time. The smallest percentage, which is greater than 50% (R-squared = 58.80%), describes the amount of variability covered by the walk-in patient wait time model. This performance measure would most likely be the least constrained since, intuitively, walk-in patients would not be as sensitive to wait times as scheduled patients. However, the validity of the regression models must be checked if the models are to be used outside this research study.

4.4.3.1 Model Validation

By using the coefficients of determination (R^2), we determine that the regression models in Section 4.4.2 provide some adequacy for fitting the simulated data. However, to address validity of the models, we use the data-splitting (cross-validation) method to determine if the models can be used outside the sample simulated data. For each experiment or case, the simulation model is replicated 30 times resulting in 1680 data points. With cross-validation, the data was evenly split into a testing sample and a validation sample. The regression models from Section 4.4.2 are derived from the testing sample of 840 data points. To validate these regression models, we used the remaining data set to evaluate the validity of the regression models. Each regression model was executed to provide a sample of 56 predicted response variables. These values were then compared to the validation set of data from our simulated data. The measure of model validity is the mean squared prediction error,

$$(\mathrm{MSE}_{\mathrm{pred}}) = \frac{\sum_{i=n+1}^{n+m}(y_i-\widehat{y_i})^2}{m-(k+1)},$$

where n = the number of cases in testing set

m = the number of the last case in the validation set (m = 112)

y_i = the observed response from the testing dataset

$\widehat{y_i}$ = the predicted value of the regression model

In Table 4-12, the values for the respective model's $\mathrm{MSE}_{\mathrm{pred}}$ are listed and compared to the MSE of the least-squares fit.

Table 4-12: Comparison for Model Validity

Performance Measures (Regression Model)	**MSE_{pred}**	**$MSE_{least\text{-}squares}$**
Average Scheduled Patient Wait Time	5.11	8.23
Average Walk-In Patient Wait Time	13.687	11.529
Average Number of Walk-In Patients Seen	1.608*	1.052
Average Length of Overtime	361.25	205.1

*Three identical cases (center runs) were omitted due to results being highly skewed

From Table 4-12, three regression models have a comparable mean squared error value to the least squares error. The mean squared error of the prediction model for Average Length of Overtime is much higher than the least squares model, and thus must be used with caution. To use each model for predicting the estimated performance measures of similar primary care clinics, we note that the models are constructed with coded variables. What this means is that the regression models do not accept raw data values, apart from the quantitative decision variables; no-show rate and walk-in rate. Instead, the models provide an estimate of performance based on replacing the qualitative independent variables with “1” and “-1”. Considering that a manager may want to know what the expected waiting time would be for scheduled patients based on a combination of factors. If the no-show rate is high and the walk-in rate is low (10%), then the manager can use different combinations of high and low levels of scheduling, capacity, and patient flow decisions to estimate the average waiting time for a patient with an appointment. For example, when the no-show rate is set to 10%, the walk-in rate is 14 patients per day, the scheduling policy is open-access, the capacity policy is 5 residents and 3 interns, and the patient flow encounters significant time in faculty evaluation, the estimated scheduled patient wait time is approximately 23 minutes. Note that capacity decisions do not have a significant effect on this performance measure.

Ultimately, this research also yielded a spinoff result, which is aimed at answering the following type of question(s): Does the integrative strategy of combining scheduling and capacity planning decisions have a significant impact on the number of walk-in patients that are treated? From the analysis of our simulated experiments, we can conclude with 95% confidence that the integrated approach does not have a significant effect on the number of walk in patents seen. The hypothesis for this research was to determine if a joint decision of three efficiency strategies would significantly impact the performance of clinic efficiency. The results from Section 4.4.2 suggest that two of the three strategies have a significant impact on most of clinic efficiency metrics we measured. Only in one case, “Average Length of Overtime”, were all three strategies found to be significantly effective: appointment scheduling, capacity management, and patient flow design.

This research is the first to develop a simulation model and designed experiments to analyze the effects and interactions of efficiency strategies on performance measures for a teaching-oriented primary care clinic. From the outcomes of this research, it is suggested to clinic managers and improvement specialist of primary care clinics, particularly of those with physician residents or advance medical practitioners on staff, to avoid implementation of more than two efficiency strategies in a joint decision as more than two joint strategies lack significant impact and lose the ability to predict outcomes.

CHAPTER 5 CONCLUSION AND FUTURE RESEARCH DIRECTION

This research is focused on efficiency strategies used for improving the clinic performance of primary care facilities in the health care industry. There are several efficiency strategies, however, the scope of this research encompassed three main strategies: patient flow design, appointment scheduling decisions, and capacity management strategies. Previous research explored strategies singularly or in limited combination. We explored all three and found that no previous research study has applied a simulation methodology to (academic) teaching clinics where efficiency strategies are different. However, we followed the research study conducted by Shi et al. (2014) at a regional Veterans Affairs (VA) primary care clinic. The research of Shi et al. did not address possible interaction between clinic operational parameters such as appointment scheduling policies and patient flow design. As such, our focus on this research area was: how does the joint interaction of efficiency strategies affect the clinic performance measures of a primary care clinic; waiting times for scheduled and walk-in patients, the number of walk in patients seen and treated, and the average length of overtime.

We based our system of study on a local primary care clinic, the Orlando Veterans Affairs Medical Center (VAMC). We described in CHAPTER 3, what data was collected, how our simulation model was constructed and validated, and how are resulting simulated output compared to real-life clinic output. With a suitable model that we considered and an evaluative tool for our research question, we summarized our scenario analysis methodology, which was hinged on a factorial experimental design. We included in our design, 5 factors or independent variables which were run or simulated at high and low levels. We ran our simulation 30 times for a solid sample size;

and also to strengthen the underlying assumptions of normality. From our simulation model, we collected performance data that was used for our response variables (dependent variable).

Once our sample data was collected from the simulation, we built models for estimating the performance measures of interest. Before doing so, we checked for the satisfaction of the underlying assumptions upon which the regression analysis was performed. These assumptions included normal, independent, uncorrelated errors, and a constant variance. Using residual analysis, we confirmed that these assumptions held true for each proposed linear model. The resulting regression lines were fitted and the linear models were presented in Section 4.4.2.

The three resulting models: for scheduled patient wait time, for scheduled patient wait time, and for walk-in patients seen, produced relatively good coverage of variances, and the validation set also supported the models. However, the fourth model, the length of overtime model, should be used with caution since 3 outlier experiments caused a very large error in the prediction set. Of all the four models, only the length of overtime found the joint effect of all three strategies for efficiency to be significant. Our analysis of the results allowed us to estimate any of the four performance measures with 95% confidence. It is with this confidence that our hypothesis about:

(1) the impact of the joint interaction between scheduling decisions, capacity management strategies, and patient flow design does not hold true as the length of overtime measures are significantly affected by the three joint strategies. However, more work is needed to build a linear relationship between this effect and the length of overtime response
(2) the impact of the joint interactions between scheduling decisions and capacity hold true to be significant only for the number of walk-in patients seen and length of overtime

(3) the impact of the joint interaction between scheduling and patient flow design proves to be significant for only scheduled patient wait time
(4) the impact of the joint interaction between capacity management and patient flow design has no direct significance on any clinic efficiency measure

Therefore, we recommend that, based on this particular clinic system, improvement projects be implemented from a scheduling and patient flow analysis point of view to have significant impact on the wait time of scheduled patients when walk-in patients are present. This recommendation would save time on capacity planning efforts that may not be impactful. This recommendation also falls in line with White et al. (2011), which found that increasing capacity in their clinic study had little effect on their performance measures of interest.

5.1 Direction of Future Research

Computer simulation, in particular the use of discrete event simulation has shown what insights are possible due to the ability to model complex systems. Being able to model and validate simulated data has the potential for providing meaningful information to decision makers. Because the health care system is so complex, it is difficult to produce a model that can be used by the majority of all types of healthcare clinics, even those with walk-in/urgent care services. Therefore, a generalized model or framework for creating a model would be very useful to managers and quality engineers who deciding on methods to implement efficiency strategies.

We also acknowledge the cost of quality as a future research path. Due to the expensive nature of trial and error to improve quality, it would be beneficial to see what impact financial incentives would be on these management decisions. In future, we would like to explore how the addition of financial constraints would impact such managerial decisions.

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