University of Alberta

Reengineering Primary Health Care for Information and Communication Technology

by

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Abstract

Health care organizations are increasingly looking towards information and communication technology to make fundamental changes for quality improvement. Despite numerous potential benefits, the integration of information and communication technology in health care is still hampered by various barriers, including impacts on workflow. This work examines how business processes in primary health care can be reengineered to accommodate the use of information and communications technology by developing a comprehensive process model of primary care, examining the impacts of ICTs on these processes and determining changes in workflow to optimise benefits. Using discrete-event modeling and simulation, we demonstrate a reduction in the utilization of resources, an increase in appointment attendance, and a cost benefit from the use of selected information and communication technologies in the patient care process. This work contributes to research on reengineering primary care by identifying ways to leverage the capabilities of information and communication technology through process redesign.

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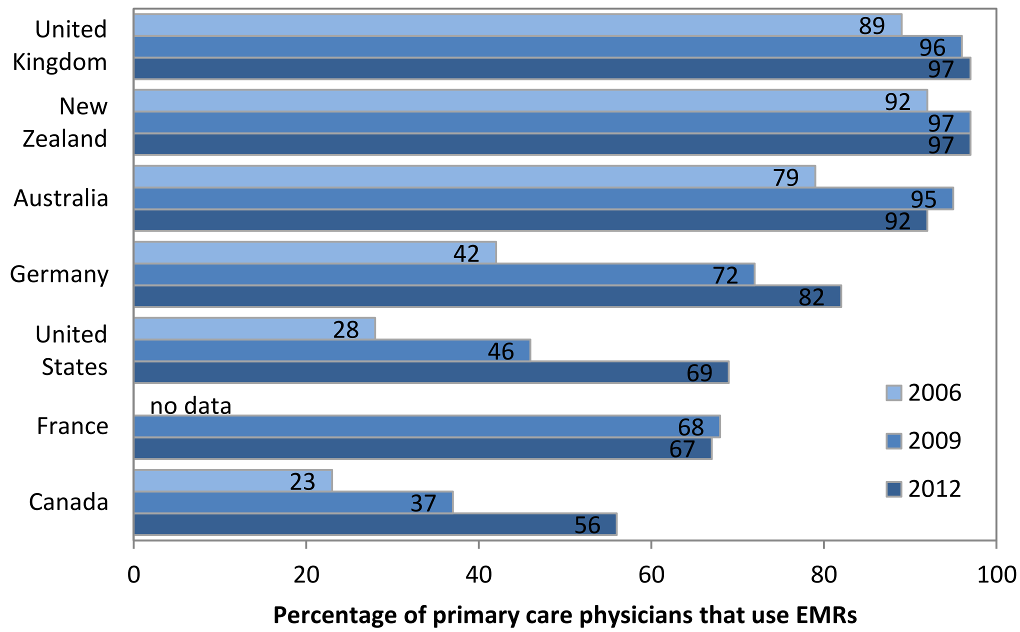
1 Introduction

Efficiency and effectiveness are critical qualities of a sustainable health care system – these aspects along with acceptability, accessibility, appropriateness, competence, continuity, and safety, are how Canadians measure our health system performance (Canadian Institute for Health Information, 2009). Our health care system needs improvement and not a minor one; the majority of Canadians feel that fundamental change is required to make the system work better (The Commonwealth Fund, 2011). Improving the efficiency of our health care system will only become more critical as the demand on the system continually grows.

Health care organizations are increasingly looking towards information and communication technology (ICT) to increase efficiency and the ICT health care (eHealth) market is growing rapidly to meet the demand (Organisation for Economic Co-operation and Development, 2010b). Great progress has been made in ICT development for health care and its use "can result in care that is both higher in quality, safer, and more responsive to patients' needs and, at the same time, more efficient (appropriate, available, and less wasteful)" (Organisation for Economic Co-operation and Development, 2010a). The Conference Board of Canada found that the use of ICTs "results in substantial enhancement to patient care and greater productivity" (The Conference Board of Canada, 2004).

Despite recognizing the potential benefits, Canada is slow to implement ICTs in health care in an international comparison (The Conference Board of Canada, 2010). For instance, in the use of electronic medical records (EMRs), Canada has very low implementation rates compared to other countries. As shown in Figure 1-1, in 2006 only 23 percent of Canadian primary care physicians used EMRs (Schoen, et al., 2006). That rate has increased to 56 percent in 2012, but still does not compare to countries like the United Kingdom, New Zealand, and Australia, where nearly all primary care physicians use EMRs and have done so for years (Schoen, et al., 2012).



(Adapted from Commonwealth Fund international Health Policy Survey of Primary Care Physicians, 2006 cited by Schoen, et al., 2006, p.w558; 2009 cited by Schoen, et al., 2009, p.w1175; 2012 cited by Schoen, et al., 2012, p.2809)

Figure 1-1: International comparison of primary care physicians' use of electronic medical records (percent that use EMRs) over time

Fueled by the potential benefits of integrating ICTs in health care, considerable research has been done to identify and remove barriers to implementation. An international review found that "privacy, patient safety, provider/patient relations, staff anxiety, time factors, quality of care, finances, efficiency, and liability" were factors concerning implementers (Ludwick and Doucette, 2009a). Barriers in the Canadian health care system include "lack of cooperation among jurisdictions and organizations, concerns about the privacy and security implications of ICTs, and perceptions of financial risks and uncertain returns (health and financial)" (The Conference Board of Canada, 2010).

A subsequent review of ICT implementation in health care found that workflow impact was the second most frequently reported adoption criteria, reported in 29 of the 68 studies reviewed, and was exceeded in relevance only by user attitude; other factors, in decreasing relevance, were interoperability, technical support, communication among users, and expert support (Castillo, Martinez-Garcia and Pulido, 2010). In addition to the studies reviewed by Castillo, Martinez-Garcia and Pulido (2010), Lee, et al. (2005) also report that successful adoption of ICTs in healthcare requires close attention to workflow while other studies found that ICTs must be functionally integrated into workflow processes (Wong, et al., 2000; The Center for Quality and Productivity Improvement, 2010).

There are various programs to support ICT adoption in health care and most guidelines and recommendations include mention of the impact on workflow. National guidelines for EMR adoption in primary health care, such as the EMR Toolkit published by Health Canada (Health Canada, 2006), and provincial programs, such as the Physician Office System Program (POSP) in Alberta, Physician Information Technology Office (PITO) in British Columbia, and the Transition Support Program (TSP) in Ontario, advise implementers to assess changes to workflow in preparation of EMR adoption. However, guidance on how workflows will change, or how workflows should be changed to optimise the impacts and benefits of using ICTs is lacking.

The need for radical changes in our health care system, the potential gains from implementing ICTs, and the impacts that these ICTs have on workflow processes forms the foundation of this work – how the business processes of primary health care can be reengineered to accommodate the use of ICTs. To achieve this objective, the goals of this research are to develop a comprehensive process model of primary care, examine the impacts of ICTs on these health care processes, and determine changes in workflow to optimise the benefits of ICT usage.

The health care system in Alberta is a prime location for this research as it is in a climate of change. In 2009, the province centralized health care services from many regional health authorities to a single provincial authority (Alberta Health, 2013) followed by the release of Alberta's Five Year Health Action Plan and supporting performance measure targets (Alberta Health Services, 2013a). This work will contribute to the research on ICT implementation in health care by supplementing the guidance relating to workflow impacts of ICTs, which may be relevant to various stakeholders in eHealth, including academia, health care providers and institutions, consumers, and ICT industry (Information and Communications Technology Council, 2009). We hope this guidance will improve the success of ICT adoption to promote radical changes to health care and improve our health system performance.

A brief discussion of business process reengineering and information and communication technology in health care is provided in Chapter 2. Chapter 3 introduces the methodology of this research and the remaining chapters present several approaches taken to address the research question with a concluding discussion in Chapter 7.

2 Background

2.1 Business Process Reengineering

Business process reengineering (BPR) is an approach of business management, of which the origins are generally attributed to articles by Davenport and Short (1990) in Sloan Management Review and by Hammer (1990) in Harvard Business Review. The concept of business process reengineering has also been called business process redesign (Davenport and Short, 1990) and process innovation (Davenport, 1993), among others, and various definitions of reengineering have been proposed.

Davenport and Short (1990) define business process redesign as "the analysis and design of work flows and processes within and between organizations." Hammer and Champy (1993) define reengineering as "the fundamental rethinking and radical redesign of business processes to achieve dramatic improvements in critical, contemporary measures of performance, such as cost, quality, service, and speed." Hammer and Stanton later streamline the definition and offer the "official definition" of engineering as "the fundamental rethinking and radical redesign of business processes to bring about dramatic improvements in performance" (Hammer and Stanton, 1995).

Davenport subsequently and more holistically defines process innovation to "encompass the envisioning of new strategies, the actual process design activity, and the implementation of the change in all its complex technological, human, and organizational dimensions," in which business process reengineering or redesign refers only to the design activity (Davenport, 1993). Relating specifically to health care, Champy and Greenspun (2010) refine the definition of reengineering as "the radical improvement of health care delivery processes to enhance quality and dramatically lower costs, while also greatly expanding patient accessibility to that improved care."

The common theme among these definitions of business process reengineering is that they establish a distinction from process improvement; that is, radical rather than incremental change. This distinction is reflected by the two types of process change identified by Andrews and Schurman (1994) on organizational transformation at the University of Alberta Hospital. Process improvement can be described as "first-order change [which] seeks to stabilize and refine existing processes *within a system* [emphasis added]" (Andrews and Schurman, 1994, p.39). Business process reengineering can be described as "second-order change [which] seeks to break through historical levels of performance by making changes *in the system* [emphasis added]" which is "fundamentally more important" (Andrews and Schurman, 1994, p.39).

Davenport and Short (1990) suggest that the partnership of business process reengineering and information and communication technologies is the new industrial engineering evolving from the roots of Frederick Taylor's scientific management. Therefore, it seems fitting that the goals of business process reengineering include the evolution of business focus since Taylor's work - quantity in the 60s, cost in the 70s, quality in the 80s, lead time in the 90s, and service in the 21st century (Tersine, R. cited by Lindsay et al. 2003). It is also fitting that business process reengineering draws upon a variety of the tools and techniques ranging from industrial engineering to leadership and change management. The perspective of business process reengineering in this work will draw upon those various fields.

Finally, before further exploring the role of information and communication technology in business process reengineering, a brief sampling of definitions of business process is offered. Davenport and Short (1990, p.12) define a business process as "a set of logically related tasks performed to achieve a defined business outcome." Hammer and Champy (1993, p.35) define a business process as "a collection of activities that takes one or more kinds of inputs and creates an output that is of value to the customer." Champy and Greenspun (2010, p. 18) expand upon this definition to point out that in health care, the customer can be the patient, the clinician, or the payer. Processes in primary care include administrative processes and clinical processes; some common processes include patient scheduling, billing and revenue, immunizations, specialist referrals, and pharmacy and prescription management (Ontario MD, n.d.)

The Role of Information and Communication Technology in Business Process Reengineering

In their seminal work, Davenport and Short (1990) suggest nine capabilities of information and communication technologies and describe how these capabilities can impact organizations as a lever for business process reengineering. These capabilities and impacts of information and communication technologies are summarised in Table 2-1.

Table 2-1: Capabilities and impacts of information and communications technology

Capability	Organizational impact
Automational	Eliminate, replace or reduce human labor from a process
Informational	Capture vast amounts of detailed process information for purposes of understanding
Sequential	Change the sequence of tasks in a process, often enabling parallelism, or allowing multiple tasks to be worked on simultaneously
Tracking	Closely monitor and track process and task status, inputs and outputs
Analytical	Improve analysis of information and decision making
Geographical	Coordinate processes and transfer information with rapidity and ease across large distances, making processes independent of geography
Integrative	Coordinate between tasks and processes to transform unstructured processes into routinised transactions
Knowledge Management	Capture and disseminate intellectual assets, knowledge and expertise to improve the process
Disintermediation	Eliminate intermediaries from a process by connecting parties within a process that would otherwise communicate through an (internal or external) intermediary

(Adapted from Davenport and Short, 1990, p.17; Davenport, 1993, p.51)

More importantly, it is the recursive relationship between business process reengineering and information and communication technology that Davenport and Short (1990) propose as the new industrial engineering. The capabilities and impacts of information and communication technology should be considered in terms of how it can support new business processes and business processes should be considered in terms of how they can be redesigned using information and communication technology.

Similarly, Hammer and Champy (1993) provide various examples of how technology can enable business process reengineering; their examples are summarised in Table 2-2.

Table 2-2: Information and communication technologies as enablers of reengineering

Technology	Reengineering enabler
Shared databases	Information that could only appear in one place at one time can appear simultaneously in as many places as needed
Expert systems	Complex work that could only be performed by experts can be done by a generalist
Telecommunications networks	Businesses that had to choose between centralization and decentralization can simultaneously reap the benefits of centralization and decentralization
Decision support tools (database access, modeling software)	Decision-making can be part of everyone's job; managers do not have to make all the decisions
Wireless data communication and portable computers	Field personnel can send and receive information wherever they are and do not need offices where they can receive, store, retrieve, and transmit information
Interactive videodisk	The best contact with a potential buyer is effective contact, and not necessarily personal contact
Automatic identification and tracking technology	Rather than having to find out where things are, things tell you where they are
High performance computing	Plans that were revised periodically can be revised instantaneously

(Adapted from Hammer and Champy, 1993, pp.83-101)

The effects of information and communication technology on business processes and organizational structures can be succinctly described as automating, informatting (manipulating, calculating and analysing data), and communicating (Tsai, 2003, p. 106). The capabilities of information and communication technology should not only be leveraged to redesign processes, they should also be considered throughout the stages of process innovation (Davenport, 1993). Information and communication technology can be leveraged as enablers before the process is designed, as facilitators while the process is designed, and as implementers after the design is complete (Attaran, 2004).

Business Process Reengineering in Health Care

Only a few years after Davenport and Short (1990) and Hammer and Champy (1993) first wrote of business process reengineering (BPR), 56 percent of U.S. and Canadian hospitals reported already having implemented BPR by 1997, and an additional 15 percent reported having considered it (Ho, Chan and Kidwell, 1999). Despite these and other BPR initiatives since, literature on business process reengineering in health care can be difficult to find and is not clearly documented (Elkhuizen, et al., 2006) and there are mixed reviews on reported benefits in U.S. hospitals (Caccia-Bava, Guimaraes and Guimaraes, 2005).

Health care improvements take on many other forms besides business process reengineering and federal research institutions, such as the Canadian Foundation for Healthcare Improvement and the U.S. Agency for Healthcare Research and Quality, and numerous other organizations promote this work. Within primary care in Canada, one of the key initiatives that have led to transformative change in the last decade is quality improvement training and support (Hutchison, et al., 2011). The Alberta Access Improvement Measures (AIM) program guides health care teams through system performance improvements (Alberta AIM, n.d.) and similar programs are offered in other provinces.

One of the first lessons in the Alberta AIM program relates to improving patient access to care by reducing delays (Alberta AIM, 2008). This is based on the advanced access, or open access, model which applies queuing theory and principles of industrial engineering to understand the demand for service, and the variation in demand, and matching the supply of service to reduce wait times in primary care (Murray and Berwick, 2003). Subsequent subjects in the Alberta AIM program include mapping the patient journey, determining the right team and care plan, and change management (Alberta AIM, 2008).

2.2 Information and Communication Technology in Primary Health Care

Primary health care provides patients with their first and continuing direct contact with medical practitioners and often serves as gatekeepers to the Canadian health system (Jacobs, et al., 2010). Primary health care providers, or family physicians, are one of several health care options in Alberta (Alberta Health Services, 2013b). In Alberta, the Primary Care Initiative was formed to develop Primary Care Networks, networks of doctors and other health providers that coordinate local services for their patients (Primary Care Initiative, 2012). Patient access to services in a Primary Care Network is through referral from their family physician.

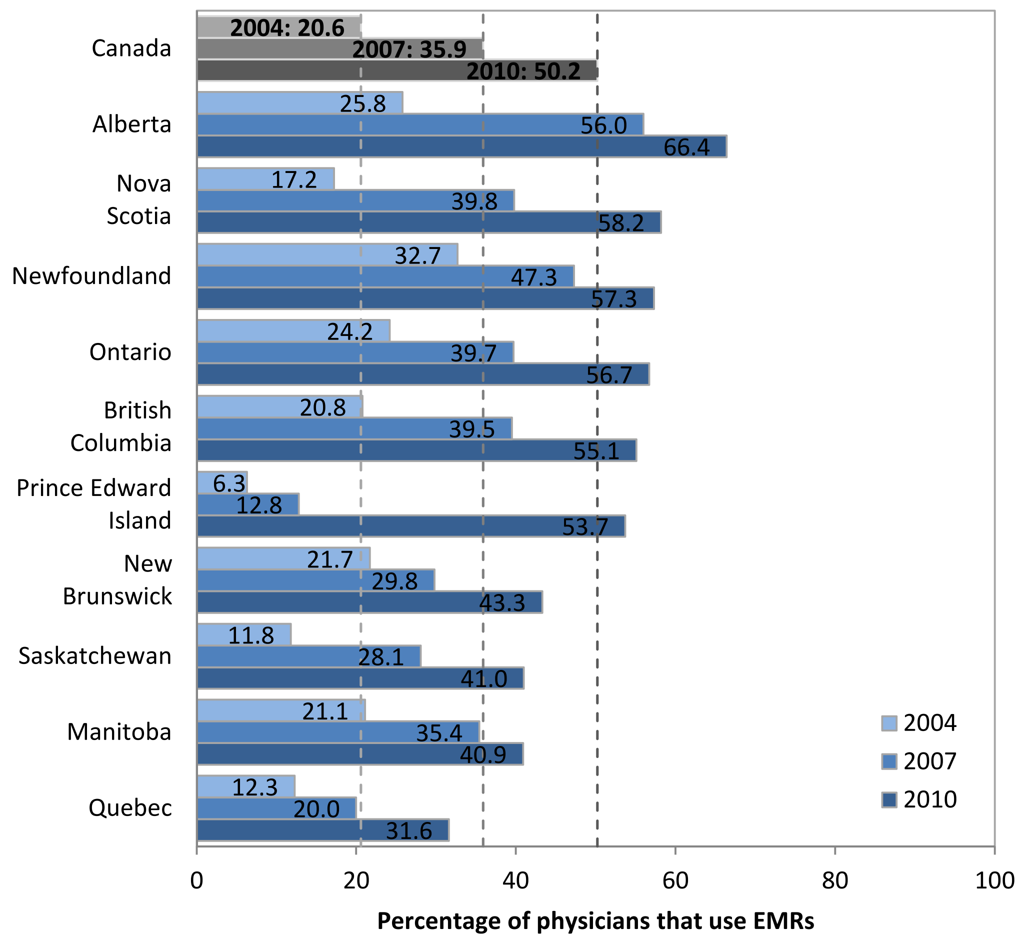
In Alberta, two health care information services were created through the use of information and communication technology: Health Link Alberta, a telephone information service, and MyHealthAlberta, a website of health resources (Alberta Health Services, 2013b). Other health care options in Alberta include: pharmacies, urgent care centres, ambulatory care centres, community health centres, family care clinics, and emergency departments (Alberta Health Services, 2013b).

There are numerous applications of information and communication technologies in the various modes of health care delivery. Within primary health care, information and communication technologies can be used in billing and administration, electronic documentation, and patient care to improve quality of care (Langley and Beasley, 2007). Surveys of technology use by primary care doctors conducted by the Commonwealth Fund include the following functions: "electronic ordering of medications and tests, computer access to test results and medication lists, computer alerts/prompts, and decision support; computerized reminder systems for prevention and follow-up care; computerized ability to list patients by diagnosis, lab results, and medications; and electronic entry of notes and medical histories" (Schoen et al. 2009, p.w1175). The application of information and communication technology particular to the primary care network studied – electronic medical records, appointment reminder systems, and patient check-in, will be discussed next.

2.2.1 Electronic Medical Records

Electronic medical records (EMRs) are software applications that manage all aspects of practice management and patient care (Ontario MD, n.d.); they are implemented within individual physician's offices and replace paper charts with electronic charts (Jacobs, et al., 2010). Electronic medical records, a partial record of a person's health information managed by one health care organization, differ from electronic health records (EHRs) and personal health records (PHRs) in their completeness and management; electronic health records are a complete record used by more than one health care organization while personal health records may be complete or partial records managed by the individual (The National Alliance for Health Information Technology, 2008; Hodge, 2011).

In Alberta, the Physician Office System Program (POSP) was created to promote the adoption and use of EMRs by physicians (Physician Office System Program, n.d.; Jacobs, et al., 2010). Practices can choose from many EMR vendors, some of which are qualified by the POSP. Potential benefits of using EMRs include improved quality of care, reduced costs, improved communication, and improved analysis of health data (Health Canada, 2006). As previously discussed, Canada lags behind internationally in EMR usage; within Canada, Alberta leads the provinces with 66 percent of primary care physicians reporting use of EMRs in 2010 above the national average of 50 percent, as shown in Figure 2-1.



(Adapted from The College of Family Physicians of Canada, Canadian Medical Association, and The Royal College of Physicians and Surgeons of Canada, 2004; 2007; 2010)

Figure 2-1: National comparison of primary care physicians' use of electronic medical records (percent that use EMRs) over time

Within Alberta, although some of the potential benefits are reported in practice, processes that are incongruent with EMRs result in workarounds (Shaw, et al., 2011) and alternate remuneration models have been suggested to allow practices the time for successful EMR implementation and increase adoption (Ludwick and Doucette, 2009b). Successful EMR implementation requires time investment as perceived benefits of EMRs increase and negative effects decrease over time (El-Kareh, et al., 2009). This work will examine the impact of EMR implementation as the PCN transitions to a paperless clinic, expanding EMR usage from administrative functions to include usage for clinical functions.

2.2.2 Appointment Reminder Systems

Appointment reminder systems replace the need for staff members at a practice to send out reminders in the mail or telephone patients to remind them of their upcoming appointments by automatically sending reminders by email, text (SMS) message, or telephone. Appointment reminder systems are often integrated with the scheduling function of the clinic's EMR and may also be used in conjunction with self-service appointment booking.

Research on workflow impacts of appointment reminder systems often centers around the effects on attendance of appointments. Hasvold and Wootton (2011) conducted a systematic review of studies on appointment reminders and nonattendance in health care appointments. Of the 29 studies reviewed, all but one reported a reduction in nonattendance as a result of appointment reminders. Only four of the 29 studies reviewed reported attendance rates comparing manual and automated reminders. The reviewers concluded that although both manual and automated reminders reduced nonattendance, manual reminders were more effective than automated reminders in reducing nonattendance.

However, only one of the four studies comparing manual and automated reminders used an automated telephone reminder system (Parikh, et al., 2010). The other three studies that compared manual and automated reminders used an automated SMS reminder system (Bos, Hoogstraten and Prahlandersen, 2005; Leong et al., 2006; Chen, et al., 2008). The reviewers also suggest that economic assessments of appointment reminders are needed and note that "none of the papers included costs and savings data to the standard of accepted guidelines for economic evaluation in health care" (Hasvold and Wootton, 2011, p.360).

In addition to the numerous studies reviewed by Hasvold and Wootton (2011), many other studies examine the use of SMS appointment reminders and the effects on nonattendance. Guy, et al. (2012) review 18 studies on the effect of appointment attendance specifically on the use of SMS reminders and found an improvement in attendance; seven of the studies reviewed are unique from the review conducted by Hasvold and Wootton (2011).

Few studies, however, were found to study automated telephone appointment reminders and fewer still provide a comparison of manual and automated telephone appointment reminders on nonattendance. Parikh, et al. (2010) report nonattendance rates for patient groups in a U.S. outpatient practice that received no appointment reminder, an automated telephone reminder and a manual telephone reminder as 23.1, 17.3, and 13.6 percent, respectively. Parikh, et al. (2010) conclude that automated reminders were significantly less effective at reducing nonattendance than manual reminders, but were attractive nonetheless for potential cost savings that were not evaluated in their study. In a dentistry setting, Almog, et al. (2003) reported a reduction in nonattendance from 23.42 percent with manual reminders to 19.17 percent after the installation of an automated system. They found the system to be cost-effective and efficient and allowed for calls to be made after normal business hours in a consistent manner while reducing nonattendance and allowing staff to focus on their patients (Almog, et al., 2003).

Other studies that examined the effect of automated telephone reminders also have mixed results. Leirer, Tanke and Morrow (1992) found that automated telephone reminders reduce nonattendance by 4 to 50 percent. Alemi and Stephens (1996) found that 82 percent of patients that received an automated reminder showed up for their appointment compared to 72 percent of patients that received no reminder. Roth, et al. (2004) found that patients that received a computerized reminder had a significantly lower broken appointment rate (4.4 percent) compared to patients that received no reminder (8.5 percent). In contrast, Maxwell, et al. (2001) found no significant difference in attendance between patients that received an automated telephone reminder, postcard reminder, and no reminder.

This work will examine the workflow impacts of an automated reminder system, provide a comparison of nonattendance rates for manual and automated reminders, and suggest changes to optimise the impacts of the technology.

2.2.3 Self-Service Technology

Self-service technologies (SSTs) are technological interfaces that enable customers to produce a service independent of direct service employee involvement (Meuter, et al., 2000). SSTs enable customers to attain basic customer service (such as account information), engage in direct transactions with a company (such as a purchase of products or services), and obtain self-help (such as tips and pointers) (Ostrom, Bitner and Meuter, 2002). Common examples of self-service technologies in service industries are automatic teller machines (ATMs) in financial services, self-service stations at fuel retailers in consumer retail services, and airline check-in in consumer transportation services.

Self-service technologies in health care facilities include patient kiosks, an interactive computer-based system designed for self-service tasks, such as new patient registration and consent forms (Rhoads and Drazen, 2009). Patient kiosks include basic components, such as a display screen and a touch screen or keypad for input, and they can also include other components, such as card readers, signature pads, and printers. There are three main forms of patient kiosks: freestanding (similar to those used in airline check-in, building directories, and ticket purchasing), countertop or wall-mounted (such as ATMs), and mobile (in the form of tablet PCs). The three forms offer similar functions but have various cost and installation considerations that render some forms better suited for certain functions. For example, mobile forms are better suited for new patient registration, as patients can sit comfortably to complete lengthy forms rather than standing for long periods at a freestanding kiosk. Patient kiosks are being deployed primarily in ambulatory and emergency department (ED) settings and are being implemented to increase patient satisfaction and achieve operational benefits.

Lowe and Cummin (2010) found that self-service technology during check-in in general practice results in significant time savings and benefits; in particular, benefits included more time to care, more accurate data, and greater ease of gathering performance indicators. Although time savings data was not collected in this study, the authors estimate that it is plausible to save the equivalent of one full-time equivalent (FTE) health-care assistant (HCA). Their prescription for the usage of technology in health care coincides with the theme of this work, that "as with all information technology, it is necessary to change the way the practice works to gain the greatest benefits" (Lowe and Cummin, 2010, p.201).

A feasibility study on the use of a tablet computer for patients to enter their medical history in an ED in Ontario, Canada, showed that the system was successfully integrated into the patient care process (Benaroia, Elinson and Zarnke, 2007). The use of a patient kiosk for medication review in an ambulatory setting also found associated workflow processes to be a key factor to successful implementation (Lesselroth, et al., 2009). In both cases, kiosks were used by patients to enter data in a format that was directly compatible with the practices' computer systems. The use of ICTs in this application increases accessibility to data and removes any intermediary transcription processes.

In this work, we will examine the workflow impact of a patient self-service check-in application on a tablet computer. Similar to completing intake forms on paper, patients complete the same forms on a tablet computer. The data is then automatically and immediately available to any number of clinicians at the PCN from their EMR, as opposed to locating and sharing a single copy in a paper chart, and does not require the manual transfer of data into an EMR.

2.3 Methods

This section provides background on methods used in business process reengineering, data collection and analysis, and forms the basis of the methodology presented in the next section.

Business Process Reengineering

Several methodologies have been introduced for business process reengineering to suit the needs of the project; Al-Mashari and Zairi (2000) provide a summary of eight "representative" methodologies. These methodologies contain some similar components, and this work draws upon the earliest work of Davenport and Short (1990). Davenport and Short (1990, p.14) first extracted a five-step approach for process redesign from their research of companies that had engaged in such change. These five steps are:

- Develop the business vision and process objectives;
- Identify the processes to be redesigned;
- Understand and measure the existing processes;
- Identify IT levers; and
- Design and build a prototype of the new process.

Rather than rationalizing each task in a process as a means to eliminate obvious inefficiencies, Davenport and Short (1990) suggest that a business vision and related objectives be developed as a first step, from which entire processes should be redesigned. Davenport and Short (1990) identify four common objectives for process redesign: cost reduction, which is important but insufficient on its own; time reduction, often accomplished by changing sequential steps into simultaneous steps; output quality, to be defined by the customer; and quality of worklife, learning and empowerment. Their experience found that specific objectives need to be quantified, with goals exceeding that which the company can expect to achieve (Davenport and Short, 1990). In developing a business vision, Kotter and Cohen (2002) caution that although detailed plans and budgets are necessary, they are alone insufficient and a vision should be sensible, clear, simple and uplifting for successful change. Champy and Greenspun (2010) believe that improving efficiency and increasing safety should be the objectives in reengineering health care, and that achieving those objectives will automatically result in reducing costs in health care delivery. Indicators of performance for the Canadian health system are acceptability, accessibility, appropriateness, competence, continuity, effectiveness, efficiency, and safety (Canadian Institute for Health Information, 2009).

In identifying processes to be redesigned, Davenport and Short (1990) suggest that a high-impact approach, in which processes that are the most important or most conflicting with the business vision are identified, is often sufficient for successful redesign whereas an exhaustive approach, in which all processes are identified, is often abandoned due to resource restrictions. The identification of processes should include its boundaries and the organizational units involved (Davenport and Short, 1990). Exploratory tools, such as fish diagrams (also known as cause and effect diagrams) and fault tree analysis can be useful in problem identification (Freivalds and Niebel, 2009). Hammer and Champy (1993) suggest dysfunction, importance, and feasibility as three selection criteria for processes to be reengineered. Excess efforts and resources are common symptoms of process dysfunction and process importance should be gauged from the process customer's perspective; factors that affect feasibility include the scope, cost, and the people involved in the reengineering project (Hammer and Champy, 1993). In seeking reengineering opportunities in health care, Champy and Greenspun (2010) suggest focusing on areas of risk and high cost, the work of the physicians and patients, and on areas where success is possible.

In the third step of process redesign, measurements of the existing processes relevant to the redesign objectives must be accurate to serve as a baseline for improvement, but Davenport and Short (1990) caution that excess measurement can distract from radical improvement. Hammer and Champy (1993) concur that existing processes need to be understood, but also warn that overanalysis can impede progress. Flowcharts are one of the most useful tools for understanding processes (Davenport, 1993) and industrial engineering offers many techniques for measurement including cost assessment and time study (Freivalds and Niebel, 2009).

In identifying IT levers, Davenport and Short suggest that new processes can be designed by identifying the capabilities of ICTs and leveraging their impacts, rather than just salvaging previous process designs; these capabilities and impacts of ICTs are shown above in Table 2-1. Hammer and Champy (1993) also provide various examples of how technology can enable business process reengineering; their examples are summarised in Table 2-2. Davenport (1993) categorizes generalized applications of ICTs in three common processes: product development, order fulfillment, and logistics. In a product development process, five key applications of ICTs include: automated design, simulation systems, tracking systems, decision analysis systems, and interorganization communication systems (Davenport, 1993). In an order fulfillment process, six applications of ICTs include: product choice systems, microanalysis and forecasting systems, voice communications systems, electronic markets, interorganization communication systems, and textual composition (Davenport, 1993). Finally, in a logistics process, five applications of ICTs include: locational, recognition, asset management, logistical planning, and telemetry systems (Davenport, 1993).

In the last step of process redesign, Davenport and Short (1990) recommend the use of computer-aided design (CAD) tools and design criteria to build a prototype of the redesigned process. It is this step of process redesign that Davenport suggests is the scope of other research in business process reengineering. Following this suggestion, we turn to Hammer's research of companies that have undergone reengineering for some principles of reengineering (1990). These include:

- Organize around outcomes, not tasks;
- Have those who use the output of the process perform the process;
- Subsume information-processing work into the real work that produces the information;
- Treat geographically dispersed resources as though they were centralized;
- Link parallel activities instead of integrating their results;
- Put the decision point where the work is performed, and build control into the process; and
- Capture information once and at the source.

Davenport also suggests that the sequence of steps may vary and subsequently adapted this framework into a "high-level approach to process innovation," which includes the following steps (Davenport, 1993, p.25):

- Identifying processes for innovation;
- Identifying change levers;
- Developing process visions;
- Understanding existing processes; and
- Designing and prototyping the new process.

As mentioned in the beginning of this section, many methodologies have been introduced for BPR and eight representative methodologies are summarised by Al-Mashari and Zairi (2000). We close this review of BPR methodologies with a six stage framework proposed by Kettinger, Teng, and Guha (1997), which was found to encompass the methodologies used in 25 cases studied; their six stages are: envision, initiate, diagnose, redesign, reconstruct, and evaluate.

Since this research is an ethnographic study of the impacts of technologies preselected by the organization, the methodology will be adapted from these approaches and will be presented in Chapter 3.

Ethnographic Research

Ethnographic research is small scale social research that draws upon a range of qualitative and quantitative methods carried out in everyday settings (Savage, 2000); classic qualitative methods include observations and key informant interviews (Sofaer, 2002). Ethnographic research has a broad range of application in health care research and is particularly useful in understanding the organization of health care (Savage, 2000) and quality improvement in health care (Sofaer, 2002).

Ethnographic research methods, such as observations and interviews have been used to model workflows in health care (Malhotra, et al. 2007) and the role of ICTs in health care (Unertl, et al., 2009). The process begins with developing a general understanding and progressively moves toward developing deeper, more detailed descriptions of workflow. Observations are conducted as unobtrusively as possible and detailed field notes are taken for subsequent data extraction; interviews with key informants clarify observations. This information gathered is used to build workflow models, which is "basically the process of simplifying reality" (Malhotra, et al., 2007). Models are verified with key informants and revised as necessary.

Modeling and Simulation

Modeling and simulation has been successfully used in various health care applications and allows the examination of alternative options with less cost and less risk than actual implementation (Barnes, et al., 1997). Jun, Jacobson and Swisher (1999) present a survey of literature on discrete-event simulation on the operation of health care facilities, particularly on the subjects of patient flow and resource allocation. Narrowing the breadth of health care topics reviewed by Jun, Jacobson and Swisher (1999) while expanding the scope of analysis methodologies, Cayirli and Veral (2003) provide a comprehensive review of studies on appointment scheduling for outpatient services. Their literature review includes relevant factors in problem formulation, performance measures in systems analysis, and analysis methodologies. Many of the approaches observed by the reviewers in the relevant literature are used in this research, including case study and quantitative modeling using queuing theory, simulation studies and the comparison of alternative systems. The performance measures used in the literature are classified as cost-based, time-based, congestion, fairness, and other measures; the performance measures considered in this work are primarily time-based measures.

The next chapter presents the methodology used in this work – a multifaceted approach to examine the impacts of ICTs and how primary care can be reengineered to accommodate the use of ICTs.

3 Methodology

Methodologies reviewed in the previous section for business process reengineering were adapted to achieve the objectives of this research. To gain an understanding of how business processes in primary health can be reengineered to accommodate the use of ICTs, a process model was developed to examine the impacts of ICTs and determine changes in workflow to optimise the benefits of ICT usage. Whereas the methodologies reviewed above selected ICTs as a lever for reengineering, this work examines the impacts of ICTs that had already been implemented or selected for implementation by the Primary Care Network (PCN). The methodology then, was adapted from the previous research, and can be summarised as follows:

- Identify ICTs for study;
- Identify processes for study;
- Understand processes and performance indicators;
- Identify impacts of selected ICTs on selected processes; and
- Redesign processes.

In identifying ICTs for this study, selection criteria considered when the ICT was or will be implemented to ensure accessibility to information related to the implementation. The ICTs selected for this study have been introduced in the previous section, which are:

- Electronic medical record (EMR);
- Automated appointment reminder system; and
- Patient self-service check-in and registration tablet application.

The processes studied were those most impacted by the implementation of the selected ICTs, determined through observation and interview of process owners. Access to information about the processes was also considered in process selection and the scope of the research was limited to administrative processes and excluded clinical processes.

A multifaceted approach was taken to understand the processes and examine the impacts of information and communication technology in primary health care. First, a discrete-event model and simulation of a simplified patient scheduling process demonstrates model development, experimental design, and sensitivity analysis for a hypothetical baseline scenario and potential alternative process scenarios. Second, a discrete-event model and simulation of an actual patient care process in the PCN examines model development and input modeling of a larger process in greater detail and the impacts of various ICTs. Third, the analysis and optimization of the actual appointment reminder process in the PCN evaluates financial viability of an automated appointment reminder system and examines the effects on the appointment reminder process to optimise the application of the technology.

Finally, a concluding discussion framed by the impacts and capabilities of ICTs assembles the learnings of this multifaceted approach in the reengineering of primary care. The capability topology suggested by Davenport (1993), shown above in Table 2-1, has been used to study the impacts of technologies in various applications, including health care (Harvey, Lefebvre and Lefebvre, 1993; Motulsky, et al., 2008), banking (Harvey, Lefebvre and Lefebvre, 1993), transport (Harvey, Lefebvre and Lefebvre, 1993; van der Heijden, et al., 1995), academia (Mandviwalla, Patnayakuni and Schuff, 2008), and the public sector (Andersen, 2006). Others have extended (Lee and Lim, 2005) and condensed (Mooney, Gurbazani and Kraemer, 1996) Davenport's (1993) topology to further develop frameworks for assessing the impacts of technology, but we will proceed with Davenport's (1993) seminal topology as it has been applied to various technologies in many applications.

Further discussion on methodology is presented in the remainder of this section and in each of the approaches taken in the following sections.

3.1 Data Collection

Data was collected by ethnographic research methods including interviews, observation, and documents to develop a workflow model. The patient care process presented in this work was developed through observation of the workflow of patient care coordinators at the PCN. Initial observations were conducted to develop an overview of the patient care process and to identify the processes most impacted by various ICTs for further study. Detailed workflow mapping was developed in subsequent observations and through consultation with the patient care coordinators. Quantitative data was gathered during observation to describe service times for the patient care processes. Over 70 hours were spent collecting data at the PCN in 33 observations during the period from January to May 2012. Observations were scheduled as best as possible to vary in day of week and time of day, but were ultimately scheduled to best accommodate the preferences of the participating patient care coordinators.

Existing records of aggregate data collected by the PCN were also reviewed and recorded to support the patient care process descriptions. This is existing data already being collected by the PCN to develop their service delivery model and includes aggregate demographic, referrals, and visit information. The sources of data were reports prepared by the PCN and generated from the PCN's electronic medical record and automated appointment reminder system.

No identifying patent information was recorded in this data collection and methods to anonymise data collection were followed during observation to support ethical research practices. Following the completion of the ARECCI Project Ethics Course Level 1, an assessment of risk for the participants of this research was conducted and determined to be minimal and mitigable. An information letter and consent form outlining the research methods and potential risks to participants was prepared as part of the application to the research ethics board and approval was granted by University of Alberta Health Research Ethics Board (HREB) Health Panel B.

3.2 Data Analysis

3.2.1 Input Modeling

The data collected through observation at the PCN and review of records is analysed to specify input models for the discrete-event model and simulation. These input models are probability distributions that describe the arrival of entities and service times for various processes. A general method for input data modeling (Law, 2007) is followed and summarised below. Two software applications were used to implement these methods: IBM SPSS Statistics and ExpertFit distribution-fitting software. Results obtained using this software was verified by manual calculation.

Sample Independence

First, as the methods used in subsequent steps for fitting theoretical probability distributions assume independence of samples, sample independence from each observation must be verified.

Sample independence within each observation can be qualitatively assessed by inspection of a scatter plot for correlation, or in the case of independence, lack of correlation. For a sample $\{X_1, X_2, \dots, X_n\}$, the x-y pairs of the scatter plot are given by (X_i, X_{i+1}) for $i = 1, 2, \cdots, n-1$.

Quantitatively, sample independence can be verified using the non-parametric runs test where the null hypothesis is sample independence. Under the null hypothesis, the number of runs is approximately normally distributed with mean and variance given as a function of the number of samples greater than and less than the sample median. If the number of runs is outside the expected range for a given confidence level, the null hypothesis of sample independence is rejected. If the samples are not independent, the empirical distribution of data can be used as the input model.

Analysis of Variance

If the samples within observations are independent, the non-parametric Kruskal-Wallis (K-W) analysis of variance test is used to verify that the samples from different observations are from the same distribution and can be combined to model as one distribution. The test statistic for the K-W test is chi-square distributed and is a function of the number of samples in each observation and the overall rank of the samples in each observation. If the samples cannot be combined to model as one distribution, the data should be reassessed to determine if different categories of data were considered in the sample and should be modeled as separate distributions.

Type of Distribution

If sufficient data has been collected (at least 10 samples), then the data will be fit to a theoretical distribution to specify an input model. If there is insufficient data, then the empirical distribution of data will be used.

Discrete probability distributions are used to specify the input models for entity generation. The five discrete probability distributions that are available in the Student Version of ExpertFit distribution-fitting software and were considered for each data sample set include:

- Uniform
- Binomial
- Geometric
- Negative binomial
- Poisson

Continuous probability distributions are used to specify the input models for service time. The seven continuous probability distributions that are available in the Student Version of ExpertFit distribution-fitting software and were considered for each data sample set include:

- Uniform
- Exponential
- Gamma
- Weibull
- Normal
- Lognormal
- Log-logistic

Shifted versions of the exponential, gamma, Weibull, lognormal, and log-logistic distributions were also considered.

Potential distributions for a data sample may be hypothesized by generating and examining a histogram and summary statistics of the data.

If there is insufficient data, a continuous, piecewise-linear empirical distribution is specified from the observed samples. For the data set

$$S \in \{X_{(1)}, X_{(2)}, \cdots, X_{(n)}\}$$

the distribution function is given as

$$F(x) = \begin{cases} 0 & , x < X_{(1)} \\ \dfrac{i-1}{n-1} + \dfrac{x - X_{(i)}}{(n-1)(X_{(i+1)} - X_{(i)})} & , X_{(i)} \leq x < X_{(i+1)}, \quad i = 1,2,\cdots,n-1 \\ 1 & , x \geq X_{(n)} \end{cases}$$

(Law, 2007), where the parenthetical subscripts denote order statistics.

Parameter Estimation

If there is sufficient data, the maximum likelihood method is used to estimate parameters for potential probability distributions. The maximum likelihood method estimates parameters of a probability distribution by choosing parameters that maximise the likelihood function. The likelihood function is the probability density function of the hypothesized probability distribution evaluated at the observed data sample. The method of maximum likelihood can be found in most statistical textbooks; Wackerly, Mendenhall and Scheaffer (2008) is one such text. A detailed treatment of this subject is not required here as Law (2007) provides a summary of maximum likelihood estimators (MLEs), and a calculation procedure where warranted, for the parameters of the distributions considered.

Distribution Selection

Once parameters for the hypothesized probability distributions have been estimated, the goodness of fit can be qualitatively assessed by graphical comparison of the observed data to the fitted theoretical distribution and quantitatively assessed using the chi-square test.

Further details on input modeling will be presented in Chapter 5 – an overview of modeling entity generation with discrete probability distributions is presented in Section 5.4; an overview of modeling service times with continuous probability distributions is presented in Section 5.5; and a comprehensive treatment can be found in Appendix B.

3.2.2 Categorical Data Analysis

The data collected through the review of records is analysed to examine the financial feasibility of an automated appointment reminder system. This data included appointment reminder outcomes and appointment attendance outcomes. Reminder outcome data and appointment attendance data that met the inclusion and exclusion criteria were cross tabulated to produce daily, weekly and summary contingency tables.

Large sample hypothesis testing and large sample confidence intervals were used to make statistical inference about sample proportions. Pearson's chi-square test for independence was used to demonstrate association of reminder and attendance outcomes and the results were verified with IBM SPSS Statistics software. Further details on categorical data analysis will be presented in Chapter 6.

3.3 Model Verification and Experimental Design

The patient care process model was developed through observation at the PCN and was verified by the patient care coordinators to reflect the processes used. Outputs from the discrete-event model and simulation, such as wait time and server utilization, were verified, when possible, by estimates generated from queue theory.

Simulation experiments were designed using large sample confidence intervals. Sufficient test simulations required for a desired confidence interval were determined given an estimate of the variance of the target parameter based on preliminary simulations. Large sample hypothesis testing and large sample confidence intervals were then used to make statistical inference about simulation outputs and compare them to alternative processes.

Further details on model verification, experimental design and statistical inference will be presented in Chapter 4.

Three approaches to examining the impacts of ICTs will be presented in the next chapters. A discrete-event model and simulation of a simplified patient scheduling process and the impact of a hypothetical online scheduling option is presented in Chapter 4. (The work presented in Chapter 4 was submitted as a project in a graduate level modeling and simulation course.) The patient care process at the PCN and the impacts of various ICTs is presented in Chapter 5. The appointment reminder process and the impacts of an automated reminder system are presented in Chapter 6. A concluding discussion is presented in Chapter 7.

4 Model and Simulation of Patient Scheduling Process

A hypothetical primary care clinic has three physicians and one patient care coordinator (PCC). A model of the patient scheduling process will be used to assess the administrative workload of their patient care coordinator and service provision to their patients, that is, how busy their patient care coordinator is in the current state of operations and how long patients typically wait on hold when they call their office to request an appointment.

To improve the level of service for their patients, the office may look for options to increase the supply of service or decrease the demand for service. For example, they may consider hiring a second patient care coordinator to increase the supply of service or introducing a self-serve online appointment scheduling system to reduce the demand for telephone service. These improvements will require a capital investment, either in extra wages for a second patient care coordinator or implementation of an online service, so it is necessary to try to predict what level of improvement, if any, can be expected from the investment. It will also be important to understand what proportion of the patient population would be receptive to an online appointment scheduling system, as well as what level of usage would result in desired effects and make the investment worthwhile.

This chapter presents the modeling, simulation and analysis of the appointment scheduling process at the hypothetical primary care clinic and the evaluation of options to improve patient service. Patient service, in this context, will be examined only from an administrative perspective focusing on the appointment scheduling process, and will not include the quality of clinical service.

The existing patient scheduling process and some alternatives are defined in Section 4.1. Sections 4.2 to 4.4 detail the model development and analysis methods with the results presented in Section 4.5. A discussion of the results is provided in Section 4.6 and conclusions are presented in Section 4.7. The work in this chapter was submitted as a project in a graduate level modeling and simulation course.

4.1 Patient Scheduling Process Overview

In the existing patient scheduling process, patients requesting an appointment telephone the office and speak to the patient care coordinator. If the patient care coordinator is busy, the patient waits on hold until the patient care coordinator becomes available. Patient calls on hold are answered by the patient care coordinator in the order in which they are received. In addition to appointment requests, the patient care coordinator also makes reminder calls to all patients who have appointments scheduled for the next day. Appointment request calls take priority over the reminders calls, that is, the patient care coordinator makes reminder calls when he/she is not speaking with a patient and there are no patients waiting on hold.

A flow chart of the patient scheduling process is shown in Figure 4-1.

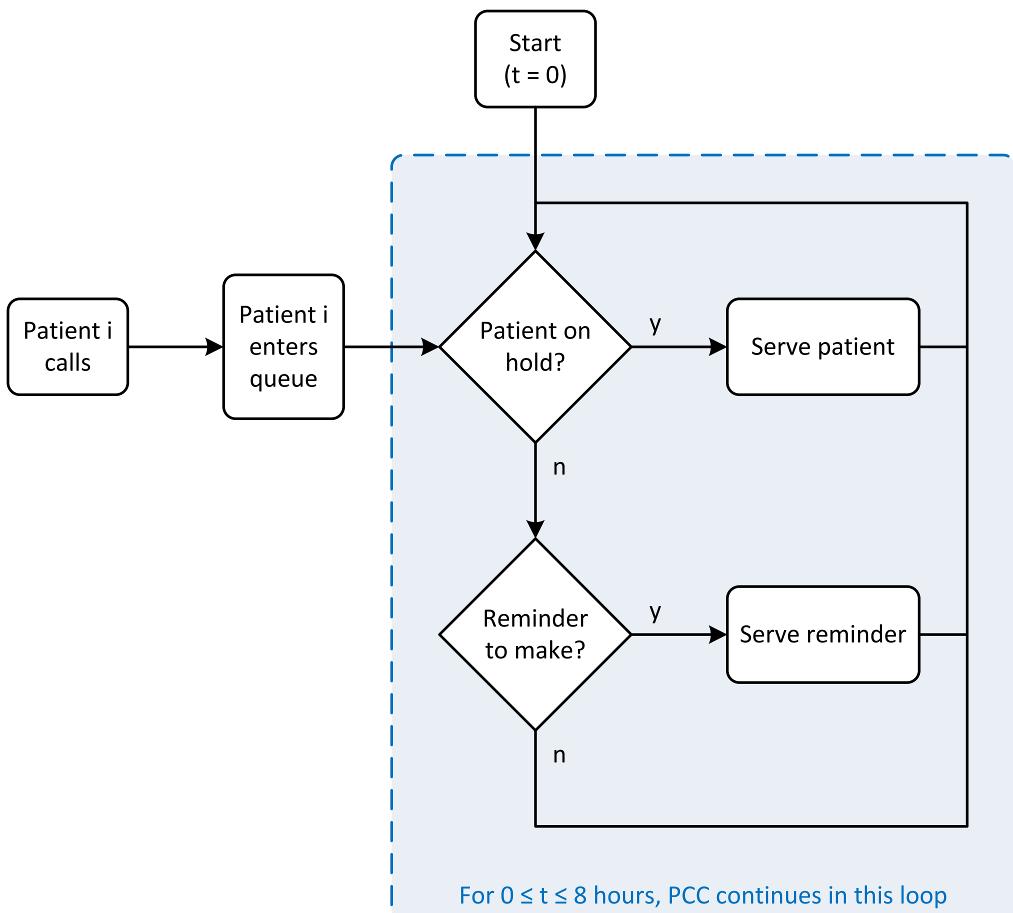


Figure 4-1: Flow chart of the patient scheduling process

4.1.1 Patient Scheduling Process Modeled as a Queuing System

The model for the patient scheduling process is based on a queuing system with a priority service discipline with two priority classes of customers. The appointment requests will be denoted class 1, as they receive priority service, and the appointment reminders will be denoted class 2. Some parameters required to describe the queue system are the arrival rate and the service time for the two priority classes. These parameters describe the demand for and supply of service in the system.

The arrival rate for appointment requests is the rate at which patients call the office to request an appointment. The service time for appointment requests is the amount of time it takes the patient care coordinator to select an appointment suitable for the patient and exchange information with the patient such as patient demographics and clinic location and appointment instructions.

The arrival rate for appointment reminders also describes when the reminders enter the queue system, which will be further discussed below. The service time for appointment reminders is the amount of time the patient care coordinator takes to make the reminder call.

Viewing the appointment scheduling process as a queuing model lends some terminology for the key metrics to evaluate the system. The performance measure utilization, ρ, of the server, can be interpreted as the proportion of time that the patient care coordinator is busy. In a priority queue discipline, the utilization of the server, ρ, is the sum of the utilization with respect to each priority class, or the proportion of time the patient care coordinator is busy serving each priority class. That is, $\rho = \rho_1 + \rho_2$. The amount of time a patient spends waiting on hold to speak with the patient care coordinator is the time in the queue, $W_q^{(1)}$. The superscript, 1, denotes the priority class of the patient appointment requests. Estimates of these key performance measures will be generated from the model.

Assume that estimates with a 95% confidence level are suitable and it is desired to estimate the utilization of the patient care coordinator within 0.05 (where ρ is a proportion in [0,1]) and the average wait time in the queue within 30 seconds. The key performance measures are summarised in Table 4-1.

Table 4-1: Key performance measures and desired accuracy of estimation

Performance Measure	Description	Desired 95% Confidence Interval
Utilization of the PCC (ρ)	Proportion of time PCC is busy	$\rho \pm 0.025$
Average time in queue ($W_q^{(1)}$)	Average time a patient waits on hold using the telephone service	$W_q^{(1)} \pm 15$ (s)

The flow chart of the patient scheduling process is shown with the key performance measures in Figure 4-2.

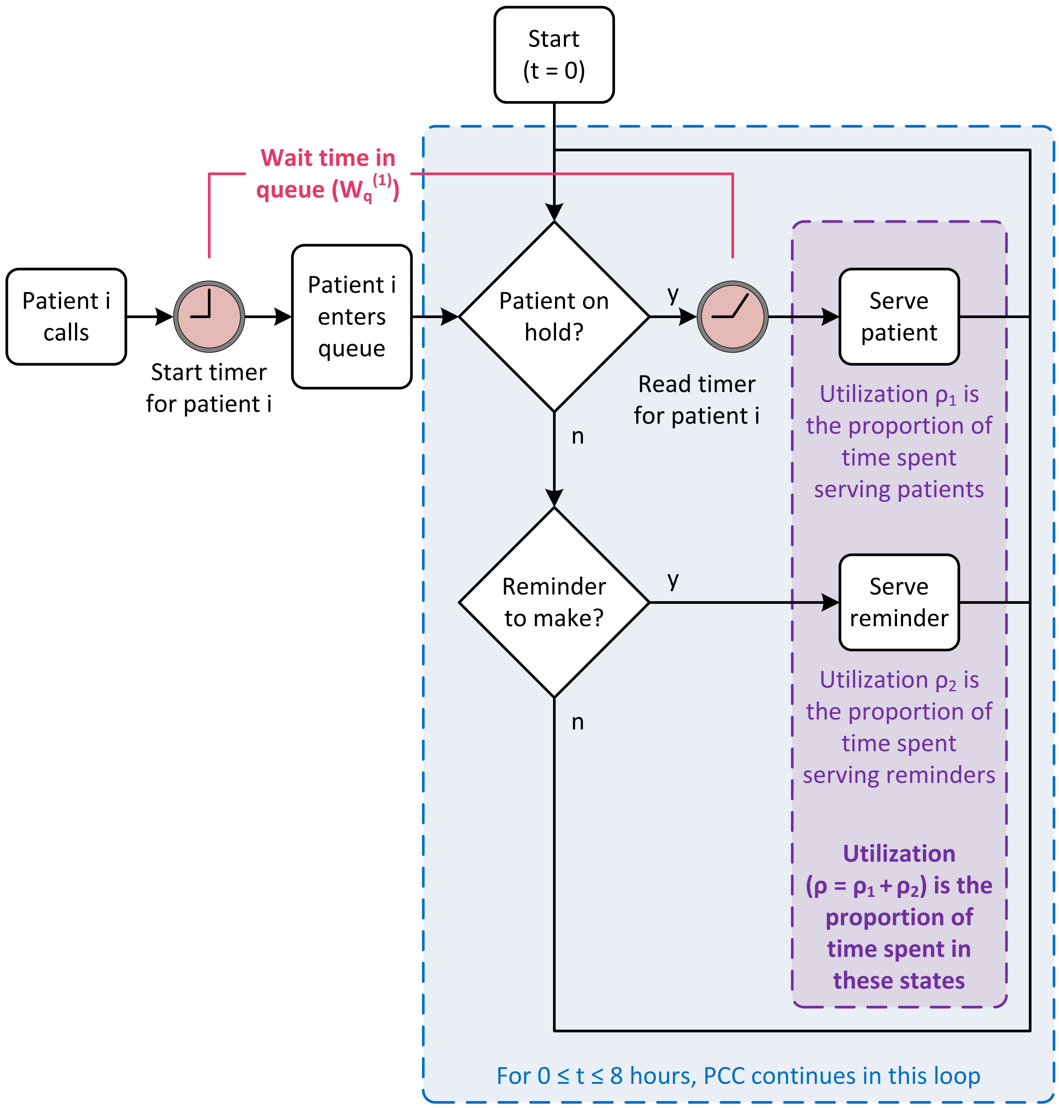


Figure 4-2: Flow chart of the patient scheduling process with key performance measures

The patient scheduling process is modeled as a $M_1\,D_2^{m}/M_1\,M_2/1/\text{PRI-FCFS}/\infty/\infty$ queue, as shown in Figure 4-3.

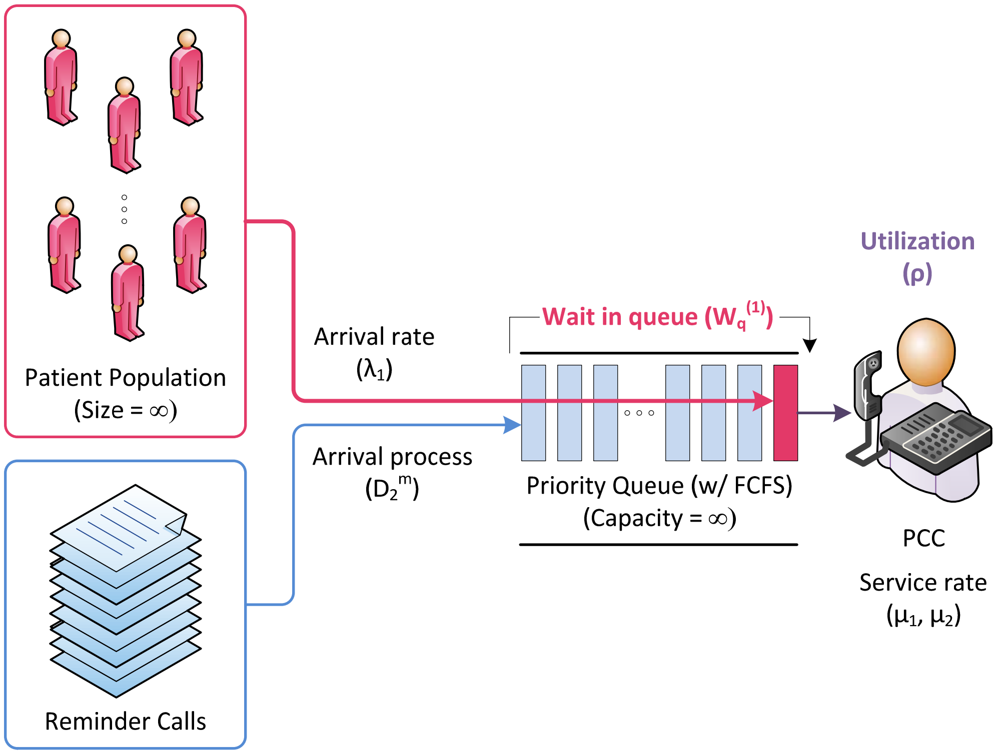


Figure 4-3: The patient scheduling process modeled as a queue

The **arrival process** for patients telephoning the office to request an appointment is assumed to be a homogeneous Poisson arrival process, with a mean arrival rate (λ_1). Then the interarrival times for appointment requests (q) are independent, identically distributed (iid) random variables having an exponential distribution (M_1), with a mean interarrival rate ($1/\lambda_1$).

This assumption neglects factors such as time of day, day of week and seasonal call volume fluctuations. In reality, more appointment requests may be experienced first thing in the morning, on Mondays (if the office closed on weekends), during cold and flu season, or various other factors.

The demand for appointments will be estimated from published statistics for the purposes of this project. In reality, an established clinic may have data available to determine the mean interarrival rate or average daily or annual call volumes.

According to data published by the Organisation for Economic Co-operation and Development (OECD), in Canada in 2007, the number of general practitioners per 1000 population is 1.0 and the annual number of doctor's consultations per capita is 5.8 (OECD, 2009). We can interpret the first statistics to assume that each physician serves a population of 1000 patients.

The expected annual requests for appointments (or annual call volume) for an office with three physicians can then be estimated as 3 x 1000 x 5.8, or 17,400.

If we assume that the office is open for eight hours each day and there are approximately 20 working days per month, then the average arrival rate (λ_1) for a homogeneous Poisson process in calls per minute can then be expressed as

$$\lambda_1 \left[\frac{calls}{minute}\right] = \frac{17400 \left[\frac{calls}{year}\right]}{12 \left[\frac{months}{year}\right] x\ 20 \left[\frac{days}{month}\right] x\ 8 \left[\frac{hours}{day}\right] x\ 60 \left[\frac{minutes}{hour}\right]} = 0.151$$

Finally, the mean interarrival time ($1/\lambda_1$) in minutes per call can be expressed as

$$\frac{1}{\lambda_1} \left[\frac{minutes}{call}\right] = \frac{1}{0.151 \left[\frac{calls}{minute}\right]} = 6.62$$

The list of reminder calls that the PCC must make in the day is available at the start of the day (within the first minute). The number of reminder calls (m) that must be made each day is assumed to be a normally distributed random variable.

For an annual appointment volume of 17,400, the average daily appointment volume, using the same assumptions for working days in a year as above, is 72.5. Although the interarrival times for appointment request calls are assumed to be exponentially distributed (and hence have a variance equal to its mean), we assume that the patient care coordinator tries to balance the daily work load for the physicians and the variance for the daily appointment volume will be less than the variance for the call arrivals. The two assumed distributions are compatible since the appointments for all the requests received in one day will not be scheduled all in the same day.

We will assume that the number of reminders that must be made daily is normally distributed with a mean of 72.5 and a standard deviation of 2.5. This implies that 99.9% of the time, there are between 65 to 80 appointments scheduled for the day.

If we assume that the PCC turns on the computer first thing in the morning and the appointment management software generates a list of reminder to be made within one minute, then the interarrival times for the appointment reminders is one (minute) divided by the number of reminders (m), a normally distributed random number. Hence, the arrival process of the reminder calls is deterministic with a random variable m for the total number of reminders (D_2^m).

The **service process** is assumed to have service times (μ) that are iid and exponentially distributed (M_1, M_2). For a patient requesting an appointment, the mean service time is assumed to be four minutes (μ_1). The mean service time for a reminder call is assumed to be one minute (μ_2).

We assume that the office has one patient care coordinator and therefore the **number of servers** is one.

The **queue discipline** is modeled as a non-preemptive priority queue, with appointment requests taking priority over reminder calls. Appointment requests are served on a first come, first served (FCFS) basis with callers waiting on hold if the patient care coordinator is currently busy and that the calls are answered in the order in which they are received. Reminder calls are made when the patient care coordinator is idle and there are no patients waiting on hold. If a patient calls while the patient care coordinator is making a reminder call, the PCC finishes the reminder call and then serves the next patient in the queue.

The **maximum allowable number of customers in the system** is assumed to be infinite. That is, the number of lines available for callers to be on hold is assumed to be infinite. In reality, this assumption is reasonable if the number of lines available is well above the expected number of callers in the queue.

The **size of the population** from which the customers are drawn is assumed to be infinite. This assumption is common given that the order of magnitude of the actual population exceeds that of the number of servers.

Furthermore, we assume that callers do not balk or renege. The assumption that callers do not balk, that is arrive, but do not enter the queue (usually because there are already numerous callers on hold) is reasonable because generally callers do not know how many other callers are in the queue. We also assume that callers do not renege, that is enter the queue, but hang up the call before being served, which is more likely if the average waiting time is short. These assumptions allow the modeling of an equilibrium system in which the number arrivals is equal to the number of departures.

A summary of parameters used to model the patient scheduling process as a queue is given in Table 4-2.

Table 4-2: Summary of parameters in queue model of patient scheduling process

Parameter	Value / Distribution
Interarrival time ($1/\lambda_1$) for appointment requests (q)	$1/\lambda_1 \sim Exponential\ (mean = 6.62\ minutes)$
Number of reminder calls per day (m)	$m \sim Normal\ (mean\ =\ 72.5, standard\ deviation\ =\ 2.5)$
Interarrival time ($1/\lambda_2$) for appointment reminders (m)	$1/\lambda_2 \sim Deterministic\ (1/m)$
Service time ($1/\mu_1$) for appointment requests	$1/\mu_1 \sim Exponential\ (mean = 4\ minutes)$
Service time ($1/\mu_2$) for reminder calls	$1/\mu_2 \sim Exponential\ (mean = 1\ minute)$
Number of servers	1 PCC
Queue discipline	First come, first served (FCFS) with priority given to appointment requests; no preemption
System capacity	Infinite
Population size	Infinite

4.1.2 Patient Scheduling Process with Two Patient Care Coordinators

One alternative that will be evaluated for improving service level is to hire a second patient care coordinator, or increase the supply of service. The patient scheduling process with two patient care coordinators is also modeled as a queue, and it will be the same as the previous model in all parameters except there are now two servers instead of one. The service rate distributions of the two patient care coordinators are identical: that is, one patient care coordinator is not faster or slower than the other, on average. Patient calls are answered in the order in which they are received by the first available patient care coordinator.

The key performance measures will again be utilization (of each patient care coordinator) and the wait in queue. The appointment scheduling process with two patient care coordinators is modeled as a $M_1\,D_2^m/M_1\,M_2/2/\text{PRI-FCFS}/\infty/\infty$ queue, as shown in Figure 4-4.

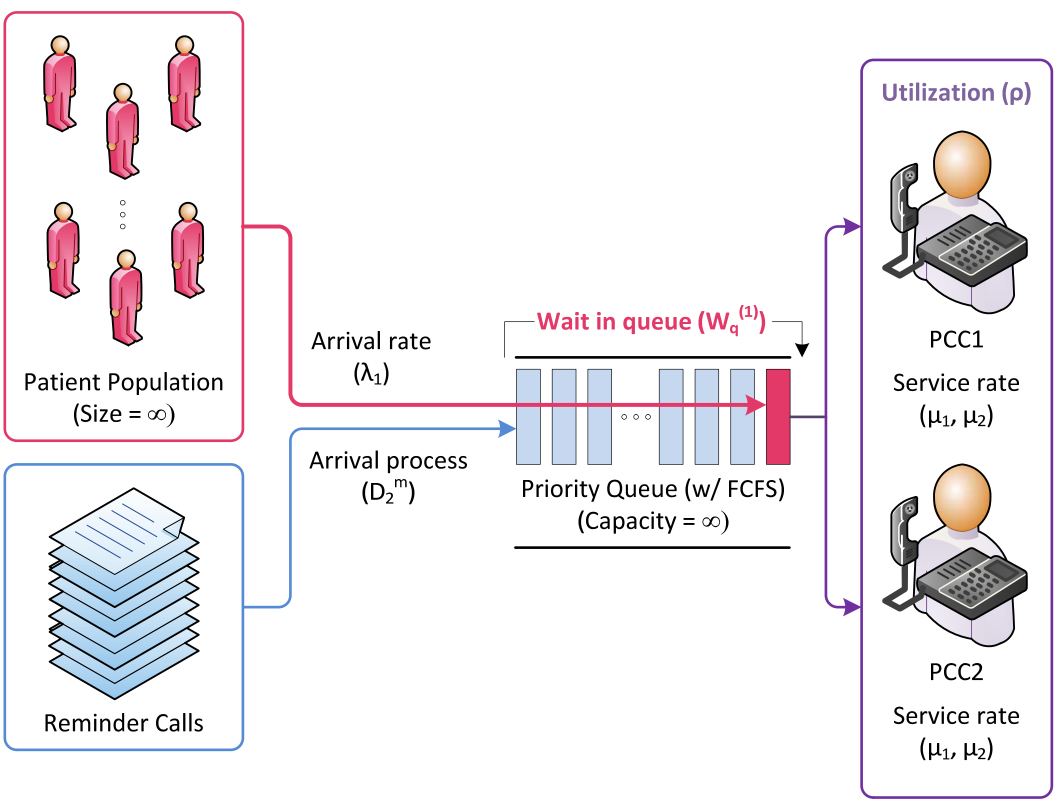


Figure 4-4: The patient scheduling process with two PCCs modeled as a queue

A summary of parameters used to model the alternate patient scheduling process with two patient care coordinators is given in Table 4-3.

Table 4-3: Summary of parameters in queue model of patient scheduling process with two PCCs

Parameter	Value / Distribution
Interarrival time ($1/\lambda_1$) for appointment requests (q)	$1/\lambda_1 \sim Exponential\ (mean = 6.62\ minutes)$
Number of reminder calls per day (m)	$m \sim Normal\ (mean\ =\ 72.5, standard\ deviation\ =\ 2.5)$
Interarrival time ($1/\lambda_2$) for appointment reminders (m)	$1/\lambda_2 \sim Deterministic\ (1/m)$
Service time ($1/\mu_1$) for appointment requests	$1/\mu_1 \sim Exponential\ (mean = 4\ minutes)$
Service time ($1/\mu_2$) for reminder calls	$1/\mu_2 \sim Exponential\ (mean = 1\ minute)$
Number of servers	2 PCCs
Queue discipline	First come, first served (FCFS) with priority given to appointment requests; no preemption
System capacity	Infinite
Population size	Infinite

4.1.3 Patient Scheduling Process with Online Service

Another alternative that will be evaluated is the implementation of a self-service online appointment scheduling system, or a decrease in demand for telephone service. This process will again be modeled as a queue. In the online patient scheduling process, an online appointment service has been made available and a certain proportion of patients use this service instead of the telephone service. It is assumed that overall demand for appointment requests remains the same as in the previous models; however, a certain proportion of patients will decide to use the online service instead of telephoning the clinic and do not enter the queue for telephone service. This results in a reduction in the arrival rate λ_1.

Similarly, for the list of reminder calls, a certain proportion of the list will contain appointments that were made using the online service. The reminders for the appointments that were made online are served electronically, via email, and therefore do not enter the queue for service, resulting in a reduction in the arrival rate.

The online patient scheduling process is modeled as a $M_1 D_2^m/M_1 M_2/1$/PRI-FCFS/∞/∞ queue as shown in Figure 4-5.

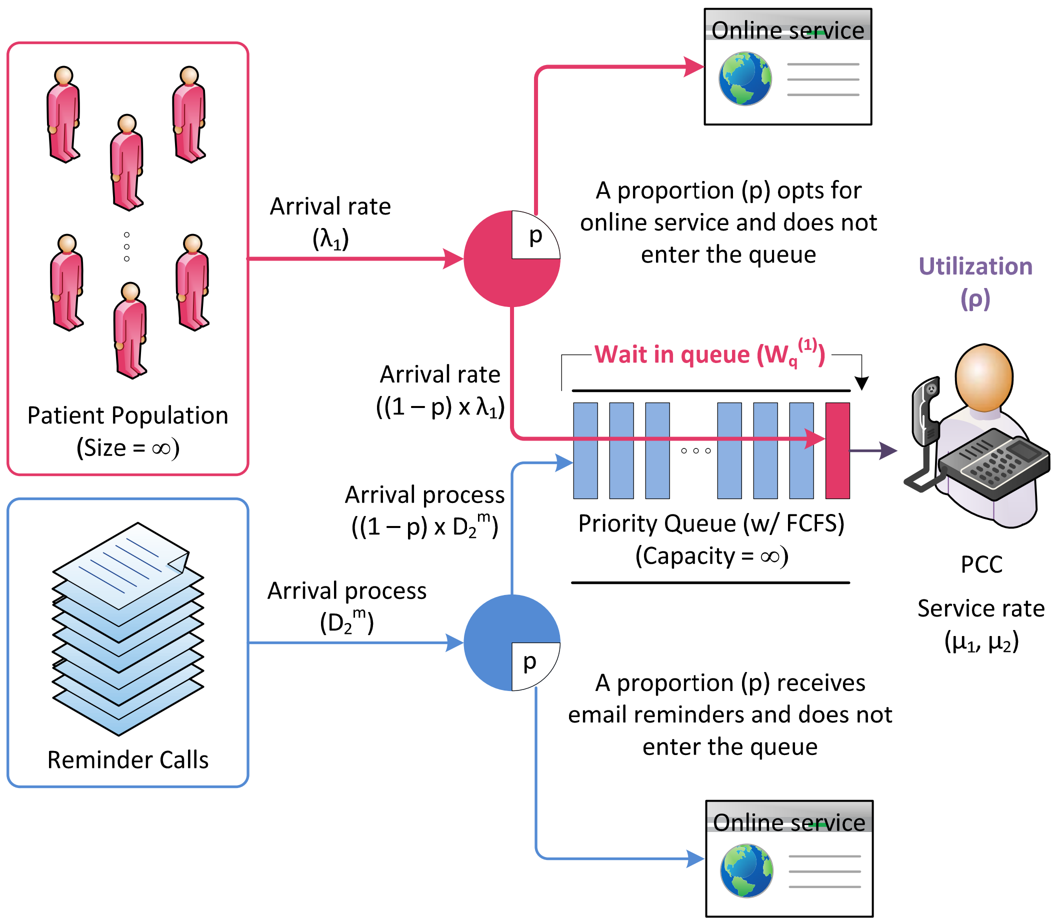


Figure 4-5: The online patient scheduling process modeled as a queue

The key performance measures are again utilization and the wait in queue. Various levels of usage rates (proportion of patients who opt to use the online service) will be modeled which will provide some insight into the level of participation that will be required to achieve desired performance measures.

A summary of parameters used to model the alternative patient scheduling process is given in Table 4-4.

Table 4-4: Summary of parameters in queue model of online patient scheduling process

Parameter	Value / Distribution
Online service usage rate	p
Interarrival time ($1/\lambda_1$) for appointment requests (q)	$1/\lambda_1 \sim Exponential\ (mean = (1-p) \times 6.62\ minutes)$
Number of reminder calls per day (m)	$m \sim (1-p) \times Normal\ (mean\ =\ 72.5, standard\ deviation\ =\ 2.5)$
Interarrival time ($1/\lambda_2$) for appointment reminders (m)	$1/\lambda_2 \sim Deterministic\ (1/m)$
Service time ($1/\mu_1$) for appointment requests	$1/\mu_1 \sim Exponential\ (mean = 4\ minutes)$
Service time ($1/\mu_2$) for reminder calls	$1/\mu_2 \sim Exponential\ (mean = 1\ minute)$
Number of servers	2 PCCs
Queue discipline	First come, first served (FCFS) with priority given to appointment requests; no preemption
System capacity	Infinite
Population size	Infinite

4.1.4 Summary of Patient Scheduling Processes

The patient scheduling process will be examined by developing a discrete-event model. The model will be used to determine the utilization of the PCC and the average wait on hold for the existing patient scheduling process.

The effect of increasing the supply of service will be examined by modifying the number of servers in the model. This will be used to evaluate the option of employing two PCCs.

The effect of decreasing the demand of service will be examined by modifying the arrival process of the appointment requests and appointment reminders. This will be used to evaluate the option of implementing an online appointment scheduling system, where a proportion of the patient population will use the online service instead of the telephone service.

A summary of the patient scheduling process and alternative processes that will be presented is given in Table 4-5.

Table 4-5: Summary of patient scheduling processes

Process	Service Options	Change in Process
Existing process	Telephone only (1 server)	Baseline
Alternative process 1	Telephone only (2 servers)	Increase supply
Alternative process 2	Telephone (1 server) and online (with usage rate p)	Decrease demand

4.2 Model Development

A model of the patient scheduling process described in the previous section will be developed to examine the state of the current process and then modified to analyse process alternatives. In the discrete-event model, appointment requests (q) and appointment reminders (m) are represented by entities. Appointment request entities and appointment reminder entities are generated, assigned attributes, pass through a queue where they are served by the PCC, and finally flow into a sink upon service completion. The simulation clock time is interpreted in minutes and the model run length is set to the equivalent of an eight-hour work day, or 480 minutes.

The SimEvents model of the patient scheduling process is shown in Figure 4-6. The development of the model is described in detail in Appendix A.

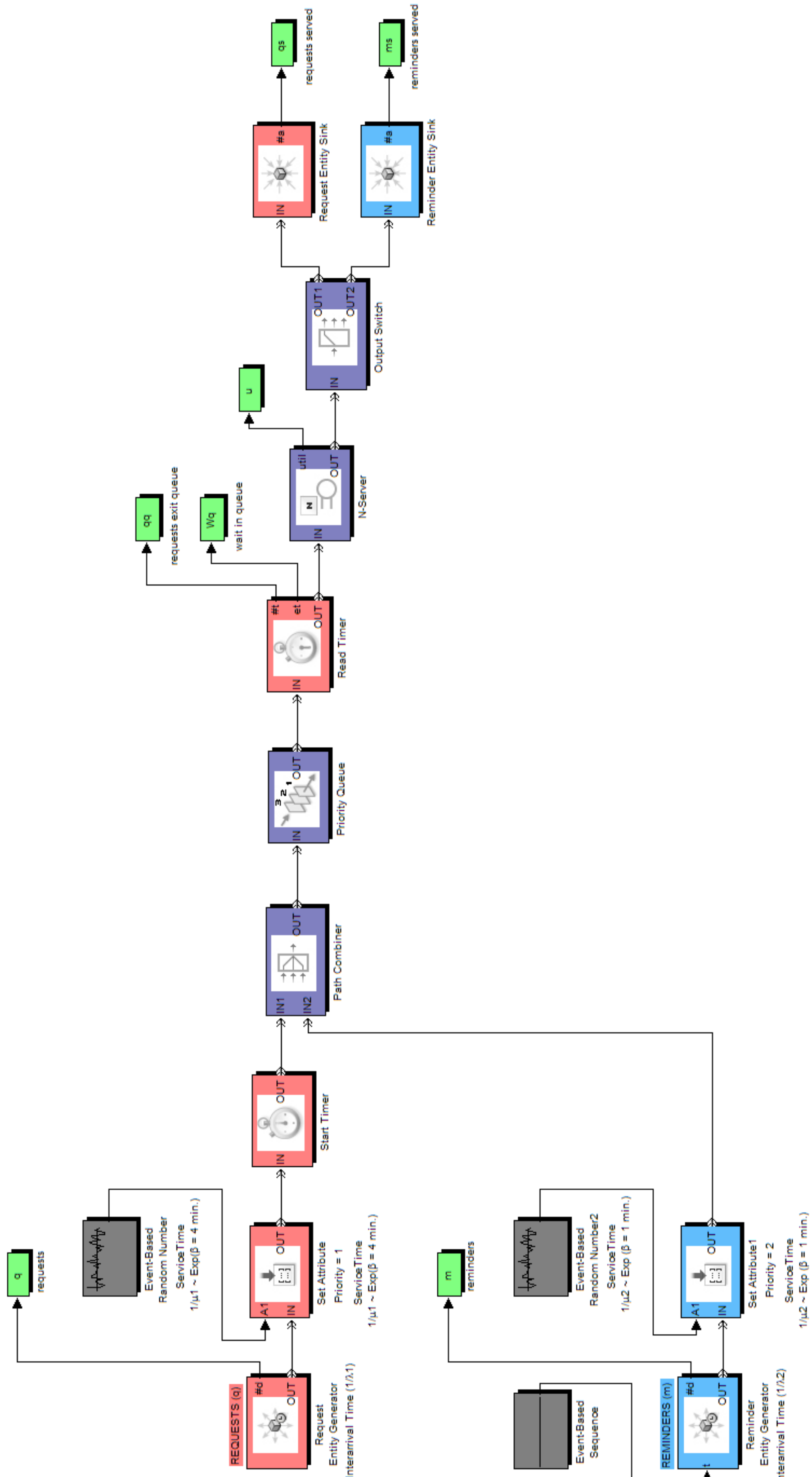


Figure 4-6: SimEvents model of the patient scheduling process

A MATLAB function (simPS) is used to specify the number of simulation runs, the number of servers, and the proportion of online service users. The function runs the simulation and displays selected statistics and figures. The MATLAB code also changes the initial seed used to generate the random numbers used in Monte Carlo sampling so that each simulation run is unique and independent. Note the MATLAB function simeventsstartup('des') should be called to assign default model settings for discrete-event simulation.

The MATLAB function is used with the following parameters, as displayed in the help contents for the function, as shown in Figure 4-7.

```
>> help simPS
  Simulates patient scheduling process.
  simPS(n, s, p) performs n simulation runs,
  with s number of PCCs (servers), and
  p percentage of online usage (reduction in demand).
  Outputs selected summary statistics,
  a sample patient chart and a histogram of wait times.
```

Figure 4-7: MATLAB function simPS description

The function calculates the mean interarrival time for the appointment requests based on the base demand in the existing process, with a reduction p, if nonzero, and sets the parameter in the Time-Based Entity Generator block. The total number of reminder entities is generated from a random number with a normal distribution, based on the base demand in the existing process, with a reduction p, if nonzero. This number is then used to specify the intergeneration times for the reminder entities so that the reminder entities are all generated within the first minute of the simulation run. The parameter in the Event-Based Sequence block is then set to these values by the function. The number of servers input is used to set the parameter in the N-server block.

Statistics are calculated and displayed in the simulation summary for the mean, variance, minimum and maximum of the following variables:

- utilization (of the PCC, daily)
- wait in queue (daily average, in minutes)
- number of appointment requests that entered the system (daily)
- number of appointment requests that were served (daily)
- number of appointment requests that were not served (daily)
- number of reminders (daily)
- number of reminders that were served (daily)
- number of reminders that were not served (daily)

A visual representation of the patients using the telephone service is displayed as a patient chart using the last simulation run for the sample data. A histogram of the wait times of each appointment request entity (patients) in the simulation is displayed.

A pseudo code representation of the MATLAB function simPS is shown in Figure 4-8.

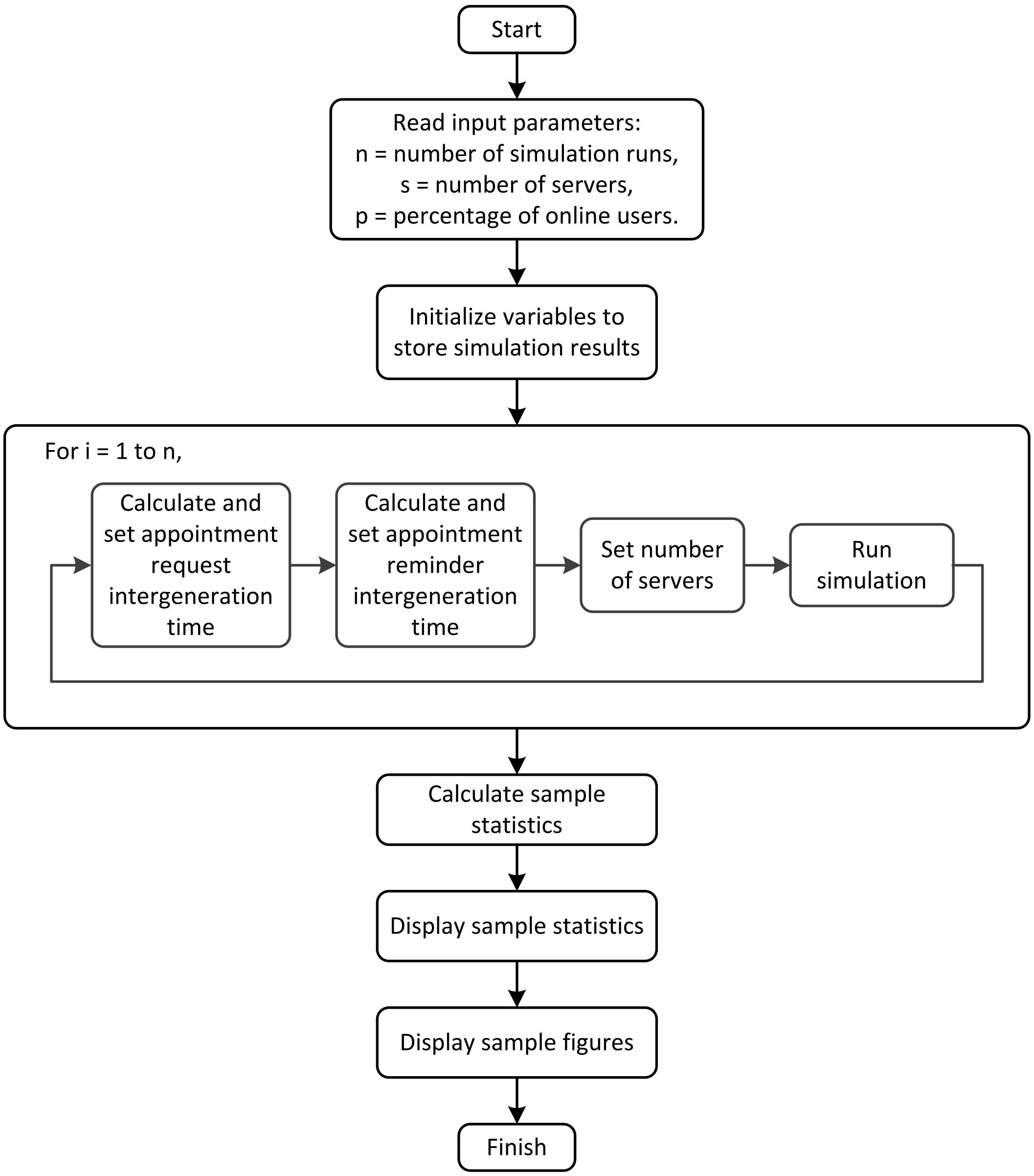


Figure 4-8: Pseudo code representation of MATLAB function simPS

The MATLAB code for the function simPS is given in Appendix A.

4.3 Model Verification and Validation

Model Verification

The summary statistics and the figures of sample data can be examined to ensure that the model has been implemented correctly. The number of appointment request entities and reminder entities are designed to be generated from known distributions, so the mean and variance of these values can be verified. Of course, the simulation output can only be expected to approach these values for a large number of simulation runs, so some discrepancy can be expected for a small number of trials runs.

Furthermore, the number of patients in the process can be examined in the figure of the sample data to ensure that the flow of patients is as expected. That is, one would expect that the number of patients served would never exceed the number entering the queue or the system.

Expected Outputs for Existing Patient Scheduling Process

Unfortunately, closed form expressions could not be found for the utilization and wait time in queue for the $M_1 D_2^m/M_1 M_2/1/PRI\text{-}FCFS/\infty/\infty$ queue system. Fortunately, there are closed form expressions for the $M_1 M_2/M_1 M_2/1/PRI\text{-}FCFS/\infty/\infty$ queue system, which we can use to approximate values expected for the patient scheduling system.

For a non-preemptive priority queue system, Pooch and Wall (1993) write:

> Suppose that a total of r priority classes of customers are serviced by a single-channel service facility. Assume that the priority class numbers are assigned such that a lower number implies a higher priority. Suppose also that the arrival process of the kth class is Poisson with rate λ_k, while the service time required for the kth class customer is exponential with rate μ_k. Then define
>
> $$\rho_k = \frac{\lambda_k}{\mu_k}, 1 \leq k \leq r$$
>
> and the system will reach steady state if $\sum_{k=1}^{r} \rho_k < 1$. It is convenient to define $\sigma_k = \sum_{i=1}^{k} \rho_i$. Then the requirement for the system to reach steady state is $\sigma_r < 1$.

If the system has reached steady state, the expected waiting time (time in the queue) for a customer in the ith priority class is given by

$$W_q^{(i)} = \frac{\sum_{k=1}^{r}\left(\frac{\rho_k}{\mu_k}\right)}{(1-\ \sigma_{i-1})(1-\sigma_i)}$$

(p. 366)

In the patient scheduling process, we have a Poisson arrival for class 1 (requests, q) and a general distribution for class 2 (reminders, m). Let's approximate the arrival rate λ_2 as the expected number of reminders divided by the minutes in the day to get

$$\lambda_2 = \frac{E[m]}{T} = \frac{72.5\ [reminders]}{480\ [minutes]} = 0.1510\ \left[\frac{reminders}{minute}\right]$$

In other words, we assume that the reminder entities arrive throughout the day instead of all within the first minute of the day.

Then

$$\rho = \ \rho_1 + \ \rho_2 = \frac{\lambda_1}{\mu_1} + \frac{\lambda_2}{\mu_2} = 0.60 + 0.15 = \ 0.76$$

Since the utilization can be interpreted as the proportion of time that the server is busy, we can derive an alternate expression for utilization as

$$\rho = \ \rho_1 + \ \rho_2 = \frac{E[q]\ E\left[\frac{1}{\mu_1}\right]}{T} + \frac{E[m]\ E\left[\frac{1}{\mu_2}\right]}{T}$$

where $E[q]$ = expected number of requests to be served (daily) = 72.5

$E[1/\mu_1]$ = expected service time for requests (in minutes) = 4

$E[m]$ = expected number of reminders to be served (daily) = 72.5

$E[1/\mu_2]$ = expected service time for reminders (in minutes) = 1

T = total time in a day (in minutes) = 480

The result of this expression is the same as the result obtained above.

Using the same approximation for the arrival rate of the reminder entities as above, we can calculate the average wait in the queue for patients requesting an appointment as

$$W_q^{(1)} = \frac{\left(\frac{\rho_1}{\mu_1} + \frac{\rho_2}{\mu_2}\right)}{1 - \rho_1} = 6.5\ [minutes]\ or\ 6{:}30\ [mm{:}ss]$$

Alternatively, if we temporarily ignore the reminder entities altogether, we can calculate the wait in queue for the M/M/1 system to be

$$W_q = \frac{\lambda}{\mu(\mu - \lambda)} = 6.1\ [minutes]\ or\ 6{:}06\ [mm{:}ss]$$

For the $D_2^m/M_1\,M_2/1$/PRI-FCFS/∞/∞ queue system, we may expect the wait in queue for patients in the range of 6.1 to 6.5 minutes.

This analysis provides estimates for the utilization and wait in queue for the existing patient scheduling process (where there is one PCC and no online system).

Expected Outputs for Patient Scheduling Process with Two PCCs

We can use the results above to further estimate the values expected for the alternative process (where there are two PCCs). If we temporarily ignore the second priority class of reminders, we can borrow results from the simpler M/M/1 and M/M/2 queue systems, to estimate the expected reduction in utilization and waiting time in the queue.

For the M/M/1 system, utilization is given by $\rho = \lambda/\mu$ and for the M/M/C system, by $\rho = \lambda/C\mu$. Hence, we can expect that the utilization will be reduced to one-half since there are two servers instead of one. An estimate of the utilization in this case is 0.38.

For the M/M/C system, Pooch and Wall (1993) provide a closed form expression for W_q as follows:

$$W_q = \left[\frac{(\lambda/\mu)^C \mu}{(C-1)!\,(C\mu - \lambda)^2}\right] P_0$$

$$P_0 = \left[\sum_{j=0}^{C-1} \frac{1}{j!}\left(\frac{\lambda}{\mu}\right)^j + \frac{1}{C!}\left(\frac{\lambda}{\mu}\right)^C \left(\frac{C\mu}{C\mu - \lambda}\right)\right]^{-1}$$

(p. 362)

P_0 is the probability that there are no customers in the system.

For C = 2 servers, the expression for W_q (after some algebra) reduces to

$$W_q = \frac{-\lambda^2}{\mu(\lambda - 2\mu)(\lambda + 2\mu)}$$

Substituting the values for λ_1 and μ_1 into the expression for W_q for the M/M/2 queue results in 0.4 minutes. Recall the result for the M/M/1 queue was determined above to be 6.1 minutes. The results from this simplified case show that there is approximately a 93% reduction in the wait in queue when the number of servers increases from one to two. One can show that this ratio holds for some variation in the arrival rate and the service rate. Therefore, an estimate of the wait in queue for the priority queue with two servers is 93% of the estimate for one server.

Using the estimate obtained above for the wait in the priority queue for priority class one (6.1 to 6.5 minutes), the estimated wait time in the two server queue is approximately 0.43 to 0.46 minutes, or 25 to 27 seconds.

Expected Outputs for Patient Scheduling Process with Online Service

For the second alternative, where the demand is reduced by a proportion p of patients that use the online service, we can use the expressions above and replace the arrival rates λ_i with reduced arrival rates $(1 - p)\,\lambda_i$ to derive the following relationships.

$$\rho_p = \rho_{1_p} + \rho_{2_p} = \frac{\lambda_{1_p}}{\mu_1} + \frac{\lambda_{2_p}}{\mu_2} = \frac{(1-p)\lambda_1}{\mu_1} + \frac{(1-p)\lambda_2}{\mu_2}$$

$$= (1-p)\rho_1 + (1-p)\rho_2 = (1-p)\rho$$

$$W_q^{(1)}{}_p = \frac{\left(\frac{\rho_{1_p}}{\mu_1} + \frac{\rho_{2_p}}{\mu_2}\right)}{1-\rho_{1_p}} = \frac{\left(\frac{(1-p)\rho_1}{\mu_1} + \frac{(1-p)\rho_2}{\mu_2}\right)}{1-(1-p)\rho_1} = \frac{(1-p)(1-\rho_1)}{(1-(1-p)\rho_1)} W_q^{(1)}$$

Substituting for $\rho = 0.76$ and $\rho_1 = 0.60$, gives the following estimates for utilization and wait in queue when the demand is reduced by a proportion p.

$$\rho_p = 0.76(1-p)$$

$$W_q^{(1)}{}_p = \frac{2\,(1-p)}{3p+2}\, W_q^{(1)}$$

A model verification summary is provided in Table 4-6.

Table 4-6: Model verification summary

Parameter / Key Performance Measure	Patient Scheduling Process		
	Existing process (one server)	**Alternative process (two servers)**	**Alternative process (one server, online usage rate p)**
Requests (mean)	72.5	72.5	72.5 x (1 – p)
Requests (variance)	72.5	72.5	72.5 x (1 – p)
Reminders (mean)	72.5	72.5	72.5 x (1 – p)
Reminder (variance)	6.25	6.25	6.25
Utilization (ρ)	0.76	0.38	0.76 x (1 – p)
Wait in queue ($W_q^{(1)}$) (minutes)	6.1 – 6.5	0.43 – 0.46	(6.1 – 6.5) x $\frac{2\,(1-p)}{3p+2}$

Model Validation

Since this is a hypothetical physician office, actual data cannot be obtained to compare with the simulation results. In reality, one could collect data from the actual office to determine statistics on call volume and pattern and appointment volume and pattern. One could also monitor the patient care coordinator to determine the actual utilization and log the actual wait times of callers over a long period of time and compare these results with the output of the simulation to validate the model.

4.4 Experimental Design and Analysis of Alternative Processes

4.4.1 Experimental Design

Once the models have been verified, a simulation of the processes will be conducted to estimate the system performance. The key performance measures and the desired accuracy of estimation identified in Section 4.1.1 are repeated below in Table 4-7.

Table 4-7: Key performance measures and desired accuracy of estimation

Performance Measure	Description	Desired 95% Confidence Interval
Utilization of the PCC (ρ)	Proportion of time PCC is busy	$\rho \pm 0.025$
Average time in queue ($W_q^{(1)}$)	Average time a patient waits on hold using the telephone service	$W_q^{(1)} \pm 15$ (s)

Each simulation run will produce one data point, or one sample, for each performance measure. Recall that the simulation run length is the equivalent of one day. Then the output of the simulation run will be the proportion of time the PCC was busy during that (simulated) day and the average time a patient waits on hold for the calls received that day. Clearly, these performance measures will vary from day to day, or from one simulation run to the next. Although the results of one day provides an estimate of the performance measures, a more accurate estimate can be obtained by obtaining a series of samples, and generating an average from the samples. One approach would be to run the simulation an infinite number of times, from which one could expect to generate a really accurate estimate. This is not practical, and obviously not practicable.

Instead, we can determine a suitable number of simulation runs to obtain a desired accuracy with some knowledge of the variance of the parameter we wish to estimate. Because the variance of the actual parameter (σ^2) is not known, we estimate this variance with the variance of the sampled data (s^2).

Suppose we run n simulation runs and obtain n estimates for the key performance measure θ. For large samples, we can expect that the sampling distribution of estimates $(\theta_1, \theta_2, \cdots \theta_n)$ approaches a normal distribution. Then $Z = \frac{\bar{\theta} - \theta}{\sigma_{\bar{\theta}}}$ approaches the standard normal distribution, where

$\bar{\theta} = \frac{1}{n} \sum_{i=1}^{n} \theta_i$ is the point estimator of the parameter θ, and

$\sigma_{\bar{\theta}} = \frac{\sigma}{\sqrt{n}} \approx \frac{s}{\sqrt{n}}$ is the standard error of the estimator $\bar{\theta}$,

and we can expect $100(1-\alpha)\%$ of the estimates to be within $z_{\alpha/2}\sigma_{\bar{\theta}}$ of the actual parameter θ. For a 95% confidence interval ($\alpha = 0.05$) we have $z_{0.025} = 1.96$.

Then we can equate the desired confidence interval to $1.96\sigma_{\bar{\theta}}$, or $2\sigma_{\bar{\theta}}$ for a conservative estimate and easier calculation, to estimate the number of simulation runs required to obtain the desired accuracy of estimation.

For the key performance measure of utilization (ρ), the desired confidence interval is 0.025. Equating $0.025 = 2 \frac{s(\rho)}{\sqrt{n}}$, yields $n_1 = 6400\, s^2(\rho)$, where $s^2(\rho)$ is the sample variance of the parameter ρ.

For the key performance measure of the average wait in queue ($W_q^{(1)}$), the desired confidence interval is 15 seconds, or 0.25 minutes. Equating $0.25 = 2 \frac{s(W_q^{(1)})}{\sqrt{n}}$, yields $n_2 = 64\, s^2(W_q^{(1)})$, where $s^2(W_q^{(1)})$ is the sample variance of the parameter ($W_q^{(1)}$).

For each patient scheduling process, a preliminary set of 30 simulation runs will be used to generate preliminary estimates of the key performance measures. From the preliminary estimates, the number of simulation runs required to generate the desired estimation accuracy of the key performance measures will be calculated. Since there are two performance measures of interest, and hence two estimates of the number of required runs, the larger estimate of the two will be used and rounded up to the nearest set of 100 simulation runs.

The experimental design is summarised in Figure 4-9.

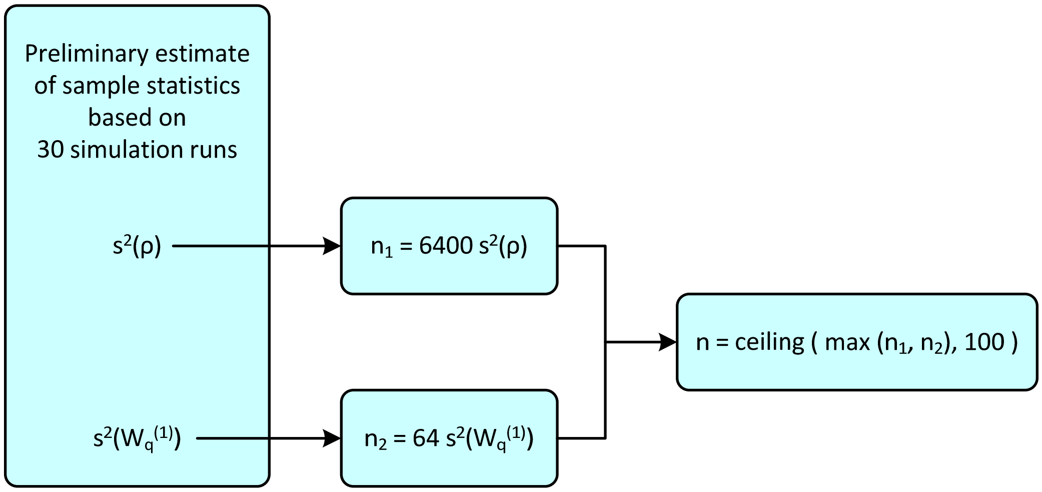


Figure 4-9: Experimental design to determine number of simulation runs

4.4.2 Parameter Estimation

Once the number of simulation runs has been determined from the preliminary runs, a simulation will be conducted to generate an interval estimate with the desired accuracy for the two key performance measures.

We can construct a $100(1-\alpha)\%$ confidence interval for a parameter θ that we wish to estimate from a sample $(\theta_1, \theta_2, \cdots \theta_n)$ as

$$\bar{\theta} \pm t_{(\alpha/2,n-1)}\sigma_{\bar{\theta}}$$

where $t_{(\alpha/2,n-1)}$ is the value of t-distribution with $n-1$ degrees of freedom such that $P(-t_{\alpha/2} \leq T \leq t_{\alpha/2}) = 1-\alpha$. The t-distribution is used for parameter estimation and the comparison of alternatives in the next section instead of the normal distribution so that no assumption is made on the sample size, or number of simulation runs. The resulting confidence intervals will have a slightly larger range than if the normal distribution had been used, but the difference will become negligible as the t-distribution approaches the normal distribution for increasing degrees of freedom, or number of simulations.

The 95% confidence interval for utilization ρ will be

$$\bar{\rho} \pm t_{(0.025,n-1)}\sqrt{\frac{s^2(\rho)}{n}}$$

where $\bar{\rho}$ is the mean utilization and $s^2(\rho)$ is the sample variance in utilization output from the simulation runs.

The 95% confidence interval for the average wait in the queue $W_q^{(1)}$ will be

$$\overline{W_q^{(1)}} \pm t_{(0.025,n-1)}\sqrt{\frac{s^2(W_q^{(1)})}{n}}$$

where $\overline{W_q^{(1)}}$ is the mean wait in queue and $s^2(W_q^{(1)})$ is the sample variance of the wait in queue output from the simulation runs.

These confidence intervals resulting from the number of simulation runs estimated from the preliminary statistics should be within the desired estimation accuracy. If they are not, the number of simulation runs should be increased until a confidence interval of the desired estimation accuracy can be generated.

4.4.3 Comparison of Alternative Processes

Suppose an estimate of a key performance measure generated by simulating the existing process with n_0 simulation runs is given by $\bar{\theta}_0$ with a sample variance of s_0^2 and an estimate of that measure generated by simulating an alternate process with n_1 simulation runs is given by $\bar{\theta}_1$ with a sample variance of s_1^2. Suppose that a smaller value of θ indicates a more desirable outcome, for example, in the wait in queue. Suppose the result of the alternate process appears to be an improvement over the existing process, that is $\bar{\theta}_1 < \bar{\theta}_0$, and assume that the variance of the actual measure in the two processes are equal, that is $\sigma_1^2 = \sigma_0^2$. Hypothesis testing will be used to compare the two results.

To show that the alternate process is indeed an improvement over the existing process, we will form the null hypothesis, H_0: $\theta_1 - \theta_0 = 0$ $(\theta_1 = \theta_0)$ and the alternative hypothesis, H_a: $\theta_1 - \theta_0 < 0$ $(\theta_1 < \theta_0)$.

The test statistic is given by

$$T = \frac{\overline{\theta_1} - \overline{\theta_0}}{S_p\sqrt{\frac{1}{n_1} + \frac{1}{n_0}}}$$

where

$$S_p = \sqrt{\frac{(n_1 - 1)s_1^2 + (n_0 - 1)s_0^2}{n_1 + n_0 - 2}}$$

is the pooled estimator for σ^2.

If the test statistic falls in the rejection region $\{t < -t_{\alpha,n_1+n_0-2}\}$, then we can reject the null hypothesis in favor of the alternative hypothesis. We can then conclude that there is sufficient evidence (at an α level of significance) that $\theta_1 < \theta_0$ and the alternate process offers an improvement over the existing process. There is a probability of α that the null hypothesis will be rejected when it is true.

4.5 Results

This section provides the results of the patient scheduling process evaluation, following the analysis methods outlined in Section 4.4. The SimEvents model and MATLAB function developed in Section 4.2 will be used to simulate the existing patient scheduling process and its alternatives.

In each scenario, the model will be verified through trial runs, preliminary runs will be conducted to determine the experimental design, and the simulation will be conducted to generate interval estimates of the key performance measures.

4.5.1 Existing Patient Scheduling Process

In the existing patient scheduling process, the telephone service is the only service option and there is one patient care coordinator.

Model Verification

Ten trial runs of this simulation are conducted using the MATLAB function simPS(10,1,0). The MATLAB command window is shown in Figure 4-10.

```
>> simPS(10,1,0)
**********************************************************************
*  Patient Scheduling Simulation                                     *
*  Number of simulation runs: 10                                     *
*  Number of servers: 1                                              *
*  Online usage rate: 0  %                                           *
*                                                                    *
*  Simulation statistics                                             *
*                          mean     variance    minimum     maximum  *
*  utilization             0.760    0.010       0.637       0.944    *
*  wait in queue           6.51     9.57        2.25        9.16     *
*                                                                    *
*  requests                72.3     67          62          89       *
*  requests served         69.3     79          59          89       *
*  requests not served     3.0      3           0           5        *
*                                                                    *
*  reminders               72.2     8           68          76       *
*  reminders served        72.2     8           68          76       *
*  reminders not served    0.0      0           0           0        *
**********************************************************************
```

Figure 4-10: Sample output for simPS(10,1,0)

The sample figures showing the flow of patients in the system and the histogram of the wait times are shown in Figure 4-11 and Figure 4-12, respectively.

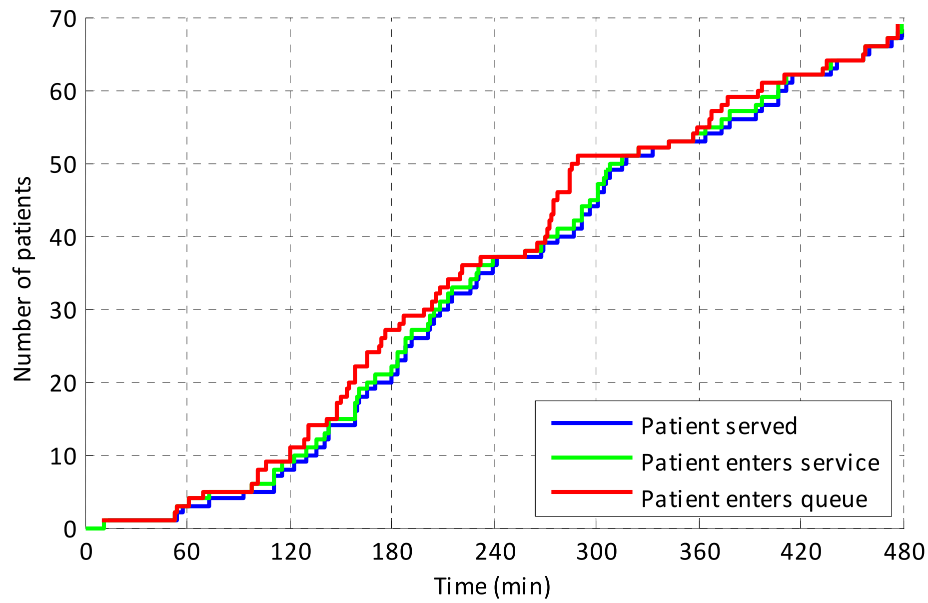


Figure 4-11: Sample patient chart for simPS(10,1,0)

We verify from the patient chart that the patients enter the queue for service, exit the queue to be served, and complete service and leave the system. We note that the number of patients served never exceeds the number of patients that have arrived in the queue.

We also observe the wait time in the queue (the horizontal distance between the red and green lines) and the number of patients waiting on hold (the vertical distance between the red and green lines) varies through the day.

The service times (the horizontal distance between the green and blue lines) also vary - one could verify that these service times follow the exponential distribution as designed. In this scenario where there is one server, we observe that the number of patients being served at any particular time (the vertical distance between the green and blue lines) never exceeds one.

Also interesting to note is that some requests that have entered the queue do not get served. In this representation of the process, the simulation ends after precisely 480 minutes. That is, the patient care coordinator finishes the work day after precisely 8 hours, and does not serve any patients left on hold at that time, and even hangs up on the call in progress at that time! We can see that patients calling the office right before the office is about to close for the day may not receive service, and may even be hung up on.

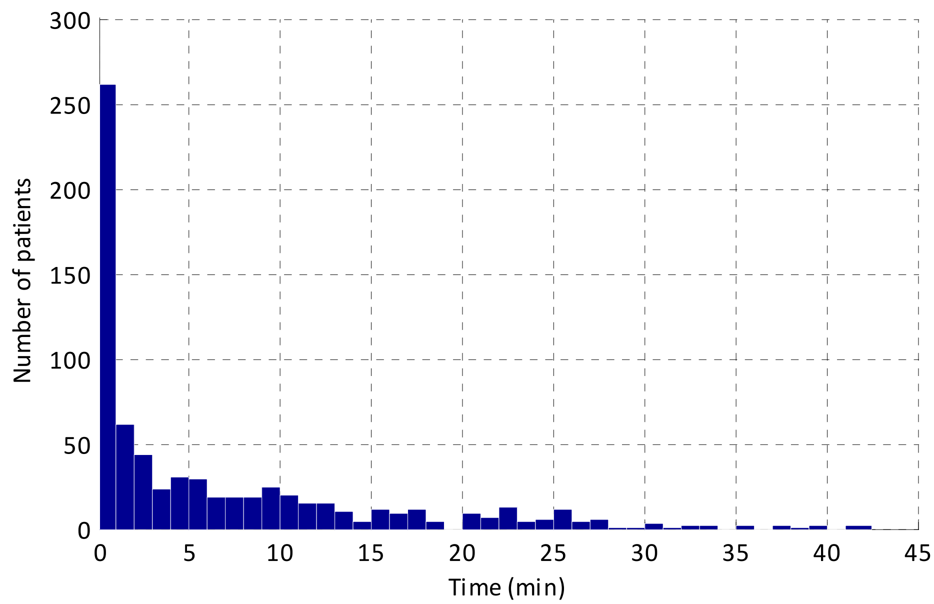


Figure 4-12: Sample wait time histogram for simPS(10,1,0)

The histogram of wait times provides further insight into the interpretation of the average wait time statistic. Although the average wait time is 6.51 minutes, the large majority of callers experience a wait time much shorter than the average.

The outputs of the simulation are compared with the expected values derived in Section 4.3 as verification of the model. The results are as expected and are summarised in Table 4-8.

Table 4-8: Verification summary for simPS(10,1,0)

Parameter / Key Performance Measure	Expected Value	Obtained Value	Accept
Requests (mean)	72.5	72.3	✓
Requests (variance)	72.5	67	✓
Reminders (mean)	72.5	72.2	✓
Reminders (variance)	6.25	8	✓
Utilization (ρ)	0.76	0.760	✓
Wait in queue ($W_q^{(1)}$)	6.1 – 6.5	6.51	✓

Experimental Design

Following the verification and validation from the trial runs, we conduct a set of preliminary simulation runs to estimate the variance in the key performance measures, using the MATLAB function, simPS(30,1,0). The MATLAB command window is shown in Figure 4-13.

```
>> simPS(30,1,0)
*********************************************************************
*  Patient Scheduling Simulation                                    *
*  Number of simulation runs: 30                                    *
*  Number of servers: 1                                             *
*  Online usage rate: 0  %                                          *
*                                                                   *
*  Simulation statistics                                            *
*                       mean     variance    minimum     maximum    *
*  utilization          0.764    0.009       0.618       0.980      *
*  wait in queue        6.20     17.90       1.97        16.73      *
*                                                                   *
*  requests             72.9     61          61          85         *
*  requests served      71.3     57          60          84         *
*  requests not served  1.6      4           0           10         *
*                                                                   *
*  reminders            73.4     5           70          78         *
*  reminders served     73.4     5           70          78         *
*  reminders not served 0.0      0           0           0          *
*********************************************************************
```

Figure 4-13: Sample output for simPS(30,1,0)

The experimental design, or the number of simulation runs, that we estimate will be required to generate interval estimates of the key performance measures with the desired confidence interval is calculated and summarised in Table 4-9.

Table 4-9: Number of simulation runs calculated from preliminary simulation simPS(30,1,0)

Sample Statistic	Obtained Value	Number of simulation runs
$s^2(\rho)$	0.009	$n_1 =$ 58
$s^2(W_q^{(1)})$	17.90	$n_2 =$ 1146
		n = 1200

Process Simulation

A simulation is conducted to generate an interval estimate of the key performance measures with the desired accuracy of estimation, using the MATLAB function simPS(1200,1,0). The MATLAB command window is shown in Figure 4-14.

```
>> simPS(1200,1,0)
**********************************************************************
*  Patient Scheduling Simulation                                     *
*  Number of simulation runs: 1200                                   *
*  Number of servers: 1                                              *
*  Online usage rate: 0  %                                           *
*                                                                    *
*  Simulation statistics                                             *
*                        mean     variance    minimum     maximum    *
*  utilization           0.746    0.010       0.494       0.995      *
*  wait in queue         5.98     16.23       1.26        27.00      *
*                                                                    *
*  requests              72.7     67          56          89         *
*  requests served       71.2     69          53          89         *
*  requests not served   1.5      3           0           12         *
*                                                                    *
*  reminders             72.6     6           65          81         *
*  reminders served      72.6     6           65          81         *
*  reminders not served  0.0      0           0           0          *
**********************************************************************
```

Figure 4-14: Sample output for simPS(1200,1,0)

A 95% confidence interval is generated from the sample statistics for the key performance measures summarised in Table 4-10.

Table 4-10: Key performance measures for existing patient scheduling process

Performance Measure	Desired 95% Confidence Interval
Utilization of the PCC (ρ)	ρ = 0.746 ± 0.006 or (0.740, 0.752)
Average time in queue ($W_q^{(1)}$)	$W_q^{(1)}$ [mm:ss] = 5:59 ± 0:14 or (5:45, 6:12)

The histogram of wait times for each patient in each of the 1200 simulation runs is shown in Figure 4-15.

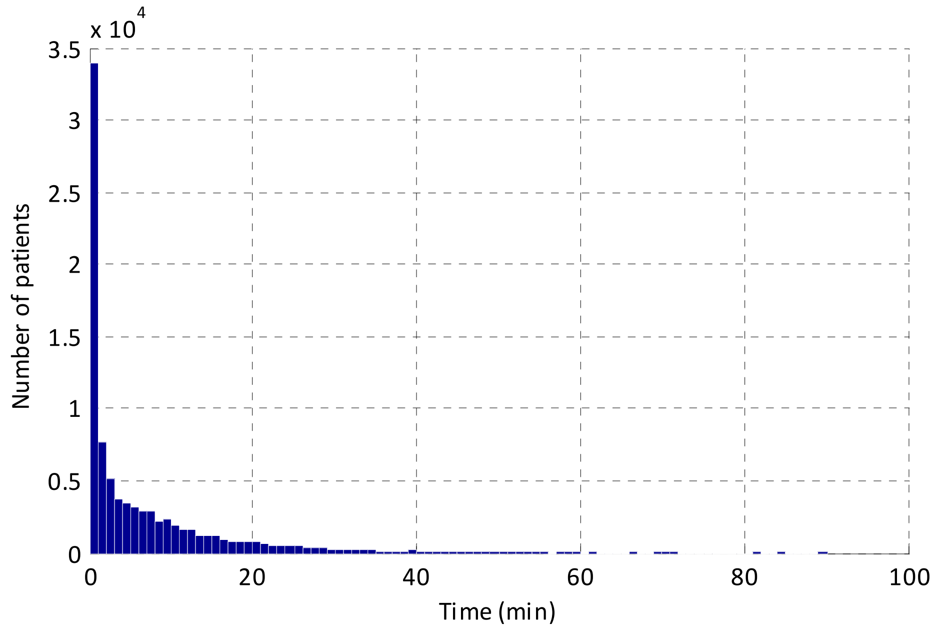


Figure 4-15: Sample wait time histogram for simPS(1200,1,0)

From this histogram, it clear that a large majority of patients wait less than the average time reported of 6 minutes. The average statistic is common and simple to use, but may give an unnecessary negative impression of the existing system. No doubt there are some callers that do experience exceedingly long wait times, but the majority of patients do not wait very long.

4.5.2 Patient Scheduling Process with Two Patient Care Coordinators

The alternative patient scheduling process where a second patient care coordinator is available is examined. The telephone service is still the only service option, but the service supply is increased by increasing the number of servers from one to two.

Model Verification

Ten trial runs of this simulation are conducted using the MATLAB function simPS(10,2,0). The MATLAB command window is shown in Figure 4-16.

```
>> simPS(10,2,0)
**********************************************************************
*  Patient Scheduling Simulation                                     *
*  Number of simulation runs: 10                                     *
*  Number of servers: 2                                              *
*  Online usage rate: 0  %                                           *
*                                                                    *
*  Simulation statistics                                             *
*                       mean     variance    minimum     maximum     *
*  utilization          0.366    0.004       0.292       0.476       *
*  wait in queue        0.50     0.08        0.16        1.13        *
*                                                                    *
*  requests             66.5     75          57          87          *
*  requests served      66.3     74          57          87          *
*  requests not served  0.2      0           0           2           *
*                                                                    *
*  reminders            73.1     7           69          77          *
*  reminders served     73.1     7           69          77          *
*  reminders not served 0.0      0           0           0           *
**********************************************************************
```

Figure 4-16: Sample output for simPS(10,2,0)

The sample figures showing the flow of patients in the system and the histogram of the wait times are shown in Figure 4-17 and Figure 4-18, respectively.

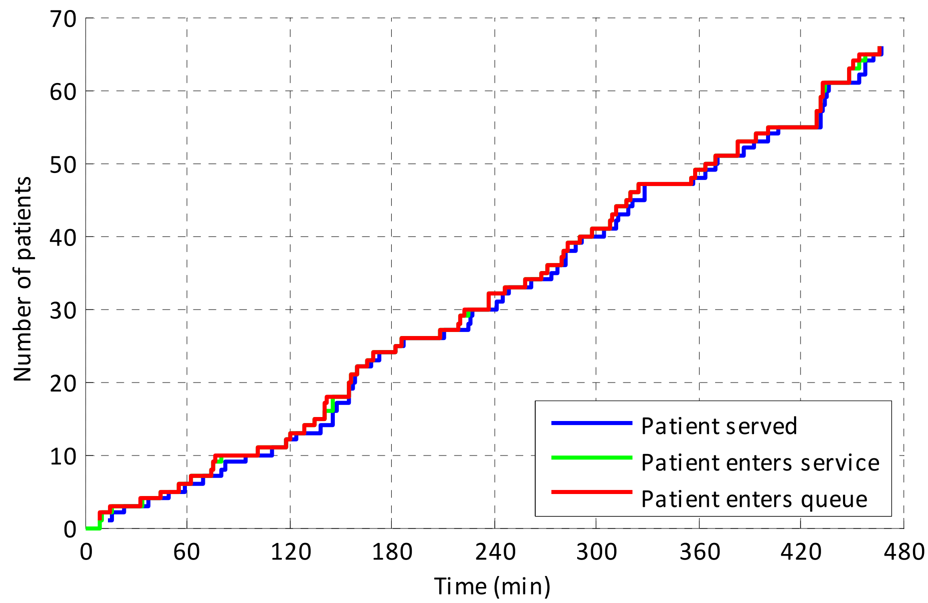


Figure 4-17: Sample patient chart for simPS(10,2,0)

Again, we verify from the patient chart that the patients enter the queue for service, exit the queue to be served, and complete service and leave the system. Similarly, we note that the number of patients served never exceeds the number of patients that have arrived in the queue and that the wait time in the queue varies through the day.

Comparing the sample patient chart with that obtained in the existing system (Figure 4-11), the average wait in the queue (the horizontal distance between the red and green lines) as well as the number of callers waiting on hold (the vertical distance between the red and green lines) appear to have reduced. Many callers experience no wait at all and therefore the green line is not always visible in the chart as the portions of the red and green lines are identical.

Similarly, service times (the horizontal distance between the green and blue lines) vary and in this scenario, where there are two servers, the number of patients being served at any particular time (the vertical distance between the green and blue lines) never exceeds two.

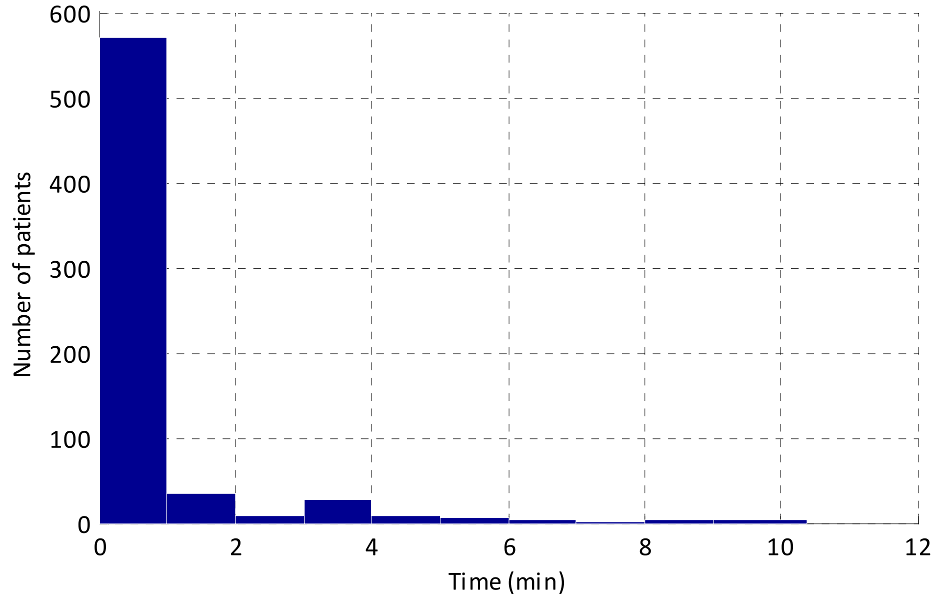


Figure 4-18: Sample wait time histogram for simPS(10,2,0)

Comparing the wait time histogram with that obtained in the existing system (Figure 4-12), we observe that the maximum wait experienced by any patient is reduced and a larger portion of the callers experience a shorter wait time.

The outputs of the simulation are compared with the expected values derived in Section 4.3 as verification of the model. The results are as expected and are summarised in Table 4-11.

Table 4-11: Verification summary for simPS(10,2,0)

Parameter / Key Performance Measure	Expected Value	Obtained Value	Accept
Requests (mean)	72.5	66.5	✓
Requests (variance)	72.5	75	✓
Reminders (mean)	72.5	73.1	✓
Reminders (variance)	6.25	7	✓
Utilization (ρ)	0.38	0.366	✓
Wait in queue ($W_q^{(1)}$)	0.43 – 0.46	0.50	✓

Experimental Design

Following the verification from the trial runs, we conduct a set of preliminary simulation runs to estimate the variance in the key performance measures, using the MATLAB function, simPS(30,2,0). The MATLAB command window is shown in Figure 4-19.

```
>> simPS(30,2,0)
**********************************************************************
*  Patient Scheduling Simulation                                     *
*  Number of simulation runs: 30                                     *
*  Number of servers: 2                                              *
*  Online usage rate: 0  %                                           *
*                                                                    *
*  Simulation statistics                                             *
*                         mean     variance    minimum     maximum   *
*  utilization            0.373    0.003       0.260       0.494     *
*  wait in queue          0.48     0.26        0.04        1.88      *
*                                                                    *
*  requests               71.8     64          58          83        *
*  requests served        71.2     61          58          82        *
*  requests not served    0.6      0           0           2         *
*                                                                    *
*  reminders              73.5     6           67          77        *
*  reminders served       73.5     6           67          77        *
*  reminders not served   0.0      0           0           0         *
**********************************************************************
```

Figure 4-19: Sample output for simPS(30,2,0)

The experimental design, or the number of simulation runs, that will be required to generate interval estimates of the key performance measures with the desired confidence interval is calculated and summarised in Table 4-12.

Table 4-12: Number of simulation runs calculated from preliminary simulation simPS(30,2,0)

Sample Statistic	Obtained Value	Number of simulation runs
$s^2(\rho)$	0.003	$n_1 =$ 19
$s^2(W_q{}^{(1)})$	0.26	$n_2 =$ 17
		n = 100

Process Simulation

The results of the preliminary run suggest that only 20 simulation runs are needed to generate an interval estimate of the key performance measures within the desired accuracy of estimation. The variance of the key performance measures obtained in this scenario is much lower than for the previous case. However, keeping with the experimental method, we will conduct 100 trials to generate the interval estimate of the key performance measures, using the MATLAB function, simPS(100,2,0). The MATLAB command window is shown in Figure 4-20.

```
**********************************************************************
*   Patient Scheduling Simulation                                    *
*   Number of simulation runs: 100                                   *
*   Number of servers: 2                                             *
*   Online usage rate: 0  %                                          *
*                                                                    *
*   Simulation statistics                                            *
*                         mean     variance    minimum     maximum   *
*   utilization           0.374    0.002       0.248       0.499     *
*   wait in queue         0.44     0.14        0.06        2.31      *
*                                                                    *
*   requests              72.3     71          56          89        *
*   requests served       71.6     71          55          89        *
*   requests not served   0.8      1           0           3         *
*                                                                    *
*   reminders             72.5     6           68          79        *
*   reminders served      72.5     6           68          79        *
*   reminders not served  0.0      0           0           0         *
**********************************************************************
```

Figure 4-20: Sample output for simPS(100,2,0)

A 95% confidence interval is generated from the sample statistics for the key performance measures summarised in Table 4-13.

Table 4-13: Key performance measures for patient scheduling process with two PCCs

Performance Measure	Desired 95% Confidence Interval
Utilization of the PCC (ρ)	ρ = 0.374 ± 0.009 or (0.365, 0.383)
Average time in queue ($W_q^{(1)}$)	$W_q^{(1)}$ [mm:ss] = 0:26 ± 0:04 or (0:22, 0:31)

A considerable improvement in the average wait time in queue is suggested from the output of this simulation, compared with the existing process. The histogram of wait times for each patient in each of the 100 simulation runs is shown in Figure 4-21.

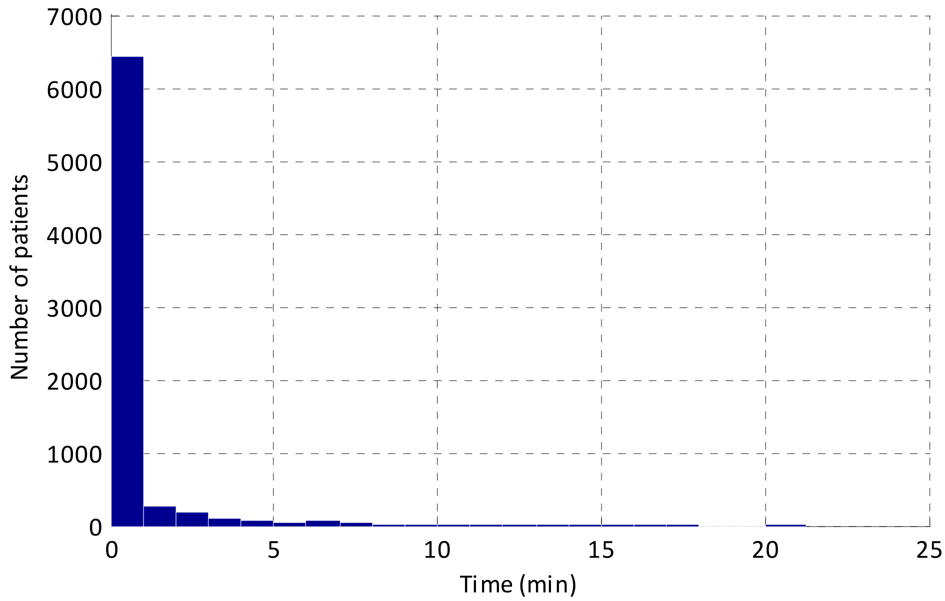


Figure 4-21: Sample wait time histogram for simPS(100,2,0)

In this scenario, the average wait time statistic is very close to the wait time experienced by most callers. That is, the mean and the mode of the sample are very close.

4.5.3 Patient Scheduling Process with Online Service Option

The alternative patient scheduling process where an online appointment scheduling system has been made available is examined. The telephone service with one patient care coordinator is still available, but the demand on the telephone system is reduced by a proportion p of patients that opt to use the online system.

The results will be provided in detail, as in the previous sections, for one value of p. Then a summary of results obtained for other values of p will be provided.

The simulation will be run first, with a value of p that may be realistic for the system. That is, if an online system is implemented, it is predicted that perhaps 20% of patients will choose this option. This is only a marginal decrease in the demand on the telephone system and it is not expected that this will produce an improvement in the wait time on hold as significant as increasing the supply of service. Subsequently, the simulation will be run with a range of values for p to determine, what level of usage, if any, could result in the significant improvement suggested in the previous section.

Model Verification

Ten trial runs of this simulation are conducted using the MATLAB function simPS(10,1,20). The MATLAB command window is shown in Figure 4-22.

```
>> simPS(10,1,20)
*********************************************************************
*  Patient Scheduling Simulation                                    *
*  Number of simulation runs: 10                                    *
*  Number of servers: 1                                             *
*  Online usage rate: 20 %                                          *
*                                                                   *
*  Simulation statistics                                            *
*                        mean     variance    minimum     maximum   *
*  utilization           0.593    0.011       0.450       0.718     *
*  wait in queue         3.29     3.49        1.32        5.54      *
*                                                                   *
*  requests              58.0     72          47          75        *
*  requests served       57.5     74          45          74        *
*  requests not served   0.5      1           0           2         *
*                                                                   *
*  reminders             57.8     5           55          61        *
*  reminders served      57.8     5           55          61        *
*  reminders not served  0.0      0           0           0         *
*********************************************************************
```

Figure 4-22: Sample output for simPS(10,1,20)

The sample figures showing the flow of patients in the system and the histogram of the wait times are shown in Figure 4-23 and Figure 4-24, respectively.

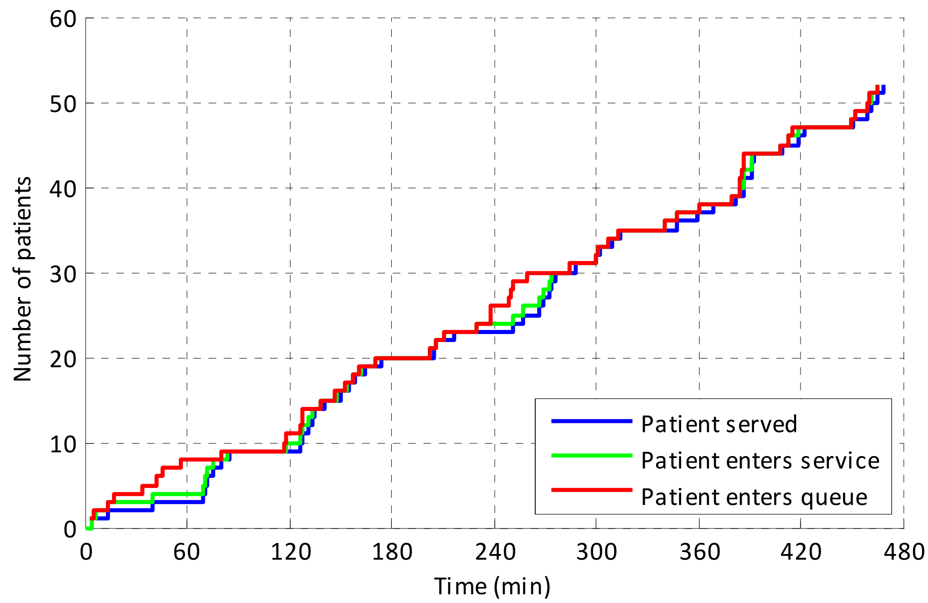


Figure 4-23: Sample patient chart for simPS(10,1,20)

Again, we verify from the patient chart that the patients enter the queue for service, exit the queue to be served, and complete service and leave the system. Similarly, we note that the number of patients served never exceeds the number of patients that have arrived in the queue and that the wait time in the queue varies through the day.

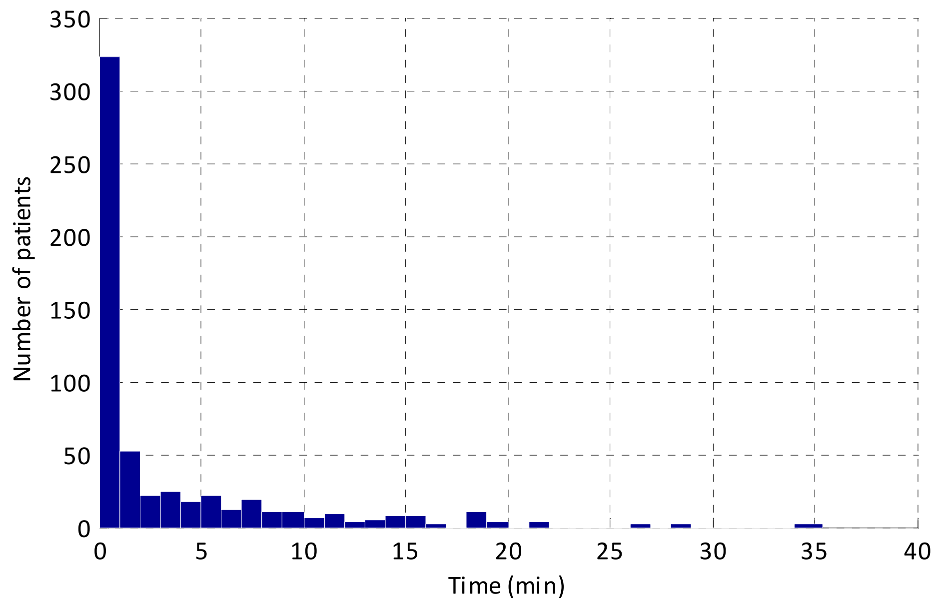


Figure 4-24: Sample wait time histogram for simPS(10,1,20)

The outputs of the simulation are compared with the expected values derived in Section 4.3 as verification of the model. The results are as expected and are summarised in Table 4-14.

Table 4-14: Verification summary for simPS(10,1,20)

Parameter / Key Performance Measure	Expected Value	Obtained Value	Accept
Requests (mean)	58.0	58.0	✓
Requests (variance)	58.0	72	✓
Reminders (mean)	58.0	57.8	✓
Reminders (variance)	6.25	5	✓
Utilization (ρ)	0.61	0.593	✓
Wait in queue ($W_q^{(1)}$)	3.8 – 4.0	3.29	✓

Experimental Design

Following the verification from the trial runs, we conduct a set of preliminary simulation runs to estimate the variance in the key performance measures, using the MATLAB function, simPS(30,1,20). The MATLAB command window is shown in Figure 4-25.

```
>> simPS(30,1,20)
***********************************************************************
*  Patient Scheduling Simulation                                      *
*  Number of simulation runs: 30                                      *
*  Number of servers: 1                                               *
*  Online usage rate: 20 %                                            *
*                                                                     *
*  Simulation statistics                                              *
*                        mean     variance    minimum     maximum     *
*  utilization           0.591    0.012       0.414       0.841       *
*  wait in queue         3.82     10.08       1.02        13.46       *
*                                                                     *
*  requests              56.2     56          44          73          *
*  requests served       55.5     57          44          73          *
*  requests not served   0.7      1           0           2           *
*                                                                     *
*  reminders             57.9     5           54          62          *
*  reminders served      57.9     5           54          62          *
*  reminders not served  0.0      0           0           0           *
***********************************************************************
```

Figure 4-25: Sample output for simPS(30,1,20)

The experimental design, or the number of simulation runs, that will be required to generate interval estimates of the key performance measures with the desired confidence interval is calculated and summarised in Table 4-15.

Table 4-15: Number of simulation runs calculated from preliminary simulation simPS(30,1,20)

Sample Statistic	Obtained Value	Number of simulation runs
$s^2(\rho)$	0.012	$n_1 = 77$
$s^2(W_q^{(1)})$	10.08	$n_2 = 645$
		n = 700

Process Simulation

A simulation is conducted to generate an interval estimate of the key performance measures with the desired accuracy of estimation, using the MATLAB function simPS(700,1,20). The MATLAB command window is shown in Figure 4-26.

```
>> simPS(700,1,20)
**********************************************************************
*  Patient Scheduling Simulation                                     *
*  Number of simulation runs: 700                                    *
*  Number of servers: 1                                              *
*  Online usage rate: 20 %                                           *
*                                                                    *
*  Simulation statistics                                             *
*                        mean     variance    minimum     maximum    *
*  utilization           0.603    0.010       0.367       0.857      *
*  wait in queue         3.75     7.15        0.50        13.46      *
*                                                                    *
*  requests              57.7     68          39          76         *
*  requests served       56.8     62          39          74         *
*  requests not served   0.9      2           0           5          *
*                                                                    *
*  reminders             58.1     6           50          66         *
*  reminders served      58.1     6           50          66         *
*  reminders not served  0.0      0           0           0          *
**********************************************************************
```

Figure 4-26: Sample output for simPS(700,1,20)

A 95% confidence interval is generated from the sample statistics for the key performance measures summarised in Table 4-16.

Table 4-16: Key performance measures for patient scheduling process with 20% online usage rate

Performance Measure	Desired 95% Confidence Interval
Utilization of the PCC (ρ)	ρ = 0.603 ± 0.007 or (0.596, 0.610)
Average time in queue ($W_q^{(1)}$)	$W_q^{(1)}$ [mm:ss] = 3:45 ± 0:12 or (3:33, 3:57)

We observe that the estimated average wait time resulting from a 20% online rate has decreased by approximately 37% from the existing process.

The histogram of wait times for each patient in each of the 700 simulation runs is shown in Figure 4-27.

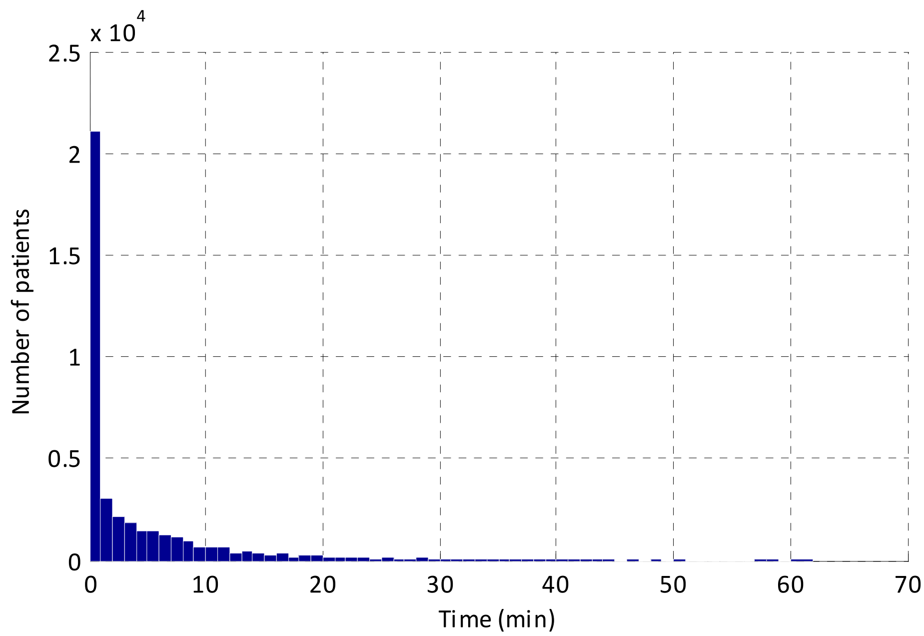


Figure 4-27: Sample wait time histogram for simPS(700,1,20)

Summary of Results for Various Usage Rates of Online Service

A range of values for p, the proportion of patients that use the online service, were simulated. For each value of p, the same analysis method presented in the previous section is followed.

A comparison of the average wait time in queue for the alternative process scenarios is shown in Figure 4-28. The estimates and the 95% confidence intervals are shown as well as the expected values. Note that a range of expected values is shown for the average wait time in queue. Also note the apparent rise in average wait time at the right tail of the chart is caused by the data point for the scenario with two patient care coordinators, and not to be interpreted as the trend in the data.

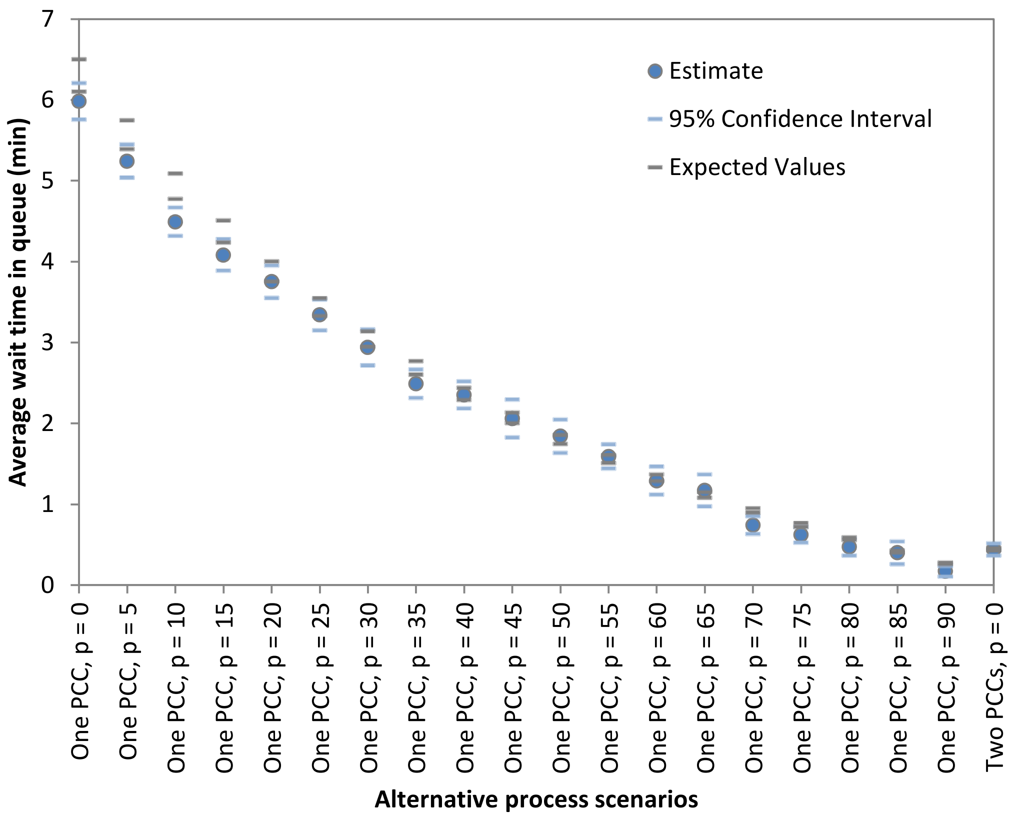


Figure 4-28: Comparison of wait in queue for alternative process scenarios

The output of the simulation matches closely to the expected values. As expected the average wait time in the queue for patients calling the office to request an appointment decreases as the demand (or call volume) decreases. It is also interesting to note that the rate of decline in the average wait time decreases for increasing values of p, the proportion of online users.

A comparison of the utilization for the alternative process scenarios is shown in Figure 4-29. The estimates and the 95% confidence intervals are shown as well as the expected values. Again, note the sharp rise in utilization at the right tail of the chart is caused by the data point for the scenario with two patient care coordinators, and not to be interpreted as the trend in the data.

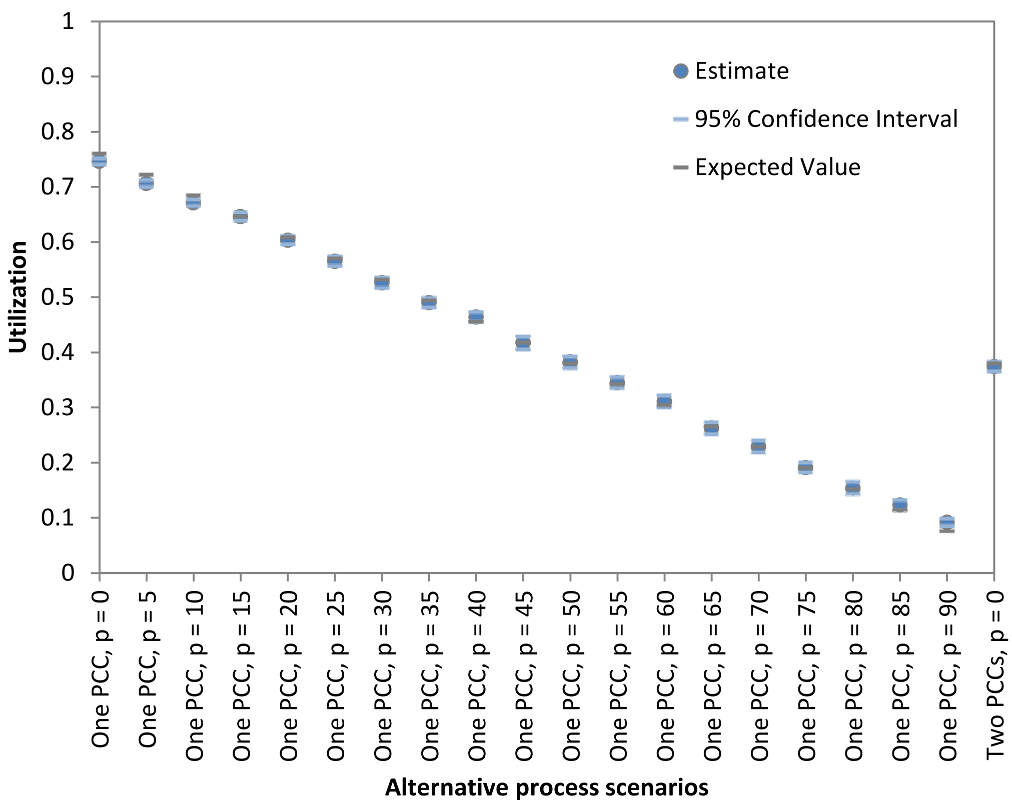


Figure 4-29: Comparison of utilization for alternative process scenarios

The output of the simulation matches closely to the expected values. As expected the utilization of the PCC decreases as the demand (or call volume) decreases.

The simulation results for various process scenarios have been presented in detail in this section and match closely with the expected values. These results will be compared and discussed in the next section. The results demonstrate the model has good predictive qualities and additional modifications to the system will be simulated to provide further insight. These results and some sensitivity analysis of the system will be provided in the following section.

4.6 Discussion

The results obtained in the previous section will be compared and discussed in this section. Other possible modifications to the system will also be examined offering some sensitivity analysis of the system. In any case, the objective of the physician's office will be to maximise utilization of the patient care coordinator while minimizing the wait time for their patients.

4.6.1 Increasing Supply of Service

One possible alternative to the existing process is to increase the supply of service by hiring a second patient care coordinator. This will decrease the wait time for patients but at a cost of decreasing the utilization of the servers.

Recall the estimated key performance measures obtained for these two scenarios obtained in the previous section. These are shown in Table 4-17.

Table 4-17: Key performance measures for patient scheduling process with one and two patient care coordinators

Patient Scheduling Process	95% Confidence Interval of Key Performance Measures	
	Utilization of the PCC (ρ)	Average time in queue ($W_q^{(1)}$)
Existing process (one server)	0.746 ± 0.006 or (0.740, 0.752)	5:59 ± 0:14 or (5:45, 6:12)
Alternative process (two servers)	0.374 ± 0.009 or (0.365, 0.383)	0:26 ± 0:04 or (0:22, 0:31)

Since the 95% confidence intervals for the key performance measures from the two processes do not overlap, it seems obvious that the two performance measures are reduced in the alternative process. However, keeping with the proposed analysis method, hypothesis testing will be used for confirmation, as outlined in Section 4.4.3. The analysis is summarised in Table 4-18.

Table 4-18: Hypothesis testing for patient scheduling process with one and two PCCs

Hypothesis testing for utilization (ρ)		
One server statistics	**Two servers statistics**	**Statistical test (α = 0.05)**
$\bar{\theta}_0 = 0.746$ $s_0^2 = 0.010$ $n_0 = 1200$	$\bar{\theta}_1 = 0.374$ $s_1^2 = 0.002$ $n_0 = 100$	H_0: $\theta_1 - \theta_0 = 0$ ($\theta_1 = \theta_0$) H_a: $\theta_1 - \theta_0 < 0$ ($\theta_1 < \theta_0$) T = -36.8836 RR: {t < -1.6460}
Conclusion: reject H_0 ($\theta_1 = \theta_0$), accept H_a ($\theta_1 < \theta_0$) (at an α level of significance)		
Hypothesis testing for average time in queue ($W_q^{(1)}$)		
One server statistics	**Two servers statistics**	**Statistical test (α = 0.05)**
$\bar{\theta}_0 = 5.98$ $s_0^2 = 16.23$ $n_0 = 1200$	$\bar{\theta}_1 = 0.44$ $s_1^2 = 0.14$ $n_0 = 100$	H_0: $\theta_1 - \theta_0 = 0$ ($\theta_1 = \theta_0$) H_a: $\theta_1 - \theta_0 < 0$ ($\theta_1 < \theta_0$) T = -13.7418 RR: {t < -1.6460}
Conclusion: reject H_0 ($\theta_1 = \theta_0$), accept H_a ($\theta_1 < \theta_0$) (at an α level of significance)		

The wait time on hold for patients calling the office is significantly reduced when there is an increase in the supply of service. A frequency distribution comparing the wait times in queue for the two scenarios, adapted from the histogram figures from the SimPS MATLAB function, is shown in Figure 4-30. Note that a proportion of patients do experience a wait time longer than ten minutes, but the chart is truncated to focus on the more frequent, shorter wait times.

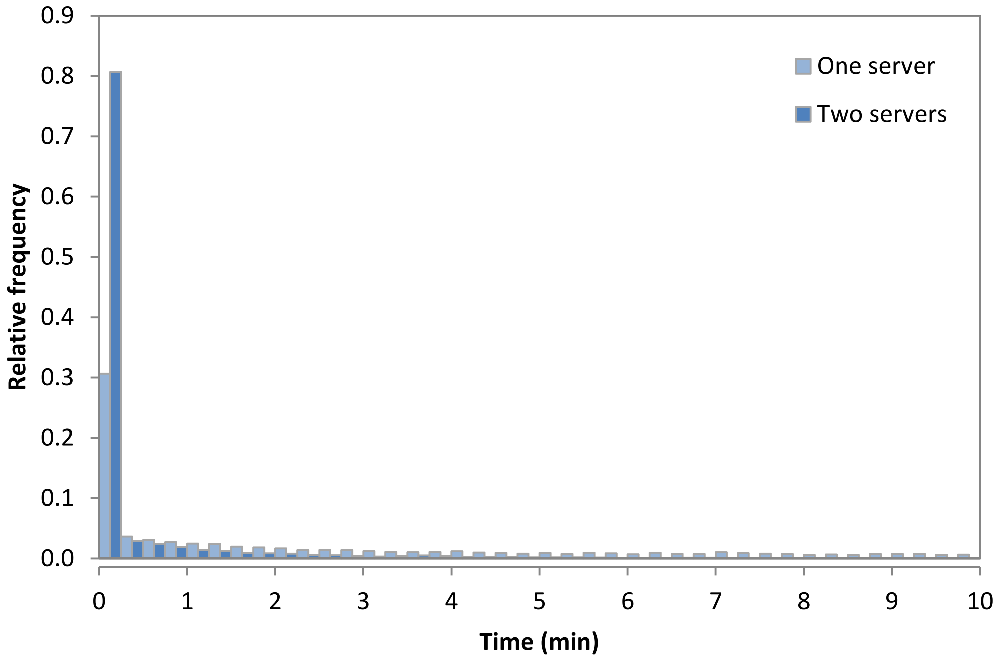


Figure 4-30: Frequency comparison of wait in queue for one and two server processes

This figure shows that 40% of patients wait less than one minute in the case of one server and 88% wait less than one minute in the case of two servers. In the case of two servers, only 7% wait more than two minutes, while in the case of one server, over 50% wait more than two minutes.

Although the scenario with two patient care coordinators offers a significant improvement in wait times for the patients, the utilization of each server is also significantly reduced. This means that the patient care coordinators are idle more often than they are busy. From the physicians' point of view, it would be difficult to justify the additional costs of hiring a second patient care coordinator without a high level of utilization for the additional resource. A better alternative may be to hire a part-time patient care coordinator to help serve the demand. The current model assumes a homogeneous Poisson arrival process for the demand; in reality, the process is likely better described by a non-homogeneous process to account for the time of day, or day of week, or other seasonal effects. If a more accurate representation of the demand could be formulated, the peak demand periods could be identified and a part-time patient care coordinator could be scheduled during the peak periods. The model would also need to be modified to simulate the effects of the part-time patient care coordinator as it currently only models PCCs in full-time efforts (integral values for s).

4.6.2 Decreasing Demand of Service

One possible alternative for decreasing the demand of the telephone service is to implement an online appointment scheduling system. This alternative would also decrease the wait time for patients using the telephone service and decrease the utilization of the server, although, likely to less extent as the scenario proposed above with two patient care coordinators.

Effects of Online Usage

The proportion of patients who would use the online system would depend on a variety of factors, such as internet availability and usage, ease of use of the online application, or age and willingness to change, among several other factors.

A physician's office could survey their existing patients to estimate the proportion of their patients who would be likely to use the online system for a more accurate input into the model. However, if we assume that 20% of patients would use the online system, we can generate the following estimates for the key performance measures, shown in Table 4-19.

Table 4-19: Key performance measures for patient scheduling process with and without online system

Patient Scheduling Process	95% Confidence Interval of Key Performance Measures	
	Utilization of the PCC (ρ)	Average time in queue ($W_q^{(1)}$)
Existing process (no online system)	0.746 ± 0.006 or (0.740, 0.752)	5:59 ± 0:14 or (5:45, 6:12)
Alternative process (online system, p = 0.20)	0.603 ± 0.007 or (0.596, 0.610)	3:45 ± 0:12 or (3:33, 3:57)

Again, since the 95% confidence intervals for the key performance measures from the two processes do not overlap, it seems obvious that the two performance measures are reduced in the alternative process. However, hypothesis testing will be used for confirmation, as outlined in Section 4.4.3. The analysis is summarised in Table 4-20.

Table 4-20: Hypothesis testing for patient scheduling process with and without online system

Hypothesis testing for utilization (ρ)		
No online system	**Online system (p = 0.20)**	**Statistical test (α = 0.05)**
$\bar{\theta}_0 = 0.746$ $s_0^2 = 0.010$ $n_0 = 1200$	$\bar{\theta}_1 = 0.603$ $s_1^2 = 0.010$ $n_0 = 700$	$H_0: \theta_1 - \theta_0 = 0$ $(\theta_1 = \theta_0)$ $H_a: \theta_1 - \theta_0 < 0$ $(\theta_1 < \theta_0)$ T = -30.0676 RR: {t < -1.6457}
Conclusion: reject H_0 ($\theta_1 = \theta_0$), accept H_a ($\theta_1 < \theta_0$) (at an α level of significance)		
Hypothesis testing for average time in queue ($W_q^{(1)}$)		
No online system	**Online system (p = 0.20)**	**Statistical test (α = 0.05)**
$\bar{\theta}_0 = 5.98$ $s_0^2 = 16.23$ $n_0 = 1200$	$\bar{\theta}_1 = 3.75$ $s_1^2 = 7.15$ $n_0 = 700$	$H_0: \theta_1 - \theta_0 = 0$ $(\theta_1 = \theta_0)$ $H_a: \theta_1 - \theta_0 < 0$ $(\theta_1 < \theta_0)$ T = -13.0620 RR: {t < -1.6457}
Conclusion: reject H_0 ($\theta_1 = \theta_0$), accept H_a ($\theta_1 < \theta_0$) (at an α level of significance)		

Although the wait time on hold is not as drastically reduced as is the case when there are two servers, there is still a significant 37% reduction in the case where 20% of patients use the online system. Although the reduced wait is for the patients who still telephone the clinic, it can be assumed that the online users experience little to no wait for service, dependent on internet connection speed.

A frequency distribution comparing the wait times in queue for the two scenarios, adapted from the histogram figures from the SimPS MATLAB function, is shown in Figure 4-31. Note that a proportion of patients do experience a wait time longer than ten minutes, but the chart is truncated to focus on the more frequent, shorter wait times.

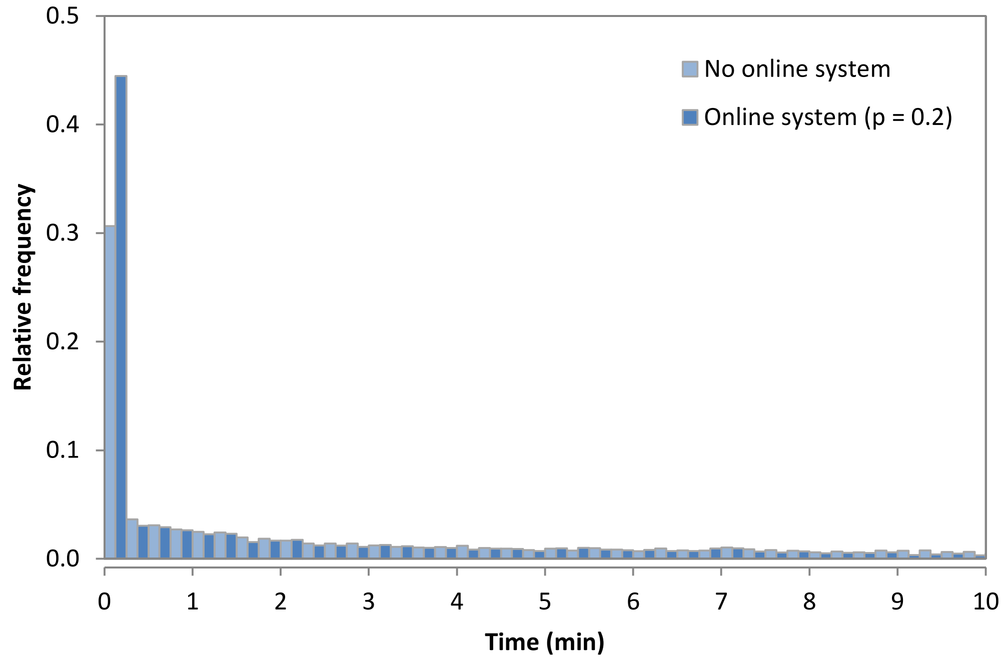


Figure 4-31: Frequency comparison of wait in queue with online system

This figure shows 40% of patients who telephone the clinic wait more than two minutes compared to the base scenario where over 50% wait over two minutes. This is a moderate improvement for telephone service and the PCC is still busy, on average, 60% of the time. This moderate improvement may not however present enough justification for the physicians' office to implement the online appointment scheduling system.

It is also interesting to note that even a small reduction in demand (or proportion of online usage) results in a proportionally higher reduction in the average wait time. The results indicate that a 20% reduction in demand for the telephone service results in a 37% decrease in wait time for the patients that continue to use the telephone service. This proportion decreases though with increasing p, or proportion of online usage, as shown in Figure 4-32. There is decreasing benefit associated with increasing p at higher levels of p – the law of diminishing returns.

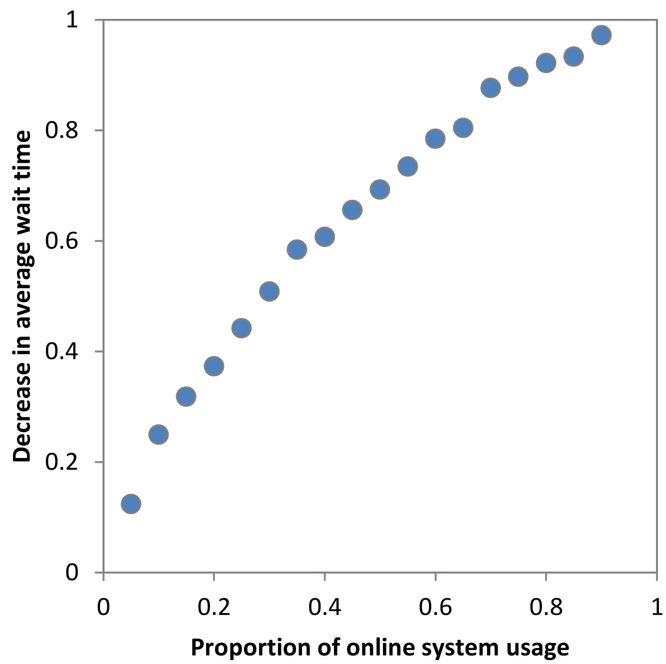


Figure 4-32: Diminishing reductions in average wait time for increasing proportion of online usage

Usage Required to Achieve Results of Increased Supply of Service

Clearly, if a larger proportion of patients decide to use the online system, the reduction in wait times for the patients that still telephone the clinic would be more significant. From the previous section, we can see that a moderate level of online usage results in a moderate decrease in the wait time for telephone service users. So what level of usage would be required to result in a reduction in wait times as significant as the case where there are two PCCs? What level of usage would be required so that a significant portion of the patients using the telephone service experience a wait time of less than two minutes?

Referring to the results for various proportions of online system usage in shown in Figure 4-28, it appears that if 85% of patients use the online system, the average wait time for patients that use the telephone service would be less than that in the case where there are two PCCs. The key performance measures for these two scenarios are repeated in Table 4-21.

Table 4-21: Key performance measures for patient scheduling process with two servers and 85% online usage

Patient Scheduling Process	95% Confidence Interval of Key Performance Measures	
	Utilization of the PCC (ρ)	Average time in queue ($W_q^{(1)}$)
Alternative process (two servers)	0.374 ± 0.009 or (0.365, 0.383)	0:26 ± 0:04 or (0:22, 0:31)
Alternative process (online system, p = 0.85)	0.123 ± 0.009 or (0.114, 0.132)	0:24 ± 0:08 or (0:16, 0:32)

However, hypothesis testing shows there is insufficient evidence to support that if 85% of patients used the online system that the wait time would be less than that in the case where there are two servers. The analysis is summarised in Table 4-22.

Table 4-22: Hypothesis testing for patient scheduling process with two servers and 85% online usage

Hypothesis testing for average time in queue ($W_q^{(1)}$)		
Two servers	**Online system (p = 0.85)**	**Statistical test (α = 0.05)**
$\bar{\theta}_0 = 0.44$ $s_0^2 = 0.14$ $n_0 = 100$	$\bar{\theta}_1 = 0.40$ $s_1^2 = 0.50$ $n_0 = 100$	$H_0: \theta_1 - \theta_0 = 0$ $(\theta_1 = \theta_0)$ $H_a: \theta_1 - \theta_0 < 0$ $(\theta_1 < \theta_0)$ T = -0.5000 RR: {t < -1.6526}
Conclusion: insufficient evidence to reject H_0 and accept H_a ($\theta_1 < \theta_0$) (at an α level of significance)		

Even though it would unrealistic to expect that 90% (or even 85%) of the patients would use the online system, it is possible that this higher usage rate would offer a reduction in wait times compared to the case of two servers. The analysis is summarised in Table 4-23.

Table 4-23: Hypothesis testing for patient scheduling process with two servers and 90% online usage

Hypothesis testing for average time in queue ($W_q^{(1)}$)		
Two servers	**Online system (p = 0.90)**	**Statistical test (α = 0.05)**
$\bar{\theta}_0=0.44$ $s_0^2=0.14$ $n_0=100$	$\bar{\theta}_1=0.17$ $s_1^2=0.11$ $n_0=100$	$H_0: \theta_1 - \theta_0 = 0$ $(\theta_1 = \theta_0)$ $H_a: \theta_1 - \theta_0 < 0$ $(\theta_1 < \theta_0)$ T = -5.4000 RR: {t < -1.6526}
Conclusion: reject H_0 ($\theta_1 = \theta_0$), accept H_a ($\theta_1 < \theta_0$) (at an α level of significance)		

If we assume an aggressive campaign to convince patients to use the online system can result in a 55% adoption rate, we can expect a frequency distribution of the wait times as shown in Figure 4-33.

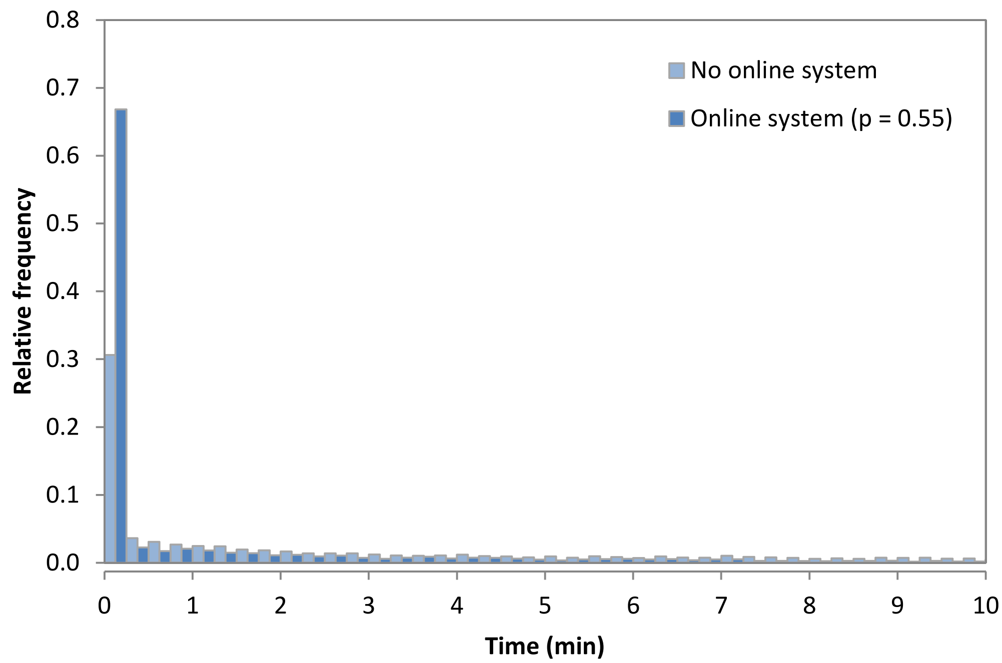


Figure 4-33: Frequency comparison of wait in queue with online system

In this scenario, we can increase the proportion of patients who wait less than two minutes from under 50% in the existing system with no online system to almost 80% if just over half the patients use the online system.

Time-Varying Nature of Technology Adoption

The discussion in the previous section focuses on the steady-state improvements that can be expected if a proportion of the patients use the online appointment scheduling system instead of the traditional method of telephoning the office. That is, what could be expected once a certain fixed proportion of patients consistently use an alternative method of scheduling appointments.

In reality, the rate of technology adoption changes over time depending on a variety of factors and is better modeled with a logistics differential equation (Stewart, 1999) than a step function. The rate of usage from the initial implementation (t = 0) might be very small and it may take some time to see an increase in usage up to some saturation level where there may be no further increase in the rate of usage.

The proportion of patients that use the online system at some time t after implementation may be modeled as

$$p(t) = \frac{K}{1 + Ae^{-rt}}$$

$$A = \frac{K - p_0}{p_0}$$

where

K = saturation level of usage, where no further increase of usage is expected

p_0 = proportion of usage at time of implementation (t = 0)

r = growth rate of usage

If we assume that the expected saturation level is 55% and this steady-state level will be reached in one year, with half of the expected usage in approximately eight months, we can formulate the following:

K = 0.55

p_0 = 0.0001 (an arbitrarily small number)

$t_{1/2}$ = 8 x 30 = 240

A = (0.55 – 0.0001) / 0.0001 = 5499

r = $ln(A)/t_{1/2}$ = ln(5499)/240 = 0.0359

and

$$p(t) = \frac{0.55}{1 + 5499e^{-0.0359t}}$$

The expected usage rate as it increases through the first year of implementation is shown in Figure 4-34.

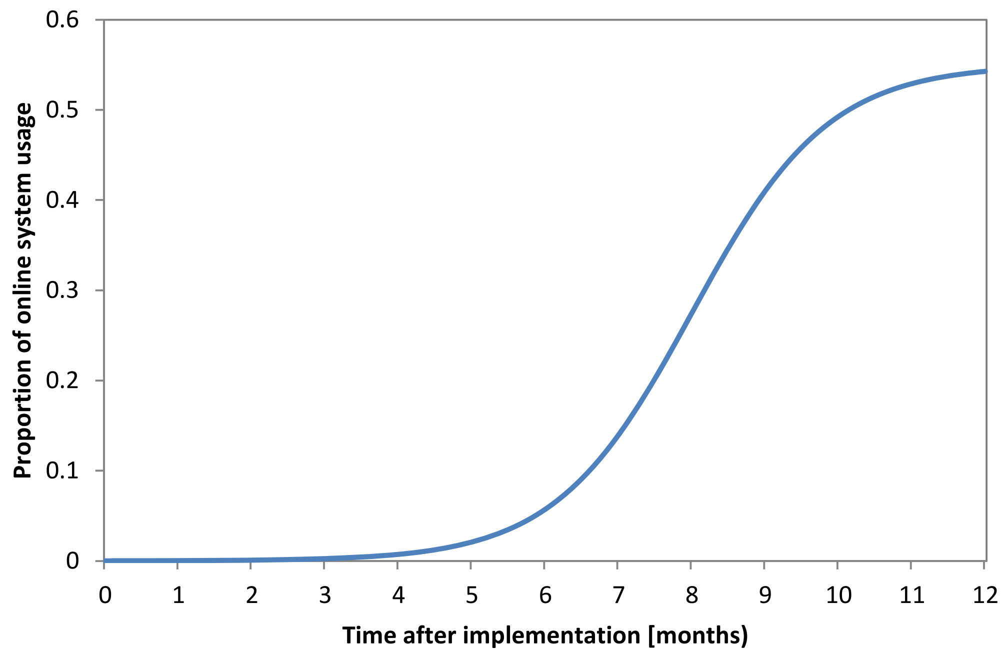


Figure 4-34: Expected increase in online system usage rate

The resulting decrease in expected average wait time for the patients that continue to use the telephone service after the implementation of the online system is shown in Figure 4-35.

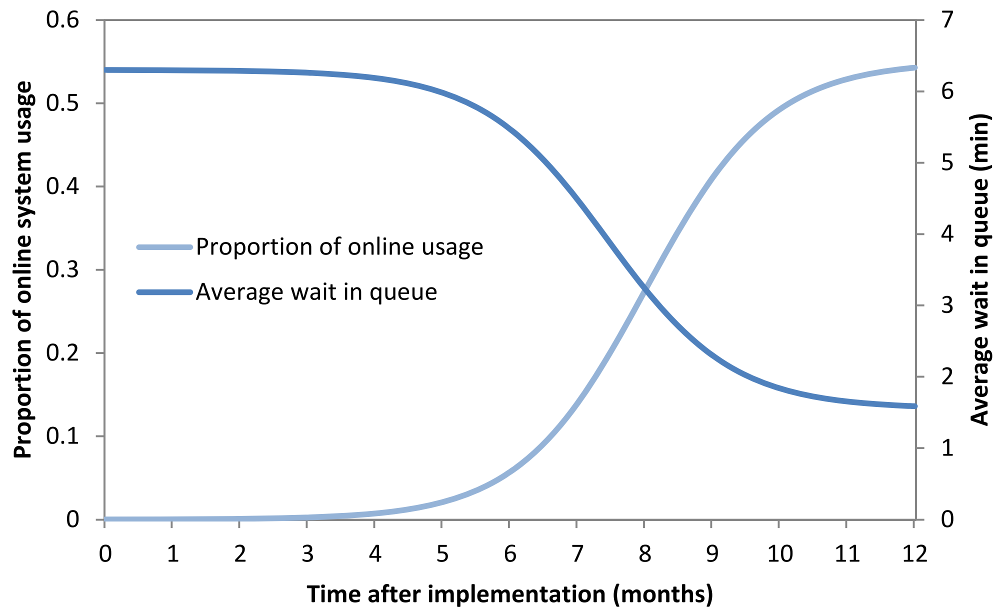


Figure 4-35: Expected decrease in average wait time with increase in online system usage rate

The utilization of the patient care coordinator can also be expected to decrease with increasing online usage, as shown in Figure 4-36. This information may be useful for planning training or additional workload for the patient care coordinator as utilization decreases.

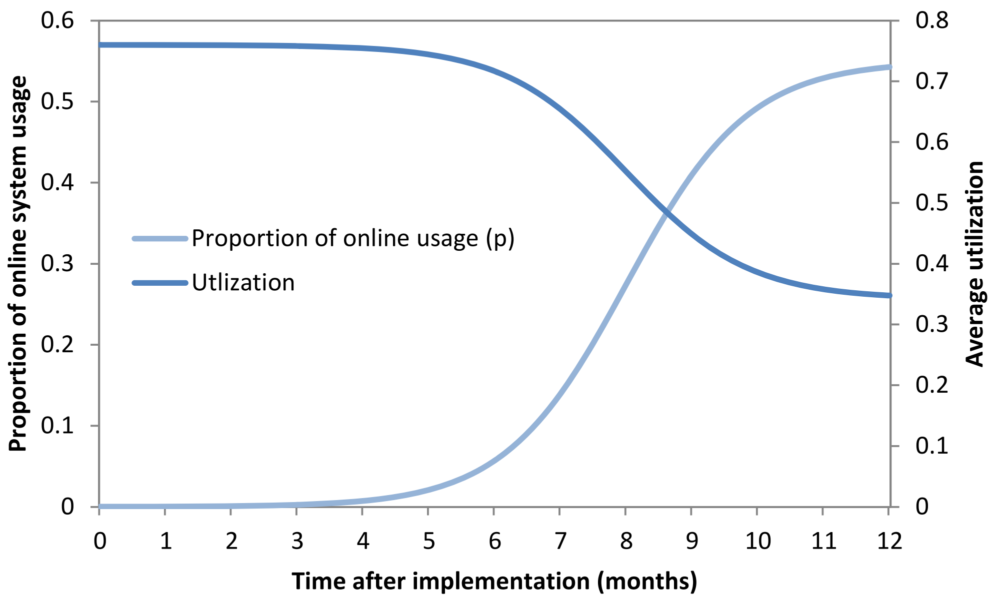


Figure 4-36: Expected decrease in average utilization with increase in online system usage rate

This analysis is based on assumptions of expected online usage and may be reformulated with parameters that might more closely describe the actual patient population. Regardless of the parameter assumptions, the point is that change takes time and expected benefits may also take time to become apparent.

4.6.3 Increasing Demand of Service

If the physicians' office decides to implement an online appointment scheduling system, they may find that patient satisfaction due to level of administrative service increases resulting in an increase in patient referrals. For the formulation of the model, we had assumed that the physician practice was well established and the patient population had reached steady state. But what if the physicians decide to accept more new patients to increase their service or to grow their practice by adding another physician? What can they expect if there is an increase in the demand for service?

From queuing theory, we know that the queue system will only reach steady state if the utilization of the server is less than one. If the utilization of the server is greater than one, we can expect that the number of callers on hold will continue to increase and some may never get served.

The physicians may wish to know how much of an increase in demand for service can they manage without hiring a second patient care coordinator (for the utilization to remain below one), or how high a proportion of online users they should try to convert to maintain some level of service that their existing patients are accustomed to.

Accepting New Patients

Assume that the physicians anticipate a 20% increase in their patient population, but the online system has just recently been implemented and there is very little usage. This scenario can be simulated using the simPS MATLAB function with a negative value for the parameter p.

The MATLAB command window is shown in Figure 4-37. Note the use of the parameter p for an increase in demand and does not reflect a negative online usage rate as indicated in sample output.

```
>> simPS(1200,1,-20)
**********************************************************************
*  Patient Scheduling Simulation                                     *
*  Number of simulation runs: 1200                                   *
*  Number of servers: 1                                              *
*  Online usage rate: -20%                                           *
*                                                                    *
*  Simulation statistics                                             *
*                       mean     variance    minimum     maximum     *
*  utilization          0.876    0.008       0.632       1.000       *
*  wait in queue        9.47     43.49       1.75        34.70       *
*                                                                    *
*  requests             85.9     85          69          109         *
*  requests served      83.5     73          65          104         *
*  requests not served  2.4      8           0           18          *
*                                                                    *
*  reminders            86.9     6           78          95          *
*  reminders served     84.2     108         18          95          *
*  reminders not served 2.7      102         0           73          *
**********************************************************************
```

Figure 4-37: Sample output for simPS(1200,1,-20)

As verification of the adapted use of the parameter p to simulate an increase in demand, we note that the mean and variance of the number of requests and the mean number of reminders is approximately 20% higher than in the existing practice, and the variance in the number of reminders remains unchanged.

For a 20% increase in patients, the utilization of the server does not exceed one, but is very high. The office can get away with not hiring a second patient care coordinator in this scenario, but the patient care coordinator will face an increase in workload and the estimated average wait time increases by 58% from the estimate of the existing practice, from 5.98 to 9.47 minutes.

The model can also be used to simulate an increase in demand by changing the patient population per physician in the m-file for the simPS MATLAB function. Changing the demand in this manner will allow the simulation to be run with various proportions of p (actually reflecting an online usage proportion instead of an increase in demand) to examine whether the increase in wait time resulting from the marginal increase in demand can be counteracted by an increased proportion of online usage.

In the section of the m-file that calculates the demand, shown below,

```
% Calculate daily demand (requests and reminders)
numberOfPhysicians = 3;
patientsPerPhysician = 1000;
consultationsPerYearPerCapita = 5.8;
workingDaysPerYear = 12 * 20;
demand = numberOfPhysicians * patientsPerPhysician * ...
    consultationsPerYearPerCapita / workingDaysPerYear;
```

the line that states

```
patientsPerPhysician = 1000;
```

would be changed to state

```
patientsPerPhysician = 1000 * 1.2;
```

for the case where the demand increases by 20%.

Implementing this change in the m-file and simulating the system for various values of p, we can show that for p = 0.2, we can expect average wait times less than the existing practice. The MATLAB command window in shown in Figure 4-38.

```
>> simPS(1200,1,20)
**********************************************************************
*  Patient Scheduling Simulation                                     *
*  Number of simulation runs: 1200                                   *
*  Number of servers: 1                                              *
*  Online usage rate: 20 %                                           *
*                                                                    *
*  Simulation statistics                                             *
*                        mean     variance    minimum     maximum    *
*  utilization           0.716    0.011       0.495       1.000      *
*  wait in queue         5.30     11.94       1.16        17.78      *
*                                                                    *
*  requests              69.7     74          54          89         *
*  requests served       68.4     79          52          89         *
*  requests not served   1.3      3           0           10         *
*                                                                    *
*  reminders             69.6     6           62          77         *
*  reminders served      69.6     6           62          77         *
*  reminders not served  0.0      0           0           2          *
**********************************************************************
```

Figure 4-38: Sample output for simPS(1200,1,20) – modified m-file

To confirm that the average wait in this scenario is less than the existing practice, we will use the hypothesis testing method summarised in Table 4-24.

Table 4-24: Hypothesis testing for patient scheduling process with 20% increase in demand and 20% online usage

Hypothesis testing for average time in queue ($W_q^{(1)}$)		
Existing practice	**20% increase in patients 20% online usage**	**Statistical test (α = 0.05)**
$\bar{\theta}_0 = 5.98$ $s_0^2 = 16.23$ $n_0 = 1200$	$\bar{\theta}_1 = 5.30$ $s_1^2 = 11.94$ $n_0 = 1200$	$H_0: \theta_1 - \theta_0 = 0$ $(\theta_1 = \theta_0)$ $H_a: \theta_1 - \theta_0 < 0$ $(\theta_1 < \theta_0)$ $T = -4.4382$ RR: $\{t < -1.6455\}$
Conclusion: reject H_0 ($\theta_1 = \theta_0$), accept H_a ($\theta_1 < \theta_0$) (at an α level of significance)		

If the physicians are expecting a 20% increase in patient volume, a 20% adoption rate of the online appointment scheduling system would reduce the increased wait time associated with the higher demand to a level less than the existing practice.

Adding a Physician

Assume that the physicians want to grow their practice and add another physician but they do not want the costs associated with hiring a second patient care coordinator. They may wish to know what the expected utilization of the patient care coordinator will be with the increased patient population or what proportion of their patients they will need to use the online service to maintain the current wait times for the patients who use the telephone service.

This scenario can be simulated by a slight modification to m-file for the simPS MATLAB function, where the number of physicians is declared. The line which states:

```
numberOfPhysicians = 3;
```

would be changed to state:

```
numberOfPhysicians = 4;
```

This change is equivalent to increasing the demand by 33%.

To generate a 95% confidence interval for the key performance measures in this scenario, we can modify the m-file, as described above and follow the analysis method presented in Section 4.4.

To verify the modified model and estimate the number of simulation runs required to generate estimates with the desired confidence intervals, we will run 30 simulations. The MATLAB command window is shown in Figure 4-39.

```
>> simPS(30,1,0)
**********************************************************************
*  Patient Scheduling Simulation                                     *
*  Number of simulation runs: 30                                     *
*  Number of servers: 1                                              *
*  Online usage rate: 0  %                                           *
*                                                                    *
*  Simulation statistics                                             *
*                         mean     variance    minimum     maximum   *
*  utilization            0.941    0.004       0.825       1.000     *
*  wait in queue          12.33    60.94       2.45        36.11     *
*                                                                    *
*  requests               95.5     96          83          121       *
*  requests served        91.5     64          80          106       *
*  requests not served    4.0      22          0           21        *
*                                                                    *
*  reminders              96.8     6           93          101       *
*  reminders served       88.2     274         37          101       *
*  reminders not served   8.6      244         0           56        *
**********************************************************************
```

Figure 4-39: Sample output for simPS(30,1,0) – modified m-file

We can verify that the mean and variance of the number of requests and the mean number of reminders is approximately 33% higher than in the existing practice, and the variance in the number of reminders remains unchanged.

The estimated number of simulation runs that will be required to generate interval estimates of the key performance measures with the desired confidence interval is calculated and summarised in Table 4-25.

Table 4-25: Number of simulation runs calculated from preliminary simulation simPS(30,1,0) – modified m-file

Sample Statistic	Obtained Value	Number of simulation runs
$s^2(\rho)$	0.004	$n_1 =$ 26
$s^2(W_q^{(1)})$	60.94	$n_2 =$ 3900
		n = 4000

We then estimate the key performance measures using the MATLAB function simPS(4000,1,0). The MATLAB command window in shown in Figure 4-40.

```
>> simPS(4000,1,0)
**********************************************************************
*  Patient Scheduling Simulation                                     *
*  Number of simulation runs: 4000                                   *
*  Number of servers: 1                                              *
*  Online usage rate: 0  %                                           *
*                                                                    *
*  Simulation statistics                                             *
*                       mean     variance    minimum     maximum     *
*  utilization          0.949    0.004       0.685       1.000       *
*  wait in queue        13.60    102.11      2.05        64.08       *
*                                                                    *
*  requests             96.5     85          74          123         *
*  requests served      92.5     66          72          120         *
*  requests not served  4.0      16          0           26          *
*                                                                    *
*  reminders            96.6     6           89          105         *
*  reminders served     83.8     460         3           105         *
*  reminders not served 12.8     459         0           96          *
**********************************************************************
```

Figure 4-40: Sample output for simPS(4000,1,0) – modified m-file

A 95% confidence interval is generated from the sample statistics for the key performance measures summarised in Table 4-26.

Table 4-26: Key performance measures for patient scheduling process with additional physician

Performance Measure	Desired 95% Confidence Interval
Utilization of the PCC (ρ)	ρ = 0.949 ± 0.002 or (0.947, 0.951)
Average time in queue ($W_q^{(1)}$)	$W_q^{(1)}$ [mm:ss] = 13:36 ± 0:19 or (13:17, 13:55)

In this scenario, the utilization of the server is very nearly one. The system is near the boundary of reaching a steady-state resulting in a very high variance in average wait times. The estimated average wait time has increased by 127% from the estimate of the existing practice, from 5.98 to 13.6 minutes.

If, however, the office can offset some of the increased demand on the telephone service due to the increase in patient population resulting from the additional physician, they can reduce the utilization and average wait time to a level near the existing practice.

Simulating the system with various values of p, we can show that for p = 0.3, we can expect average wait times less than the existing practice. The MATLAB command window in shown in Figure 4-41.

```
>> simPS(1200,1,30)
***********************************************************************
*  Patient Scheduling Simulation                                      *
*  Number of simulation runs: 1200                                    *
*  Number of servers: 1                                               *
*  Online usage rate: 30 %                                            *
*                                                                     *
*  Simulation statistics                                              *
*                       mean     variance    minimum     maximum     *
*  utilization          0.694    0.010       0.473       0.989       *
*  wait in queue        5.07     9.90        1.12        16.59       *
*                                                                     *
*  requests             68.2     72          49          89          *
*  requests served      66.9     74          48          89          *
*  requests not served  1.3      3           0           11          *
*                                                                     *
*  reminders            67.5     6           60          76          *
*  reminders served     67.5     6           60          76          *
*  reminders not served 0.0      0           0           0           *
***********************************************************************
```

Figure 4-41: Sample output for simPS(1200,1,30) – modified m-file

A 95% confidence interval is generated from the sample statistics for the key performance measures summarised in Table 4-27.

Table 4-27: Key performance measures for patient scheduling process with additional physician and 30% online usage

Performance Measure	Desired 95% Confidence Interval
Utilization of the PCC (ρ)	ρ = 0.694 ± 0.006 or (0.688, 0.700)
Average time in queue ($W_q^{(1)}$)	$W_q^{(1)}$ [mm:ss] = 5:04 ± 0:11 or (4:54, 5:15)

To confirm that the average wait in this scenario is less than the existing practice, we will use the hypothesis testing method summarised in Table 4-28.

Table 4-28: Hypothesis testing for patient scheduling process with an additional physician and 30% online usage

Hypothesis testing for average time in queue ($W_q^{(1)}$)		
Existing practice	**Additional physician 30% online usage**	**Statistical test (α = 0.05)**
$\bar{\theta}_0 = 5.98$ $s_0^2 = 16.23$ $n_0 = 1200$	$\bar{\theta}_1 = 5.07$ $s_1^2 = 9.90$ $n_0 = 1200$	$H_0: \theta_1 - \theta_0 = 0$ $(\theta_1 = \theta_0)$ $H_a: \theta_1 - \theta_0 < 0$ $(\theta_1 < \theta_0)$ T = -6.1668 RR: {t < -1.6455}
Conclusion: reject H_0 ($\theta_1 = \theta_0$), accept H_a ($\theta_1 < \theta_0$) (at an α level of significance)		

If the office wants to expand their practice by one physician, a 30% adoption rate of the online appointment scheduling system would reduce the increased wait time associated with the higher demand to a level less than the existing practice.

4.7 Conclusion

The discrete-event simulation of the existing patient process at a hypothetical primary care physician office is used to estimate the utilization of the patient care coordinator and average wait time on hold for patients calling the office. The estimate indicates a rather long wait time for some patients, with an average of approximately six minutes. Some alternative scenarios that may address these long wait times include hiring a second patient care coordinator and introducing a self-serve online appointment scheduling system.

The improvement in average wait times if the office were to hire a second patient care coordinator is significant, offering a reduction in average wait time of approximately 93%. The significant service improvement offered by increasing the supply of service also results in an underutilization of the service resources, where each patient care coordinator is only busy, on average, 37% of the day. Although the idle time may be put towards other office work, this diversion may result in negative effects on the primary responsibility of answering patient phone calls.

This result suggests that it may be more beneficial to hire a second part-time patient care coordinator to help meet the demand for service during peak demand times. As the model presented in this project assumed a homogeneous Poisson arrival process, this assumption would need to be refined to accurately reflect the variance in demand in order to identify the peak demand times during which a part-time patient care coordinator should be available.

While the analysis has focused on the minimization of average wait times while maximizing the utilization of the patient care coordinator, the actual distribution of wait times suggests that a better metric for comparison or performance target may be to reduce wait times so that a proportion of patients wait less than some specified duration.

Another alternative process that could help reduce wait times is the implementation of a self-serve online appointment scheduling system. The expected steady-state improvement in wait times for telephone service is 37% for a conservative estimate of 20% online usage. The decrease in wait times follows the law of diminishing returns for increased proportion of online users; however, it was shown that, although improbable, a 90% online usage rate would offer the same or more reduction in wait times compared with the scenario with two patient care coordinators. Further insight into the expected benefit of implementing an online system is explored by examining the time-varying nature of technology adoption.

Results also demonstrate that the implementation of an online system may help offset the increase in demand of service if the office accepts new patients or adds another physician. The analysis presents an alternative to increasing administrative overhead by investing in technology.

The patient scheduling process was modeled as a queuing system and closed form expressions for the steady-state expected values of the key performance measures from various queue systems were used to verify the model. The model of the patient scheduling process developed in this project is limited in applicability to the hypothetical primary care physician office defined for the purposes of this project. The verification and analysis of this model, though, has demonstrated that it can provide a base model from which further improvements could be implemented to more accurately reflect the patient scheduling process of a real office. In particular, the arrival process of the patient calls could be studied in reality to determine a more sophisticated representation of the process which could take into account the non-homogeneous nature of call arrivals. Service times could also be studied to determine whether the assumed exponential distribution sufficiently describes the actual process. A survey of the actual patients could provide more insight into the actual expected proportion of patients that would be receptive to using a self-serve online appointment scheduling system. Actual costs of implementation and maintenance of such a system and cost of administrative labor and the hiring process could be analysed to determine the feasibility of the alternatives presented for the actual office.

In the next section, an actual patient care process in the PCN will be modeled and simulated. Whereas the demand model and service times in this section were assumed, the demand models and service times in the next model will be developed based on actual data observed at the PCN. The scope of the model will also be increased from the appointment scheduling process to the entire administrative process of patient care. This expansion in scope also involves the modeling of the actual practices of the patient care coordinator, where certain processes have priority over others. The model will be used to estimate reduction in utilization of the patient care coordinator following the implementation of various ICTs. Some discussion will be provided on sensitivity analysis and modifications to the model to simulate business process reengineering of primary care.

5 Model and Simulation of Patient Care in the PCN

The process model of patient care in the PCN is introduced in Section 5.1. A discrete-event model and simulation is developed in SimEvents and MATLAB to quantitatively describe the process model. The definition of entities in the discrete-event model from the process model is described in Section 5.2 and the model architecture is presented in Section 5.3. Data is collected through observation at the PCN and by review of existing records to specify probability distributions describing entity generation and service times in the discrete-event simulation. Two clinics (Clinic A and Clinic B) from the PCN are examined in this simulation. Entity generation is presented in Section 5.4 and service times are presented in 5.5. The queue and server discipline is described in Section 5.6. Simulation results are presented in Section 5.7 with a discussion in Section 5.8.

5.1 Process Overview

The PCN care process starts when a referral is received for a patient from the referring family physician by the PCN and finishes at the transfer of care back to the referring family physician. A high level process model of care in the PCN is shown in Figure 5-1.

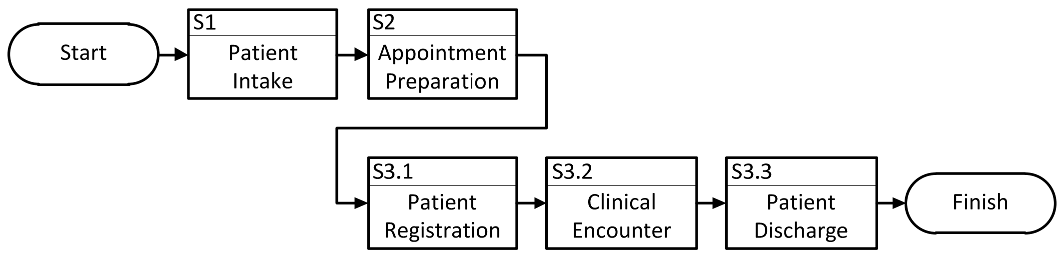


Figure 5-1: High level process model of care in PCN

The high level process model is defined in stages and associated map levels outlined by Mark Murray and Associates (MMA) for Alberta AIM: Access · Improvement · Measures (2010).

The first stage begins when a referral is received by the PCN and ends once an appointment has been scheduled. This patient intake process is illustrated with a Level 1 map. The second stage begins once the appointment has been scheduled and includes preparation prior to the appointment. This appointment preparation process is illustrated with a Level 2 map. The third stage begins when the patient arrives for their appointment and ends when the care is complete. We further divide the third stage into three processes: patient registration, clinical encounter, and patient discharge.

In the levels of mapping outlined by Mark Murray & Associates (2010), a Level 4 map is used to track the patient through the third stage and Level 3a maps illustrate the clinical encounter(s) during the appointment. As the focus of this study is the PCC and not the patient, these levels of mapping will not be used. Level 5 maps, the most detailed and complex, can be used to present details of individual processes.

A more detailed process model is shown in Figure 5-2. We will discuss each process in the following sections.

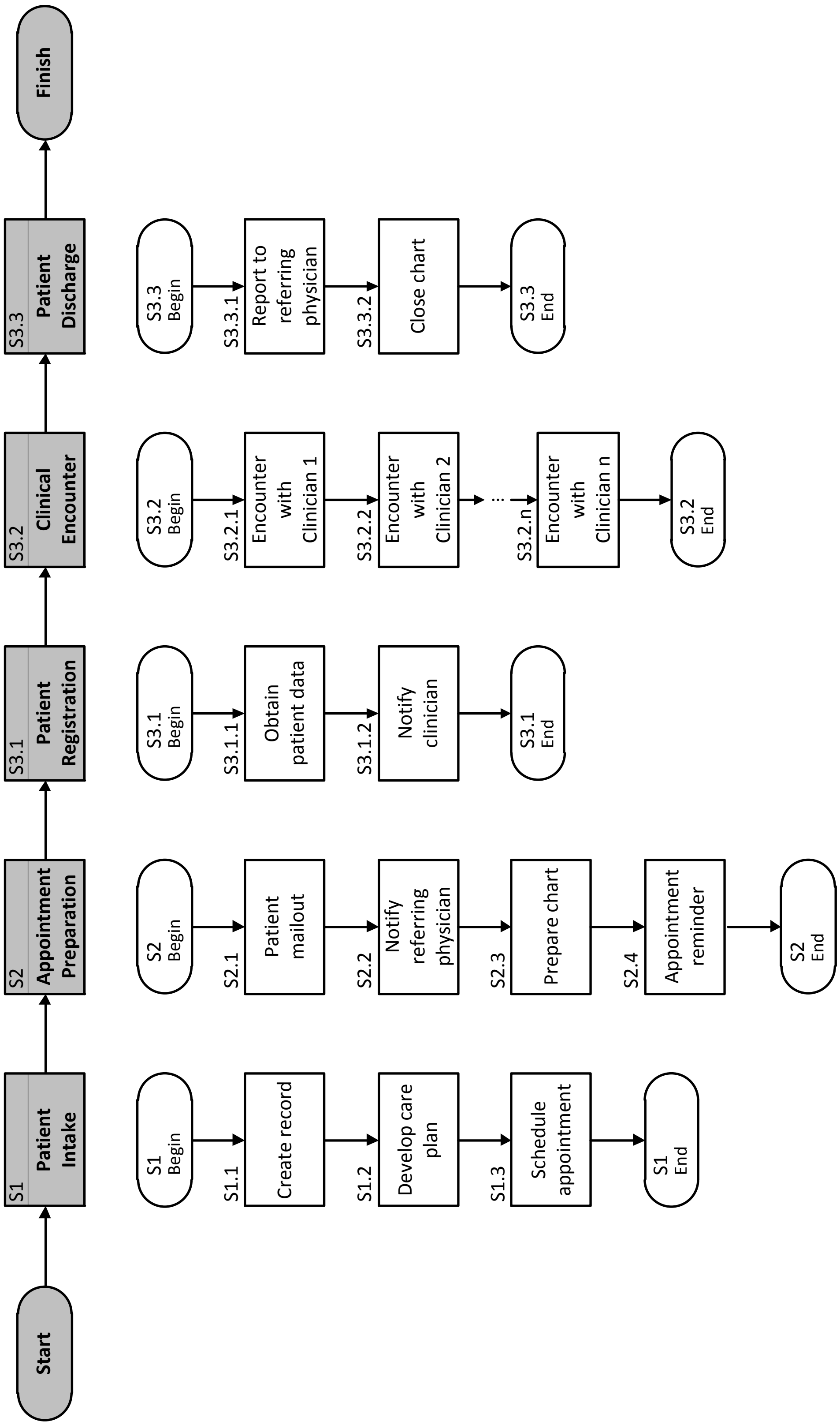


Figure 5-2: Process model

5.1.1 Patient Intake Process

The patient intake process begins when a referral is received by the PCN. The PCC creates a record for each referral and gathers other relevant patient history. The records are used to determine demand on the system by tracking the number of new referrals received by the PCN in a given time period. The referral and the patient history are reviewed by the PCC and/or clinical team to develop a care plan for the patient.

The information flow in the patient intake process is shown in Figure 5-3. For the purpose of understanding the information flow, we extend the scope of the process to the interface with the referring physician. The left portion of the figure denotes activities at the referring physician's office and the right portion of the figure denotes activities in the PCN. The top portion of the figure denotes the flow of information in a paper (physical) format and the shaded bottom portion of the figure denotes the flow of information in electronic format.

The referring physician enters data, including the patient's demographic information, relevant health history and reason for referral into a referral form (1). The referring physician's office faxes the referral (2) which is received by the PCN administrative office (3). The referral is printed (4) and delivered to the PCC (5). The PCC creates a record of the referral (6) and the referral is reviewed by the PCC and/or clinical team to develop a care plan for the patient (7).

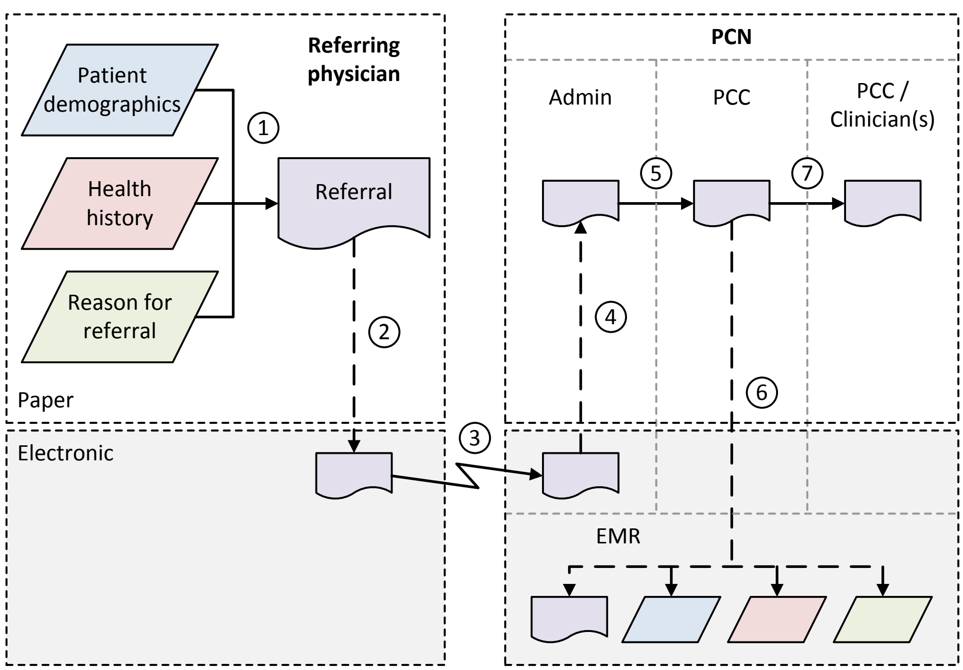


Figure 5-3: Information flow in patient intake process

Once a care plan has been developed, the PCC contacts the patient to schedule an appointment which marks the end of the patient intake process. If the PCC is unable to contact the patient after two attempts, the PCC notifies the referring family physician and the remaining stages of the process are omitted. The process may also end after the patient intake stage if the patient declines care.

5.1.2 Appointment Preparation Process

The appointment preparation process begins once the appointment has been scheduled with the patient. The PCC prepares materials to send to the patient, which may include a notice of their appointment date and time, location and directions to the clinic, and information that the patient is requested to bring for their appointment. The PCC also notifies the referring family physician of the appointment and prepares a patient chart for the clinician to review prior to the appointment. Finally, the patient is reminded of their appointment prior to the appointment date.

The appointment preparation process is impacted by the use of the electronic medical record and automated appointment reminder system in several ways. First, in sending materials to the patient, the patient care coordinator can email the information to the patient instead of using postal service if the patient prefers. Second, the patient chart becomes paperless. Rather than printing and assembling documents into a paper chart that is then filed for clinician review, returned to the patient care coordinator for patient registration, then returned to the clinician for the clinical encounter, the patient chart is created in the electronic medical record and is accessible by multiple clinic staff immediately and simultaneously. Finally, manual appointment reminders from the patient care coordinator are eliminated and replaced with an automated appointment reminder system.

If the patient does not attend their scheduled appointment and the appointment is not rescheduled, the care process may end after the appointment preparation stage and the patient registration and clinical encounter processes are omitted. The PCC notifies the referring family physician and the patient chart is closed in the patient discharge process.

5.1.3 Patient Registration Process

The patient registration process begins when the patient arrives for their scheduled appointment. The PCC prepares forms and instructs the patients on verifying demographic information and providing health history and consent for care. The PCC then transfers this information to the patient chart for the PCN clinicians. The information collected may also be analysed to track clinical outcomes. The PCC notifies the clinician of the patient's arrival and the registration process ends when the patient meets with the PCN clinician.

The patient registration process is impacted by the implementation of the self-service registration application. The same objectives are achieved, but rather than preparing and filing paper forms, a patient enters their information electronically on a tablet computer which is automatically attached to their electronic medical record.

5.1.4 Clinical Encounter Process

During the clinical encounter, the patient meets with one or more PCN clinicians and receives health care, education, and care plan. Additional patient data may be obtained during the clinical encounter that may be analysed to track clinical outcomes. The clinical encounter process requires minimal involvement from the PCC, who is occasionally involved with notifying subsequent clinicians that the patient is finished with the previous clinician and ready for their meeting. The clinical encounter process is outside the scope of this project.

5.1.5 Patient Discharge Process

The patient discharge process begins after the clinical encounter and includes the transfer of care back to the referring family physician or to another health care resource. The PCN clinicians and PCC prepare and send a report to the referring physician on the patient progress and assessment and the patient chart is closed.

Note that if the patient care plan involves more than one appointment, some of the processes (schedule appointment, appointment reminder, and clinical encounter) are repeated before completing the patient discharge process.

Before we examine each process in further detail and examine the impacts of the ICTs that have been implemented, we extract from the preceding discussion the supplier-input-process-output-customer (SIPOC) analysis summarised in Table 5-1. This analysis will help to determine the value-adding components of the process as we examine the impacts of ICTs to ensure that the customer getting the desired output through the best process using the best supplier and the correct input.

Table 5-1: PCN care process SIPOC

Stage	Supplier	Input	Process	Output	Customer
S1 Patient Intake	Referring family physician PCC and/or clinician	Referral with relevant patient history	Determine care path and contact patient	Schedule appointment	Patient
S2 Appointment Preparation	PCC	Scheduled appointment and patient history	Prepare and send patient information package, appointment notification, and patient chart	Information to patient, referring family physician and PCN clinician	Patient, referring family physician and PCN clinician
S3.1 Patient Registration	PCC and patient	Patient information and history	Transfer patient information to clinician	Patient information and history	PCN clinician
S3.2 Clinical Encounter	PCN clinician	Health care knowledge and training	Give patient health care knowledge, coaching, training, determine care path	Education	Patient
S3.3 Patient Discharge	PCC and PCN clinician	Patient assessment	Notify referring family physician of patient progress and assessment	Report	Referring family physician

5.2 Process Types and Entities

We define a number of process types from the process model and assign priority levels to each of the process types. Processes (entities) have various arrival patterns and service times. They enter a queue with priority discipline for a single server with preemption.

Recall the process model in Figure 5-2 and define the following process types.

Table 5-2: Process types

Identifier	Description	Type	Description
S1 – Patient Intake			
S1.1	Create record	1	Create record and develop care plan
S1.2	Develop care plan		
S1.3	Schedule appointment	2	Schedule appointment – First attempt
		3	Schedule appointment – Patient call back
		4	Schedule appointment – Subsequent attempt
S2 – Appointment Preparation			
S2.1	Patient mailout	5	Patient mailout
S2.2	Notify referring physician	6	Notify referring physician
S2.3	Prepare chart	7	Prepare chart
S2.4	Appointment reminder	8	Appointment reminder
S3.1 – Patient Registration			
S3.1.1	Obtain patient data	9	Obtain patient data
S3.1.2	Notify clinician	10	Notify clinician
S3.3 – Patient Discharge			
S3.3.1	Report to referring physician	11	Report to referring physician
S3.3.2	Close chart	12	Close chart
Other Tasks/Interruptions			
n/a	Other interruptions	13	Other interruptions

Create record (S1.1) and develop care plan (S1.2) are combined into one process type. At Clinic A, these two processes are combined; at clinic B, the PCC creates a record and is not responsible for developing the care plan.

Three process types are defined for schedule appointment (S1.3) to model their different arrival patterns and priority levels.

Each of the remaining subprocesses of the process model are defined as single, unique process types. One additional process type is defined for all other tasks, not directly related to process model, viewed as interruptions from this perspective.

We assign default priority levels to each of the thirteen process types, shown in Table 5-3 in descending priority. A larger value of priority attribute indicates a higher priority process type.

Table 5-3: Default priorities for process types

Type	Identifier	Description	Priority
10	S3.1.2	Notify clinician	1300
9	S3.1.1	Obtain patient data	1200
3	S1.3	Schedule appointment – patient call back	1100
13	n/a	Other interruptions	1000
1	S1.1 & S1.2	Create record and develop care plan	900
5	S2.1	Patient mailout	800
6	S2.2	Notify referring physician	700
2	S1.3	Schedule appointment – first attempt	600
4	S1.3	Schedule appointment – subsequent attempt	500
7	S2.3	Prepare chart	400
8	S2.4	Appointment reminder	300
11	S3.3.1	Report to referring physician	200
12	S3.3.2	Close chart	100

The default priorities are assigned in multiples of 100 so that if an entity is preempted, its priority attribute will be increased by 1 so that it re-enters the queue ahead of others of the same process type while maintaining its priority relative to other process types.

We also need to define a preemption matrix, shown in Table 5-4, as the preemption discipline does not directly follow the priority discipline.

$$cell(y,x) = \begin{cases} 1, & if\ Process\ type\ y\ preempts\ process\ type\ x \\ 0, & otherwise \end{cases}$$

Table 5-4: Process preemption matrix

	Type X												
Type Y	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0
3	1	0	0	0	1	1	1	0	0	0	1	1	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0
9	1	0	0	0	1	1	1	0	0	0	1	1	0
10	1	0	0	0	1	1	1	0	0	0	1	1	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0
13	1	0	0	0	1	1	1	0	0	0	1	1	0

Why is this necessary? Just because a process type is of higher priority does not necessarily mean it will preempt a lower priority process type. For example, process type 9 (obtain patient data) is of higher priority than process type 1 (create record and develop care plan) and process type 2 (schedule appointment – first attempt). However, process type 9 would preempt process type 1 but would not preempt process type 2.

We'll see later how this preemption matrix is used to dynamically assign a preemption attribute to entities as they entering the queue by polling what entity type is currently in service.

5.3 Model Development

An overview of the discrete-event model is shown in Figure 5-4. Entities representing each of the thirteen process types defined above are generated and enter a priority queue for service by a single server that allows preemption. Entities flow into a sink once service is complete.

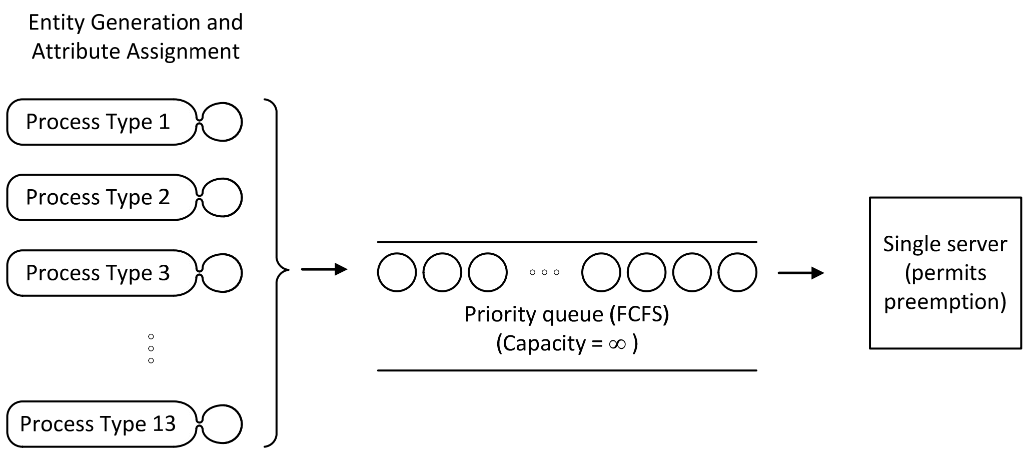


Figure 5-4: Overview of discrete-event model

The simulation clock time is interpreted in seconds and the model run length is set to the equivalent of an eight-hour work day, or 28,800 seconds. A MATLAB function (simPCC) is used to specify the clinic to simulate, number of simulation runs, and the ICT implementation state. The function runs the simulation and outputs the simulation mean and variance of server utilization.

Within the function, entity generation is specified by an input model based on data collected through observation at the PCN and review of existing records. Entity generation is discussed in more detail in Section 5.4.

As each entity is generated, data that describe its process type, service time, priority, and preemption are stored in assigned attributes. Four attributes are assigned to each entity as it is generated. The first attribute is the entity's process type. This is a static attribute and is used later to determine preemption assignment and may signal the generation of other entities upon service completion.

The second attribute is its service time, which is also specified as a probability distribution. Service time is discussed in more detail in Section 5.5.

The third attribute specifies its priority based on its process type, as shown in Table 5-3. This attribute is used in the priority queue, which will be discussed in Section 5.6.

The fourth attribute is used to specify preemption. All entities are assigned a preemption attribute value of zero by default; the preemption attribute is then dynamically assigned as the entity enters the queue. Dynamic preemption assignment will also be discussed in Section 5.6.

Entities representing various process types combine paths and enter a priority queue for service by a single server. The server discipline allows for preemption based on the process type and preemption is assessed dynamically. The queue and server discipline is discussed in more detail in Section 5.6.

5.4 Entity Generation

Entities representing each of the process types are generated according to a specified arrival pattern. For some process types, these arrival patterns are probability distributions that are fitted to empirical data obtained through observation at the PCN or review of existing records. For other process types, representative entities are generated upon some condition, such as the completion of service of another process type.

The process for modeling input data will be shown in detail for process type 1 for Clinic A. A similar process is used to generate arrival patterns for the remaining process types for Clinic A and Clinic B. A summary of the arrival patterns for each of the process types for the two clinics studied at the PCN is given at the end of this section in Table 5-7 and Table 5-8. For a detailed description of input data modeling, please refer to Appendix B.

5.4.1 Input Modeling for Entity Generation of Process Type 1 at Clinic A

The patient intake process begins when a referral is received by the PCN from the patient's physician. Referrals are received throughout the day at the administrative office and are delivered to the PCC twice daily, in the morning and afternoon. To model the arrival of referrals, or the arrival of entities representing process type 1, we estimate the number of referrals received each week, and assume an equiprobable distribution of in each of the twice daily deliveries.

The number of new referrals received at Clinic A each week over the last 100 weeks, was obtained from the PCN's records. As the techniques used in the subsequent steps of the input modeling process assume that the sample set is independent, we will first verify this assumption.

Let $X_1, X_2, \dots, X_{100}$ be the number of new referrals received in week 1, 2,…, 100, respectively, and form the null hypothesis that the X_i's are independent. We qualitatively assess the independence of the data points by inspection of the scatter plot of the empirical data with x-y pairs given by (X_i, X_{i+1}) for i = 1, 2,…, 99, as shown in Figure 5-5, and note that the data does not appear to be correlated.

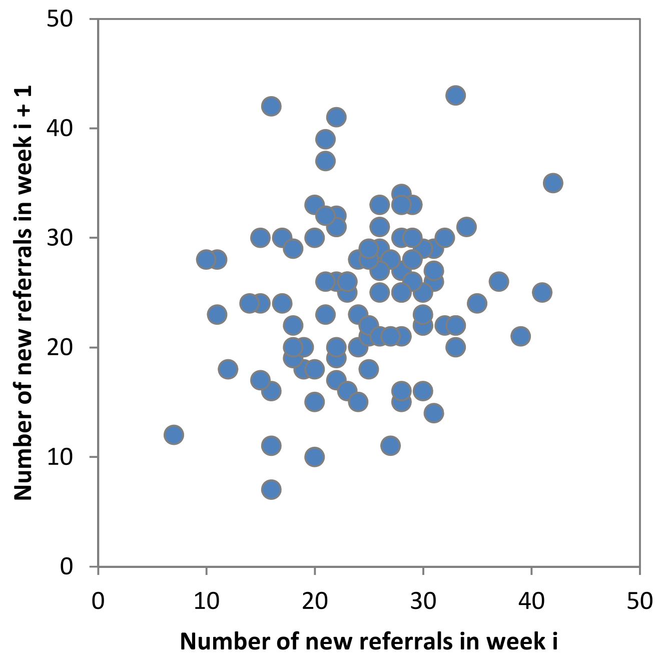


Figure 5-5: Scatter plot of empirical data for number of new referrals at Clinic A

We quantitatively confirm the assumption of independence using the runs test, which is represented graphically in Figure 5-6.

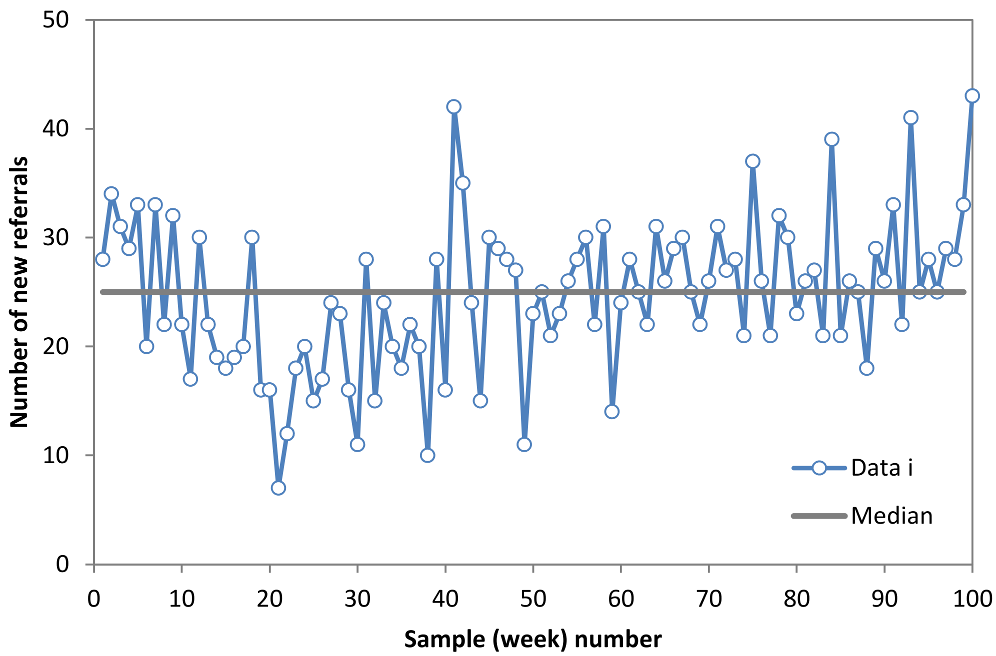


Figure 5-6: Runs test of empirical data for number of new referrals at Clinic A

From Figure 5-6, we can see that of the 100 samples with a median of 25, there are 53 samples greater than (or equal) to the median, there are 47 samples less than the median and there are 43 runs. The test statistic is -1.578 and at a significance level of $\alpha = 0.05$, we retain the null hypothesis of independence. The test result was confirmed using the runs test algorithm in SPSS.

With the assumption of independence verified, we can proceed to fit a distribution to the data. The number of new referrals received each week, over the last 100 weeks, is summarised by the statistics given Table 5-5 and the distribution is shown in Figure 5-7.

Table 5-5: Summary statistics for number of new referrals received weekly at Clinic A

Sample Size	Mean	Median	Standard Deviation	Minimum	Maximum
100	24.7	25	6.9	7	43

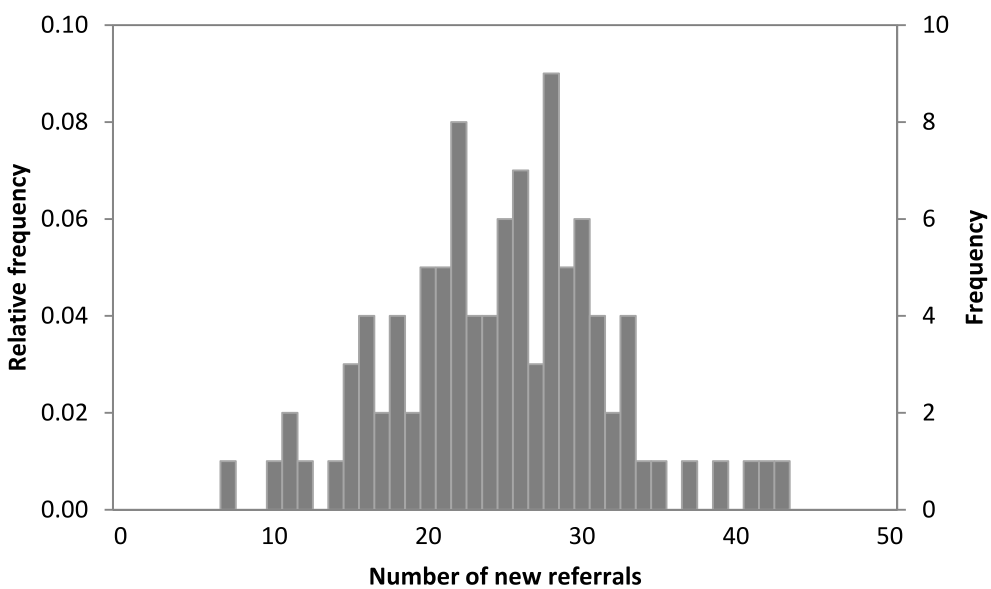


Figure 5-7: Distribution of number of new referrals at Clinic A

By examining the summary statistics and distribution of the data, we expect that the number of new referrals follows a discrete distribution with non-negative values. Visual inspection of the empirical distribution suggests that the negative binomial, Poisson, and binomial families of distributions may be appropriate. The range of the negative binomial and Poisson families of distributions support the range of the possible numbers of new referrals. The binomial distribution has a finite range but may be suitable if parameters are selected appropriately.

We will estimate the parameters for the three potential discrete distributions using the maximum likelihood estimators (MLEs) presented in Law (2007, p. 281-309). The first candidate distribution is the negative binomial distribution with 25 successes and a probability of success of 0.503. The second candidate distribution is the Poisson distribution with mean of 24.680. Estimators for the binomial distribution do not exist for this data set. The distribution parameters are verified using ExpertFit software.

A frequency comparison of the empirical data and the two fitted distributions is shown in Figure 5-8. The empirical data is shown in grey bars; the fitted negative binomial distribution is shown in blue in Figure 5-8a and the fitted Poisson distribution is shown in blue in Figure 5-8b.

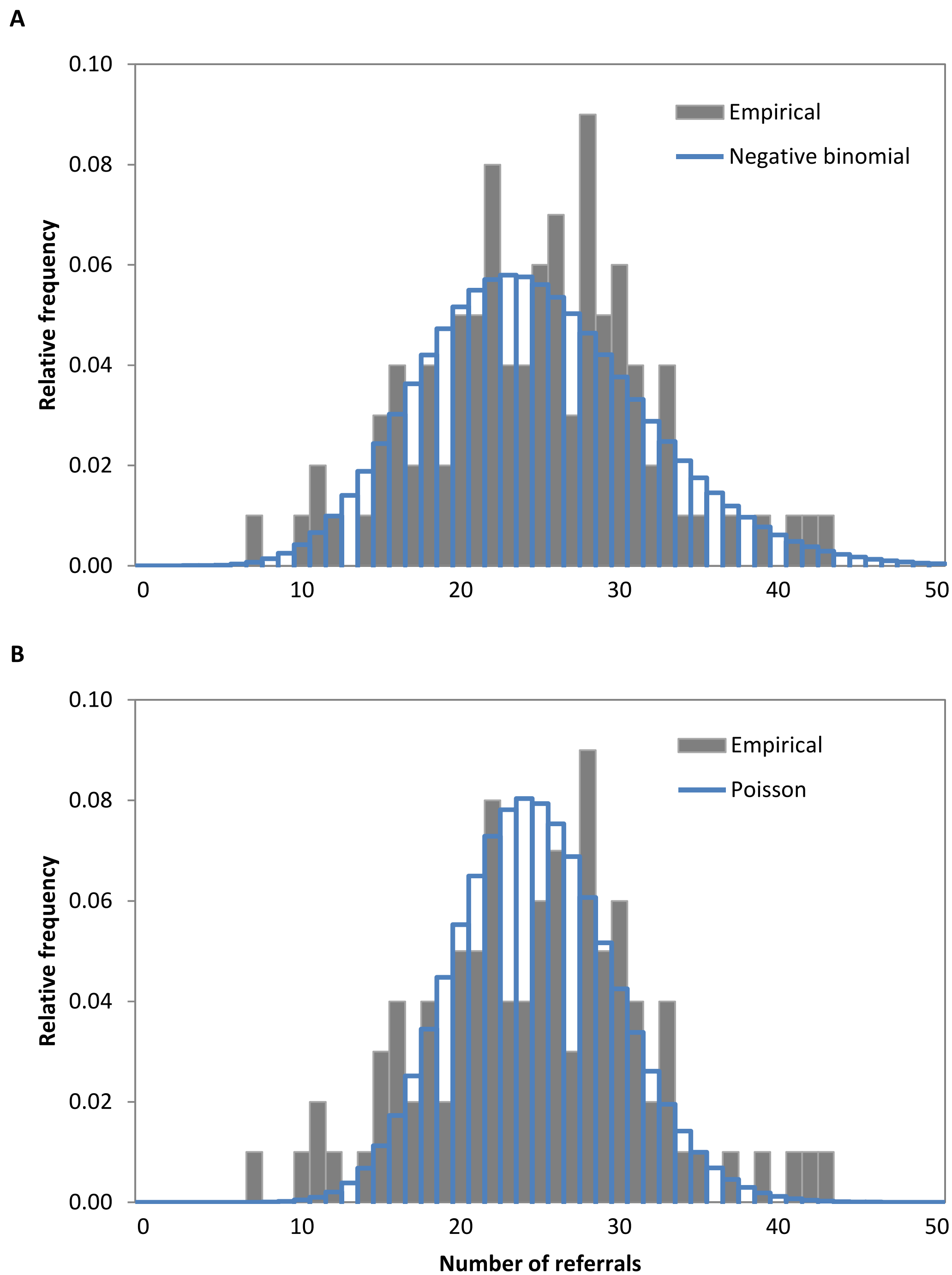


Figure 5-8: Frequency comparison of empirical data and the fitted (A) negative binomial and (B) Poisson distributions for the number of new referrals at Clinic A

A qualitative assessment of the frequency comparisons in Figure 5-8 suggests that the negative binomial distribution may be a better fit than the Poisson distribution.

The chi-square goodness-of-fit test is used to quantitatively assess the two potential distributions where the null hypothesis is the empirical data are independent, identically distributed random variables from the theoretical distribution. The intervals are selected to minimise the variance in the expected values in each interval while ensuring each interval has at least five expected values.

The chi-square goodness-of-fit test for the negative binomial and Poisson distributions is shown in Table 5-6.

Table 5-6: Chi-square goodness-of-fit test for negative binomial and Poisson distributions for the number of new referrals at Clinic A

Negative binomial (s = 25, p = 0.503)					Poisson (λ = 24.680)				
j	Interval	N_j	np_j	$\frac{(N_j-np_j)^2}{np_j}$	j	Interval	N_j	np_j	$\frac{(N_j-np_j)^2}{np_j}$
1	{0, 1, …, 18}	19	19.154	0.001	1	{0, 1,…, 20}	26	20.264	1.624
2	{19, 20, …, 22}	20	21.097	0.057	2	{21, 22, 23}	17	21.597	0.978
3	{23, 24, 25}	14	17.164	0.583	3	{24, 25}	10	15.975	2.235
4	{26, 27, …, 30}	30	22.999	2.131	4	{26, 27, 28}	19	20.488	0.108
5	{31, 32, … }	17	19.585	0.341	5	{29, 30, … }	28	21.677	1.844
			Test statistic, χ^2 =	3.114				**Test statistic, χ^2 =**	6.789
			Significance level, α =	0.05				**Significance level, α =**	0.05
			Rejection region, RR: χ^2 >	9.488				**Rejection region, RR: χ^2 >**	9.488
				Decision: Do not reject					**Decision:** Do not reject

The results of the chi-square goodness-of fit test confirm the qualitative assessment of fit from inspection of the frequency comparisons in Figure 5-8. Both distributions are acceptable, but the negative binomial distribution is a better fit for the data. This assessment is verified with ExpertFit software.

The distribution of the number of new referrals received in a week is modeled as a negative binomial distribution.

$$r_{w,A} \sim Negative\ binomial\ (s = 25,\ \ p = 0.503)$$

A frequency comparison of the empirical data and simulated data to the fitted negative binomial distributions is shown in Figure 5-9 to verify the input model describes the empirical data. The simulated data is the result of 10000 trials.

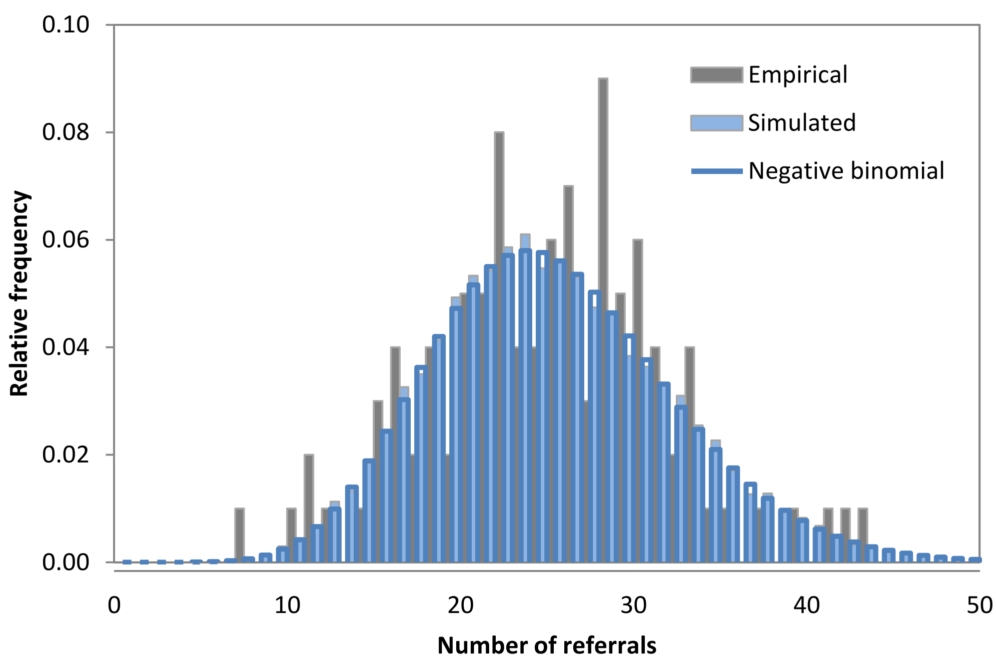


Figure 5-9: Frequency comparison of empirical data and simulated data to fitted negative binomial distribution for number of new referrals at Clinic A

Referrals are received throughout the day at the administrative office and are delivered to the PCC twice daily, in the morning and afternoon, or ten times per week. We assume an equiprobable distribution of weekly referrals in the ten weekly deliveries, or a binomial distribution with $r_{w,A}$ trials and probability of 0.1.

$$r_{am,A} \sim Binomial\left(n = r_{w,A},\ \ p = 0.1\right)$$

$$r_{pm,A} \sim Binomial\left(n = r_{w,A},\ \ p = 0.1\right)$$

Referrals are delivered from the administrative office to the PCC at approximately 10 am and 2 pm. We model the arrival time as a uniformly distributed random variable within 30 minutes of 10 am and 2 pm.

$$t_{am} \sim Uniform\ (a = 09{:}45,\ \ b = 10{:}15)$$

$$t_{pm} \sim Uniform\ (a = 13{:}45,\ \ b = 14{:}15)$$

Arrival patterns for the remaining process types at Clinic A and Clinic B are developed using this process. A summary of the arrival patterns for each of the process types for the two clinics studied at the PCN is given in Table 5-7 and Table 5-8. For a detailed description of input data modeling, please refer to Appendix B.

Table 5-7: Summary of entity generation for Clinic A

Process Type – Description	Summary of Entity Generation
1 – Create record and develop care plan	Number of referrals received each morning $r_{am,A} \sim Binomial\left(n = r_{w,A},\ \ p = 0.1\right)$ received at time $t_{am} \sim Uniform\ (a = 09{:}45,\ \ b = 10{:}15)$ and each afternoon $r_{pm,A} \sim Binomial\left(n = r_{w,A},\ \ p = 0.1\right)$ received at time $t_{pm} \sim Uniform\ (a = 13{:}45,\ \ b = 14{:}15)$ where $r_{w,A} \sim Negative\ binomial\ (s = 25,\ \ p = 0.503)$ is the number of referrals received each week with an assumed equiprobable distribution each morning and afternoon of each day of the week
2 – Schedule appointment – First attempt	Generated upon completion of process type 1 $P(success) = 16/45 \approx 0.356$ is the probability of successfully reaching the patient and scheduling an appointment
3 – Schedule appointment – Patient call back	Interarrival time of patient call backs ${}^{1}/_{\lambda_{3,A}} \sim Exponential\ \left({}^{day}/_{r_{3,A}}\right)$ where $r_{3,A} \sim Binomial\left(n = r_{w,A},\ \ p = {}^{29}/_{45} \times {}^{1}/_{3} \times {}^{1}/_{5}\right)$ Of the first attempts (process type 2) each week that were not successful $P(failure) = 1 - P(success) = 1 - 16/45 = 29/45 \approx 0.644$ assume 1 in 3 patients call back with an assumed equiprobable distribution each day of the week $P(success) = 0.95$ is the estimated probability of successfully scheduling an appointment given the patient has called back

Table 5-7: Summary of entity generation for Clinic A (continued)

Process Type – Description	Summary of Entity Generation
4 – Schedule appointment – Subsequent attempt	Number of patients requiring another attempt each day $r_{4,A} \sim Binomial\left(n = r_{w,A},\ \ p = {}^{29}/_{45} \times {}^{2}/_{3} \times {}^{1}/_{5}\right)$ Of the first attempts (process type 2) each week that were not successful, assume 2 in 3 patients will require subsequent attempt with an assumed equiprobable distribution each day of the week available at the start of each day $P(success) = 16/45 \approx 0.356$ is the probability of successfully reaching the patient and scheduling an appointment
5 – Patient mailout	Generated upon successful completion of process types 2, 3, or 4
6 – Notify referring physician	Generated upon successful completion of process types 2, 3, or 4
7 – Prepare chart	Generated upon successful completion of process types 2, 3, or 4
8 – Appointment reminder	Number of appointments requiring reminders each day $a_{d,A} \sim Binomial\left(n = a_{m,A},\ \ p = 0.05\right)$ where $a_{m,A} \sim Negative\ binomial\ (s = 18,\ \ p = 0.072)$ is the number of scheduled appointments each month with an assumed equiprobable distribution each day of the month available at the start of each day

Table 5-7: Summary of entity generation for Clinic A (continued)

Process Type – Description	Summary of Entity Generation
9 – Obtain patient data	Number of appointments scheduled each day $a_{d,A} \sim Binomial\left(n = a_{m,A},\ \ p = 0.05\right)$ where $a_{m,A} \sim Negative\ binomial\ (s = 18,\ \ p = 0.072)$ is the number of scheduled appointments each month with an assumed equiprobable distribution each day of the month arriving at time $t_{appt} \sim Normal\left(\mu = t_{schappt},\ \ \sigma = 300\right)$ where $t_{schappt,A} \sim Multinomial\left(n = a_{d,A}, Y_1 = 08{:}30, Y_2 = 08{:}45, \cdots, Y_{22} = 16{:}00, p_1 = 0.026, p_2 = 0.004, \cdots, p_{22} = 0.004\right)$ is the distribution of scheduled appointment times and it is estimated that 95% of patients arrive within 10 minutes of their scheduled appointment time
10 – Notify clinician	Generated upon completion of process type 9
11 – Report to referring physician	Interarrival time of chart closures $1/\lambda_c \sim Exponential\left({day}/{c_{d,A}}\right)$ where $c_{d,A} \sim Binomial\left(n = c_{m,A},\ \ p = 0.05\right)$ and $c_{m,A} \sim Negative\ binomial\ (s = 4,\ \ p = 0.020)$ is the number of chart closures each month with an assumed equiprobable distribution each day of the month
12 – Close chart	Generated upon completion of process type 11
13 – Other interruptions	Interarrival time of other interruptions $1/\lambda_{13} \sim Exponential\left({36.5\ hours}/{115\ interruptions}\right)$ estimated from the 115 interruptions noted during 36.5 hours of observation

Table 5-8: Summary of entity generation for Clinic B

Process Type – Description	Summary of Entity Generation
1 – Create record and develop care plan	Number of referrals received each day $r_{d,B} \sim Binomial\left(n = r_{w,B},\ \ p = 0.2\right)$ received at time $t_{pm} \sim Uniform\ (a = 13{:}25,\ \ b = 13{:}35)$ where $r_{w,B} \sim Negative\ binomial\ (s = 25,\ \ p = 0.557)$ is the number of referrals received each week with an assumed equiprobable distribution each day of the week
2 – Schedule appointment – First attempt	Generated upon completion of process type 1 $P(success) = 27/104 \approx 0.260$ is the probability of successfully reaching the patient and scheduling an appointment
3 – Schedule appointment – Patient call back	Interarrival time of patient call backs ${}^{1}/_{\lambda_{3,B}} \sim Exponential\ \left({}^{day}/_{r_{3,B}}\right)$ where $r_{3,B} \sim Binomial\left(n = r_{w,B},\ \ p = {}^{77}/_{104} \times {}^{1}/_{3} \times {}^{1}/_{5}\right)$ Of the first attempts (process type 2) each week that were not successful $P(failure) = 1 - P(success) = 1 - 27/104 = 77/104 \approx 0.740$ assume 1 in 3 patients call back with an assumed equiprobable distribution each day of the week $P(success) = 0.95$ is the estimated probability of successfully scheduling an appointment given the patient has called back

Table 5-8: Summary of entity generation for Clinic B (continued)

Process Type – Description	Summary of Entity Generation
4 – Schedule appointment – Subsequent attempt	Number of patients requiring another attempt each day $r_{4,B} \sim Binomial\left(n = r_{w,B},\ \ p = {}^{77}/_{104} \times {}^{2}/_{3} \times {}^{1}/_{5}\right)$ Of the first attempts (process type 2) each week that were not successful, assume 2 in 3 patients will require subsequent attempt with an assumed equiprobable distribution each day of the week available at the start of each day $P(success) = 27/104 \approx 0.260$ is the probability of successfully reaching the patient and scheduling an appointment
5 – Patient mailout	Generated upon successful completion of process types 2, 3, or 4
6 – Notify referring physician	Generated upon successful completion of process types 2, 3, or 4
7 – Prepare chart	Generated upon successful completion of process types 2, 3, or 4
8 – Appointment reminder	Number of appointments requiring reminders each day $a_{d,B} \sim Binomial\left(n = a_{m,B},\ \ p = 0.05\right)$ where $a_{m,B} \sim Negative\ binomial\ (s = 25,\ \ p = 0.171)$ is the number of scheduled appointments each month with an assumed equiprobable distribution each day of the month available at the start of each day

Table 5-8: Summary of entity generation for Clinic B (continued)

Process Type – Description	Summary of Entity Generation
9 – Obtain patient data	Number of appointments scheduled each day $a_{d,B} \sim Binomial\left(n = a_{m,B},\ \ p = 0.05\right)$ where $a_{m,B} \sim Negative\ binomial\ (s = 25,\ \ p = 0.171)$ is the number of scheduled appointments each month with an assumed equiprobable distribution each day of the month arriving at time $t_{appt} \sim Normal\left(\mu = t_{schappt},\ \ \sigma = 300\right)$ where $t_{schappt,B} \sim Multinomial\left(n = a_{d,B}, Y_1 = 08{:}30, Y_2 = 09{:}00, \cdots, Y_{22} = 15{:}15, p_1 = 0.122, p_2 = 0.156, \cdots, p_{22} = 0.007\right)$ is the distribution of scheduled appointment times and it is estimated that 95% of patients arrive within 10 minutes of their scheduled appointment time
10 – Notify clinician	Generated upon completion of process type 9
11 – Report to referring physician	Interarrival time of chart closures ${}^{1}/_{\lambda_c} \sim Exponential\ \left({}^{day}/_{c_{d,B}}\right)$ where $c_{d,B} \sim Binomial\left(n = c_{m,B},\ \ p = 0.05\right)$ and $c_{m,B} \sim Negative\ binomial\ (s = 14,\ \ p = 0.146)$ is the number of chart closures each month with an assumed equiprobable distribution each day of the month
12 – Close chart	Generated upon completion of process type 11
13 – Other interruptions	Interarrival time of other interruptions ${}^{1}/_{\lambda_{13}} \sim Exponential\ \left({}^{33\ hours}/_{48\ interruptions}\right)$ estimated from the 48 interruptions noted during 33 hours of observation

5.5 Service Times

The probability distributions for service times for each process type for each clinic are fitted to empirical data obtained through observation. The process for modeling input data will be shown in detail for process type 2 for Clinic B. A similar process is used to model the service times for the remaining process types for Clinic A and Clinic B. A summary of the service times for each of the process types for the two clinics studied at the PCN is given at the end of this section in Table 5-13 and Table 5-14. For a detailed description of input data modeling, please refer to Appendix B.

5.5.1 Input Modeling for Service Time of Process Type 2 at Clinic B

Once the referral has been recorded and a care plan has been developed, the PCC attempts to contact the patient to schedule an appointment, represented by process type 2. The service time for process type 2 depends on whether the attempt is successful (outcome 1). If the attempt is unsuccessful, the PCC may leave a message on an answering machine (outcome 2) or with a person (outcome 3), or may be unable to leave a message (outcome 4). The empirical distribution of outcomes observed over 104 attempts to contact patients at Clinic B is shown in Figure 5-10.

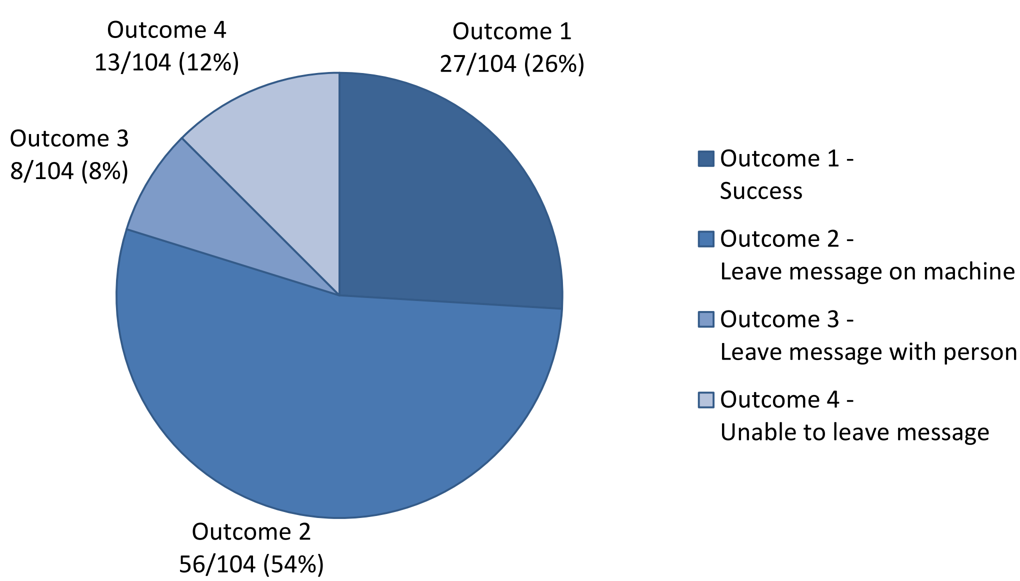


Figure 5-10: Distribution of outcomes for process type 2 at Clinic B

We will examine the input data for each of the four outcomes in turn.

Outcome 1

For the case when the PCC successfully contacts the patient and schedules an appointment, we have 27 data points gathered over 13 observations. As the samples of service time were collected over multiple observations, we first use the runs test in SPSS to verify that the samples from within each observation are independent. Then we apply the Kruskal-Wallis (K-W) test to verify that the samples are from the same distribution and can be combined to model as one distribution. The K-W test is summarised in Table 5-9 and the result was verified using the K-W test in SPSS software.

Table 5-9: Kruskal-Wallis test of empirical data for service time of outcome 1 for process type 2 at Clinic B

Observation i	Observation sample size n_i	Sum of ranks in observation R_i
1	1	23
2	1	9
3	2	10
4	1	21
5	4	46
6	1	6
7	3	59
8	2	38
9	2	31
10	1	11
11	5	70
12	1	19
13	3	35
	Test statistic, χ^2 =	9.638
	Significance level, α =	0.05
	Rejection region, RR: χ^2 >	21.026
		Decision: Do not reject

Summary statistics for the service time of outcome 1 for process type 2 at Clinic B is given in Table 5-10.

Table 5-10: Summary statistics for service time of outcome 1 for process type 2 at Clinic B

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
27	185	170	38	129	262

ExpertFit software is used to fit a theoretical distribution to the data and test the goodness-of-fit. The distribution for service time of successful outcome for process type 2 at clinic B is modeled as a lognormal distribution with shape parameter 0.198 and scale parameter 181.235.

A density-histogram plot of the empirical and simulated data and the fitted lognormal distribution is shown in Figure 5-11 to verify the input model describes the empirical data. The simulated data is the result of 10000 trials.

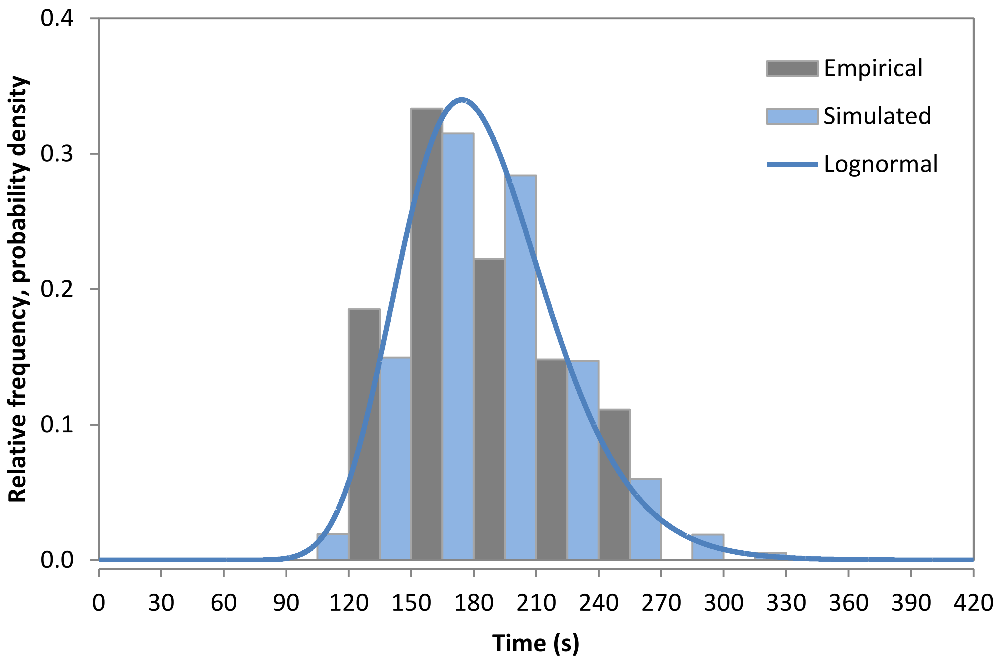


Figure 5-11: Density-histogram plot of empirical and simulated data and fitted lognormal distribution for service time of outcome 1 for process type 2 at Clinic B

Outcome 2

For the case when the PCC leaves a voice message for the patient, we have 56 data points gathered over 14 observations. Sample independence within observations is verified using the runs test in SPSS and sample homogeneity is verified using the K-W test in SPSS. Summary statistics for the service time of outcome 2 for process type 2 at Clinic B is given in Table 5-11.

Table 5-11: Summary statistics for service time of outcome 2 for process type 2 at Clinic B

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
56	69	69	15	36	128

ExpertFit software is used to fit a theoretical distribution to the data and test the goodness-of-fit. This service time for this outcome is modeled as a log-logistic distribution with shape parameter 8.835 and scale parameter 67.669. A density-histogram plot of the empirical and simulated data and the fitted log-logistic distribution is shown in Figure 5-12 to verify the input model describes the empirical data. The simulated data is the result of 10000 trials.

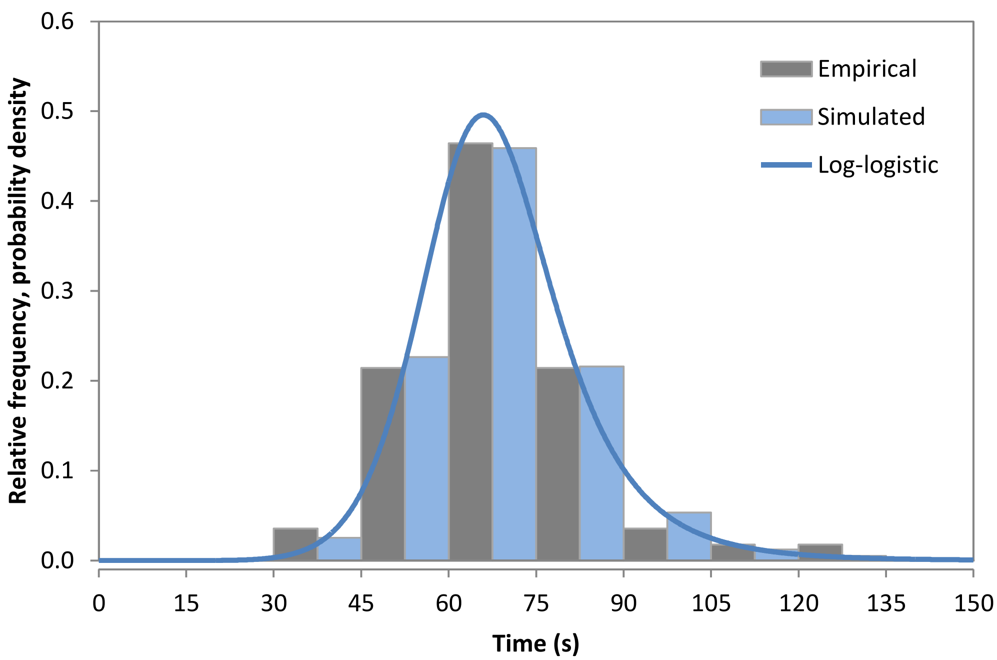


Figure 5-12: Density-histogram plot of empirical and simulated data and fitted log-logistic distribution for service time of outcome 2 for process type 2 at Clinic B

Outcome 3

For the case when the PCC leaves a message for the patient with a person, we have 8 data points gathered over 6 observations. Sample independence within observations is verified using the runs test in SPSS and sample homogeneity is verified using the K-W test in SPSS. There are not enough data points to fit a theoretical distribution so an empirical distribution will be used instead. The data set observed is

$$S \in \{129, 76, 47, 66, 58, 60, 46, 63\}$$

The empirical distribution function specified from this data set is

$$F(s) = \begin{cases} 0 & , s < 46 \\ \dfrac{s-46}{7\times 1} & , 46 \le s < 47 \\ \dfrac{1}{7} + \dfrac{s-47}{7\times 11} & , 47 \le s < 58 \\ \dfrac{2}{7} + \dfrac{s-58}{7\times 2} & , 58 \le s < 60 \\ \dfrac{3}{7} + \dfrac{s-60}{7\times 3} & , 60 \le s < 63 \\ \dfrac{4}{7} + \dfrac{s-63}{7\times 3} & , 63 \le s < 66 \\ \dfrac{5}{7} + \dfrac{s-66}{7\times 10} & , 66 \le s < 76 \\ \dfrac{6}{7} + \dfrac{s-76}{7\times 53} & , 76 \le s < 129 \\ 1 & , s \ge 129 \end{cases}$$

The empirical and simulated probability distributions are shown in Figure 5-13. The simulated data is the result of 10000 trials. Note that the two distributions are difficult to distinguish in the figure as the distributions are nearly identical.

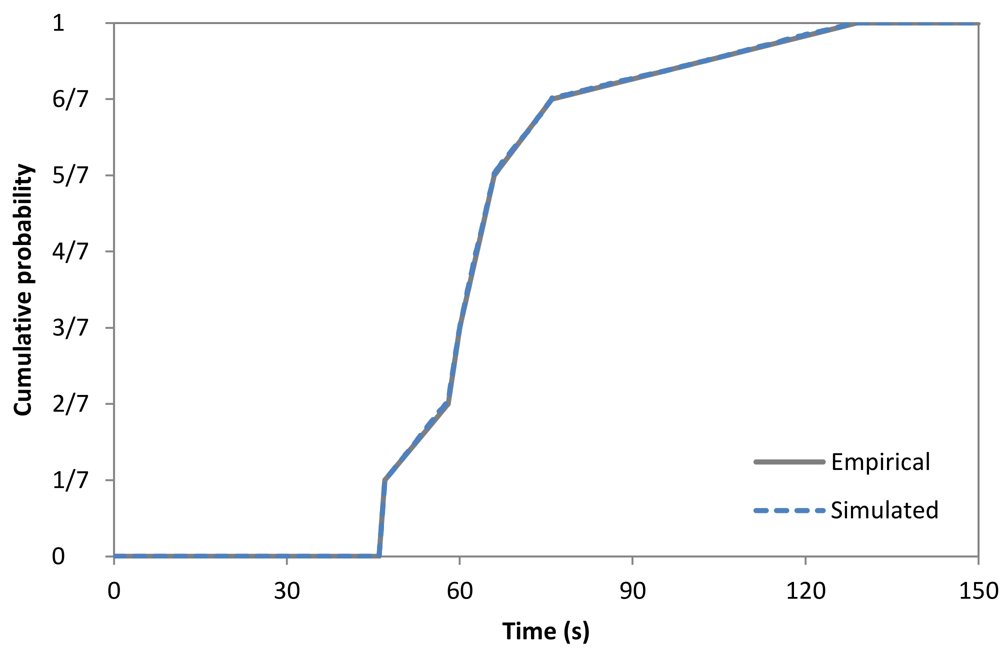


Figure 5-13: Empirical and simulated probability distribution of service time of outcome 3 for process type 2 at Clinic B

Outcome 4

For the case when the PCC is unable to leave a message, we have 13 data points gathered over 8 observations. Sample independence within observations is verified using the runs test in SPSS and sample homogeneity is verified using the K-W test in SPSS. Summary statistics for the service time of outcome 4 for process type 2 at Clinic B is given in Table 5-12.

Table 5-12: Summary statistics for service time of outcome 4 for process type 2 at Clinic B

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
13	72	69	33	23	126

ExpertFit software is used to fit a theoretical distribution to the data and test the goodness-of-fit. This service time for this outcome is modeled as a Weibull distribution with shape parameter 2.417 and scale parameter 80.850. A density-histogram plot of the empirical and simulated data and the fitted log-logistic distribution is shown in Figure 5-14 to verify the input model describes the empirical data. The simulated data is the result of 10000 trials.

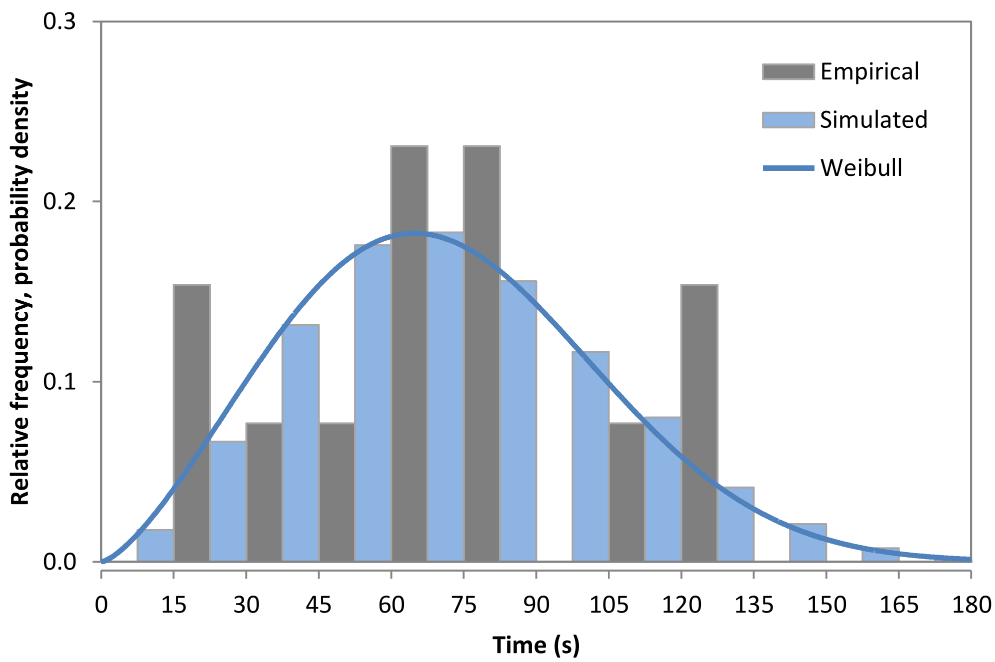


Figure 5-14: Density-histogram plot of empirical and simulated data to fitted Weibull distribution for service time of outcome 4 for process type 2 at Clinic B

Models for service times for the remaining process types at Clinic A and Clinic B are developed using this process. A summary of the service times for each of the process types for the two clinics studied at the PCN is given in Table 5-13 and Table 5-14. For a detailed description of input data modeling, please refer to Appendix B.

Table 5-13: Service time distributions for Clinic A

Process Type – Description	Service Time (S) Distribution
1 – Create record and develop care plan	$S \sim log\text{-}logistic\ (\alpha = 3.917, \beta = 164.554) + gamma\ (\alpha = 1.130, \beta = 16.817, \gamma = 9.943)$
2 – Schedule appointment – First attempt	$For\ outcome\ i \in \{1,2,3,4\},$ $S \sim \begin{cases} log\text{-}logistic\ (\alpha = 5.439, \beta = 202.478) & , i = 1 \\ log\text{-}logistic\ (\alpha = 11.580, \beta = 60.079) & , i = 2 \\ F(s) = \begin{cases} 0 & , s < 39 \\ \frac{s-39}{6 \times 25} & , 39 \leq s < 64 \\ \frac{1}{6} + \frac{s-64}{6 \times 2} & , 64 \leq s < 66 \\ \frac{2}{6} + \frac{s-66}{6 \times 4} & , 66 \leq s < 70 \\ \frac{3}{6} + \frac{s-70}{6 \times 14} & , 70 \leq s < 84 \\ \frac{4}{6} + \frac{s-84}{6 \times 13} & , 84 \leq s < 97 \\ \frac{5}{6} + \frac{s-97}{6 \times 11} & , 97 \leq s < 108 \\ 1 & , s \geq 108 \end{cases} & , i = 3 \\ F(s) = \begin{cases} 0 & , s < 70 \\ \frac{s-70}{3 \times 4} & , 70 \leq s < 74 \\ \frac{1}{3} + \frac{s-74}{3 \times 9} & , 74 \leq s < 83 \\ \frac{2}{3} + \frac{s-83}{3 \times 11} & , 83 \leq s < 94 \\ 1 & , s \geq 94 \end{cases} & , i = 4 \end{cases}$ $where\ P(i) = \begin{cases} 16/45 & , i = 1 \\ 18/45 & , i = 2 \\ 7/45 & , i = 3 \\ 4/45 & , i = 4 \end{cases}$

Table 5-13: Service time distributions for Clinic A (continued)

Process Type – Description	Service Time (S) Distribution
3 – Schedule appointment – Patient call back	$F(s) = \begin{cases} 0 & , s < 57 \\ \frac{s-57}{8 \times 60} & , 57 \le s < 117 \\ \frac{1}{8} + \frac{s-117}{8 \times 28} & , 117 \le s < 145 \\ \frac{2}{8} + \frac{s-145}{8 \times 16} & , 145 \le s < 161 \\ \frac{3}{8} + \frac{s-161}{8 \times 6} & , 161 \le s < 167 \\ \frac{4}{8} + \frac{s-167}{8 \times 38} & , 167 \le s < 205 \\ \frac{5}{8} + \frac{s-205}{8 \times 128} & , 205 \le s < 333 \\ \frac{6}{8} + \frac{s-333}{8 \times 13} & , 333 \le s < 346 \\ \frac{7}{8} + \frac{s-346}{8 \times 331} & , 346 \le s < 677 \\ 1 & , s \ge 677 \end{cases}$

Table 5-13: Service time distributions for Clinic A (continued)

Process Type – Description	Service Time (S) Distribution
4 – Schedule appointment – Subsequent attempt	$For\ outcome\ i \in \{1,2,3,4\},$ $$S \sim \begin{cases} log\text{-}logistic\ (\alpha = 5.439, \beta = 202.478) & ,i = 1 \\ log\text{-}logistic\ (\alpha = 11.580, \beta = 60.079) & ,i = 2 \\ F(s) = \begin{cases} 0 & ,s < 39 \\ \frac{s-39}{6 \times 25} & ,39 \leq s < 64 \\ \frac{1}{6} + \frac{s-64}{6 \times 2} & ,64 \leq s < 66 \\ \frac{2}{6} + \frac{s-66}{6 \times 4} & ,66 \leq s < 70 \\ \frac{3}{6} + \frac{s-70}{6 \times 14} & ,70 \leq s < 84 \\ \frac{4}{6} + \frac{s-84}{6 \times 13} & ,84 \leq s < 97 \\ \frac{5}{6} + \frac{s-97}{6 \times 11} & ,97 \leq s < 108 \\ 1 & ,s \geq 108 \end{cases} & ,i = 3 \\ F(s) = \begin{cases} 0 & ,s < 70 \\ \frac{s-70}{3 \times 4} & ,70 \leq s < 74 \\ \frac{1}{3} + \frac{s-74}{3 \times 9} & ,74 \leq s < 83 \\ \frac{2}{3} + \frac{s-83}{3 \times 11} & ,83 \leq s < 94 \\ 1 & ,s \geq 94 \end{cases} & ,i = 4 \end{cases}$$ $$where\ P(i) = \begin{cases} 16/45 & ,i = 1 \\ 18/45 & ,i = 2 \\ 7/45 & ,i = 3 \\ 4/45 & ,i = 4 \end{cases}$$

Table 5-13: Service time distributions for Clinic A (continued)

Process Type – Description	Service Time (S) Distribution
5 – Patient mailout	$\mathit{For\ time}\ t \in \{0,1\}$ $S \sim \begin{cases} F(s) = \begin{cases} 0 & ,s < 30 \\ \frac{s-30}{2\times 20} & ,30 \le s < 50 \\ \frac{1}{2} + \frac{s-50}{2\times 13} & ,50 \le s < 63 \\ 1 & ,s \ge 63 \end{cases} & ,t = 0 \\ F(s) = \begin{cases} 0 & ,s < 48 \\ \frac{s-48}{5\times 16} & ,48 \le s < 64 \\ \frac{1}{5} + \frac{s-64}{5\times 14} & ,64 \le s < 78 \\ \frac{2}{5} + \frac{s-78}{5\times 32} & ,78 \le s < 110 \\ \frac{3}{5} + \frac{s-110}{5\times 47} & ,110 \le s < 157 \\ \frac{4}{5} + \frac{s-157}{5\times 13} & ,157 \le s < 170 \\ 1 & ,s \ge 170 \end{cases} & ,t = 1 \end{cases}$
6 – Notify referring physician	$F(s) = \begin{cases} 0 & ,s < 15 \\ \frac{s-15}{8\times 11} & ,15 \le s < 26 \\ \frac{1}{8} + \frac{s-26}{8\times 11} & ,26 \le s < 37 \\ \frac{2}{8} + \frac{s-37}{8\times 2} & ,37 \le s < 39 \\ \frac{3}{8} + \frac{s-39}{8\times 21} & ,39 \le s < 60 \\ \frac{4}{8} + \frac{3(s-60)}{8\times 1} & ,60 \le s < 61 \\ \frac{7}{8} + \frac{s-61}{8\times 4} & ,61 \le s < 65 \\ 1 & ,s \ge 65 \end{cases}$

Table 5-13: Service time distributions for Clinic A (continued)

Process Type – Description	Service Time (S) Distribution
7 – Prepare chart	$For\ time\ t \in \{0,1\}$ $$S \sim \begin{cases} F(s) = \begin{cases} 0 & ,s < 45 \\ \frac{s-45}{3\times 5} & ,45 \le s < 50 \\ \frac{1}{3} + \frac{s-50}{3\times 17} & ,50 \le s < 67 \\ \frac{2}{3} + \frac{s-67}{3\times 8} & ,67 \le s < 75 \\ 1 & ,s \ge 75 \end{cases} + Weibull\ (\alpha = 3.027, \beta = 206.429) & ,t = 0 \\ F(s) = \begin{cases} 0 & ,s < 51 \\ \frac{s-51}{5\times 8} & ,51 \le s < 59 \\ \frac{1}{5} + \frac{s-59}{5\times 15} & ,59 \le s < 74 \\ \frac{2}{5} + \frac{s-74}{5\times 2} & ,74 \le s < 76 \\ \frac{3}{5} + \frac{s-76}{5\times 4} & ,76 \le s < 80 \\ \frac{4}{5} + \frac{s-80}{5\times 14} & ,80 \le s < 94 \\ 1 & ,s \ge 94 \end{cases} & ,t = 1 \end{cases}$$
8 – Appointment reminder	$For\ time\ t \in \{0,1\}$ $$S \sim \begin{cases} Weibull\ (\alpha = 3.263, \beta = 302.040, \gamma = 30) & ,t = 0 \\ S = 0 & ,t = 1 \end{cases}$$

Table 5-13: Service time distributions for Clinic A (continued)

Process Type – Description	Service Time (S) Distribution
9 – Obtain patient data	$For\ patient\ type\ p \in \{1,2\}\ and\ time\ t \in \{0,1\}$ $$S \sim \begin{cases} \left. \begin{array}{l} F(s) = \begin{cases} 0 & , s < 18 \\ \frac{s-18}{3\times 2} & , 18 \le s < 20 \\ \frac{1}{3} + \frac{s-20}{3\times 3} & , 20 \le s < 23 \\ \frac{2}{3} + \frac{s-23}{3\times 1} & , 23 \le s < 24 \\ 1 & , s \ge 24 \end{cases} \\ + log\text{-}logistic\ (\alpha = 6.688, \beta = 94.357) \\ +F(s) = \begin{cases} 0 & , s < 7 \\ \frac{s-7}{3\times 6} & , 7 \le s < 13 \\ \frac{1}{3} + \frac{2(s-13)}{3\times 7} & , 13 \le s < 20 \\ 1 & , s \ge 20 \end{cases} \end{array} \right. , t = 0 \\ \left. \begin{array}{l} gamma\ (\alpha = 0.897, \beta = 15.820, \gamma = 24.974) \\ + log\text{-}logistic\ (\alpha = 4.706, \beta = 15.820) \\ + Weibull\ (\alpha = 2.465, \beta = 47.247) \end{array} \right. , t = 1 \quad , p = 1 \\ gamma\ (\alpha = 0.744, \beta = 14.953, \gamma = 6.963) \quad , p = 2 \end{cases}$$ $$where\ P(p) = \begin{cases} 1/2 & , p = 1 \\ 1/2 & , p = 2 \end{cases}$$
10 – Notify clinician	$S \sim gamma\ (\alpha = 2.011, \beta = 10.593)$
11 – Report to referring physician	$S = 0$

Table 5-13: Service time distributions for Clinic A (continued)

Process Type – Description	Service Time (S) Distribution
12 – Close chart	$S \sim Weibull\ (\alpha = 1.339, \beta = 86.669, \gamma = 18.435)$
13 – Other interruptions	$S \sim lognormal\ (\alpha = 0.873, \beta = 62.818)$

Table 5-14: Service time distributions for Clinic B

Process Type – Description	Service Time (S) Distribution
1 – Create record and develop care plan	$F(s) = \begin{cases} 0 & ,s < 111 \\ \dfrac{s-111}{1 \times 26} & ,111 \leq s < 137 \\ 1 & ,s \geq 137 \end{cases}$
2 – Schedule appointment – First attempt	$For\ outcome\ i \in \{1,2,3,4\},$ $S \sim \begin{cases} lognormal\ (\alpha = 0.198, \beta = 181.235) & ,i = 1 \\ log\text{-}logistic\ (\alpha = 8.835, \beta = 67.669) & ,i = 2 \\ F(s) = \begin{cases} 0 & ,s < 46 \\ \dfrac{s-46}{7 \times 1} & ,46 \leq s < 47 \\ \dfrac{1}{7} + \dfrac{s-47}{7 \times 11} & ,47 \leq s < 58 \\ \dfrac{2}{7} + \dfrac{s-58}{7 \times 2} & ,58 \leq s < 60 \\ \dfrac{3}{7} + \dfrac{s-60}{7 \times 3} & ,60 \leq s < 63 \\ \dfrac{4}{7} + \dfrac{s-63}{7 \times 3} & ,63 \leq s < 66 \\ \dfrac{5}{7} + \dfrac{s-66}{7 \times 10} & ,66 \leq s < 76 \\ \dfrac{6}{7} + \dfrac{s-76}{7 \times 53} & ,76 \leq s < 129 \\ 1 & ,s \geq 129 \end{cases} & ,i = 3 \\ Weibull\ (\alpha = 2.417, \beta = 80.850) & ,i = 4 \end{cases}$ $where\ P(i) = \begin{cases} 27/104 & ,i = 1 \\ 56/104 & ,i = 2 \\ 8/104 & ,i = 3 \\ 13/104 & ,i = 4 \end{cases}$

Table 5-14: Service time distributions for Clinic B (continued)

Process Type – Description	Service Time (S) Distribution
3 – Schedule appointment – Patient call back	$S \sim log\text{-}logistic\ (\alpha = 4.502, \beta = 133.630)$
4 – Schedule appointment – Subsequent attempt	$For\ outcome\ i \in \{1,2,3,4\},$ $$S \sim \begin{cases} lognormal\ (\alpha = 0.198, \beta = 181.235) & , i = 1 \\ log\text{-}logistic\ (\alpha = 8.835, \beta = 67.669) & , i = 2 \\ F(s) = \begin{cases} 0 & , s < 46 \\ \frac{s-46}{7 \times 1} & , 46 \le s < 47 \\ \frac{1}{7} + \frac{s-47}{7 \times 11} & , 47 \le s < 58 \\ \frac{2}{7} + \frac{s-58}{7 \times 2} & , 58 \le s < 60 \\ \frac{3}{7} + \frac{s-60}{7 \times 3} & , 60 \le s < 63 \\ \frac{4}{7} + \frac{s-63}{7 \times 3} & , 63 \le s < 66 \\ \frac{5}{7} + \frac{s-66}{7 \times 10} & , 66 \le s < 76 \\ \frac{6}{7} + \frac{s-76}{7 \times 53} & , 76 \le s < 129 \\ 1 & , s \ge 129 \end{cases} & , i = 3 \\ Weibull\ (\alpha = 2.417, \beta = 80.850) & , i = 4 \end{cases}$$ $$where\ P(i) = \begin{cases} 27/104 & , i = 1 \\ 56/104 & , i = 2 \\ 8/104 & , i = 3 \\ 13/104 & , i = 4 \end{cases}$$
5 – Patient mailout	$S = 0$

Table 5-14: Service time distributions for Clinic B (continued)

Process Type – Description	Service Time (S) Distribution
6 – Notify referring physician	$S \sim Weibull\ (\alpha = 0.792, \beta = 18.186, \gamma = 12.963)$
7 – Prepare chart	$S \sim gamma\ (\alpha = 5.706, \beta = 2.892)$ $+\ log\text{-}logistic\ (\alpha = 3.492, \beta = 94.980)$
8 – Appointment reminder	$For\ time\ t \in \{0,1\}$ $S \sim \begin{cases} Weibull\ (\alpha = 3.263, \beta = 302.040, \gamma = 30) & , t = 0 \\ S = 0 & , t = 1 \end{cases}$
9 – Obtain patient data	$S \sim Weibull\ (\alpha = 1.072, \beta = 23.486, \gamma = 15.882)$
10 – Notify clinician	$S \sim log\text{-}logistic\ (\alpha = 3.486, \beta = 31.353)$
11 – Report to referring physician	$S \sim lognormal\ (\alpha = 0.616, \beta = 137.753)$
12 – Close chart	$S \sim Weibull\ (\alpha = 1.339, \beta = 86.669, \gamma = 18.435)$
13 – Other interruptions	$S \sim gamma\ (\alpha = 2.093, \beta = 33.884)$

5.6 Queue and Server Discipline

Once entities are generated as specified by the input models and are assigned attributes describing its process type, service time, priority, and preemption, they enter a priority queue for service by a single server that allows for preemption.

The priority queue sorts entities based on its Priority attribute in descending order. That is, entities with larger Priority attributes will go to the head of the queue. Entities with equal Priority attributes are sorted in the order of arrival. The entity at the head of the queue moves to the server block if the server is available.

Recall that entities are assigned a default preemption value of zero with dynamic preemption assignment. As an entity enters the queue, it polls for the process type of the entity currently being served. If the entity entering the queue should preempt the entity currently being served, as specified in Table 5-4, the entity entering the queue is assigned a Preemption attribute value of one.

The server allows for preemption based on the Preemption attribute in descending order. That is, an entity at the head of the queue with a larger Preemption attribute will preempt an entity in service with a lower Preemption attribute. The dynamic preemption assignment design is tested and its functionality is verified using the test cases shown in Table 5-15.

Table 5-15: Test cases for functional verification of dynamic preemption assignment design

An entity enters the queue when …	**… while the server is …**		
	idle	serving an entity that should be preempted	serving an entity that should not be preempted
the queue is empty	✓	✓	✓
there is a higher priority entity at the head of the queue	n/a	n/a	✓
there is an equal priority entity at the head of the queue	n/a	n/a	✓
there is a lower priority entity at the head of the queue	n/a	✓	✓

If an entity is preempted from service, two of its attributes are modified before it reenters the queue. First, the Priority attribute is increased by one so that when the entity reenters the queue it moves ahead of other entities of the same process type without moving ahead of higher priority entity types. Recall that Priority attributes were assigned in intervals of 100 to allow for this reassignment. Second, the Service Time attribute is reassigned to equal the sum of its residual service time and a nominal switching time to account for the interruption. The residual service time is the difference between the entity's original service time and the time that the entity spent in service prior to preemption. The nominal switching time is ten seconds.

After entities have completed service, they are sorted by process types before flowing into an entity sink. Entities are sorted after service because some process types trigger the generation of entities of other process types as described in Section 5.4.

5.7 Results

The simulation outputs the utilization of the patient care coordinator in the patient care process. Note that the utilization does not include time spent on other responsibilities, but only on the processes described in the patient care process model; this is useful for assessing the impacts of the ICTs on the patient care process. An experimental design similar to that presented in Section 4.4 estimates the number of simulation runs necessary to estimate the utilization of the PCC within a desired confidence interval based on the sample variance obtained through a preliminary set of 30 simulation runs. Estimates of the utilization (ρ) of the PCC will be generated within 0.05 (where ρ is a proportion in [0,1]) with a 95% confidence interval. Parameter estimation and comparison methods follow that presented in Section 4.4.

The 95% confidence interval for the utilization of the PCC at Clinic A in the ICT pre-implementation state is 0.407 ± 0.018 or (0.389,0.425). In the ICT post-implementation state, the 95% confidence interval for the utilization of the PCC at Clinic A is 0.280 ± 0.017 or (0.263,0.297), which is a significant reduction (at $\alpha = 0.05$) from the pre-implementation state.

The 95% confidence interval for the utilization of the PCC at Clinic B in the ICT pre-implementation state is 0.226 ± 0.017 or (0.209,0.243). Clinic B had not completed ICT implementation during the study period, so the post-implementation state for Clinic B includes only the implementation of the automated appointment reminder system. Considering the partial post-implementation state for Clinic B, the 95% confidence interval for the utilization of the PCC at Clinic B is 0.158 ± 0.017 or (0.141,0.175), which is already a significant reduction (at $\alpha = 0.05$) from the pre-implementation state.

The 95% confidence interval of the utilization of the PCC at Clinic A and Clinic B in the pre and post ICT implementation states is shown in Figure 5-15.

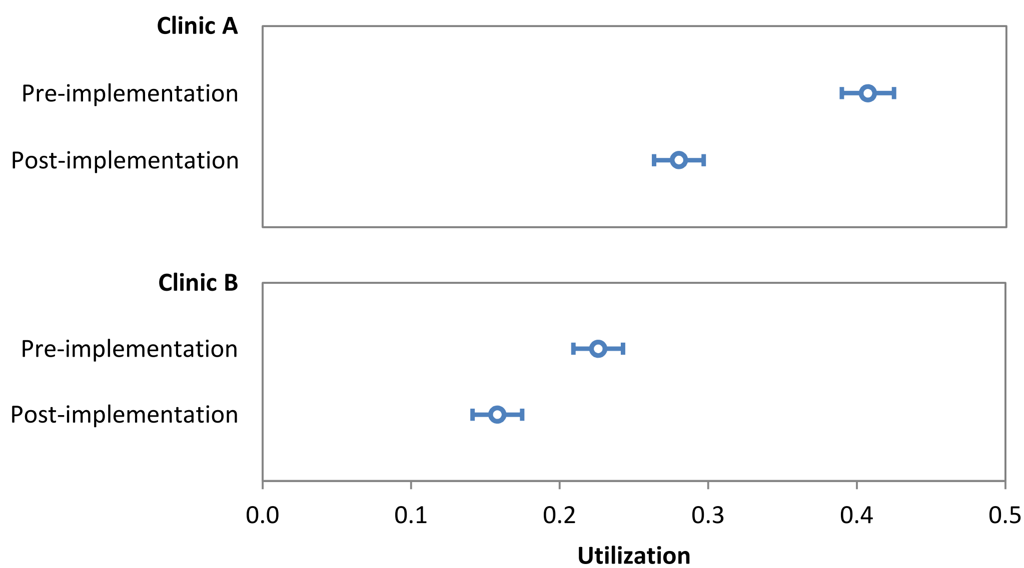


Figure 5-15: Utilization at Clinic A and Clinic B pre and post ICT implementation

5.8 Discussion

The results presented in the previous section shows that utilization significantly decreased after ICT implementation. This decrease is seen at Clinic B even though the clinic had only partially completed implementation and further decrease is expected upon completion. To estimate the utilization at Clinic B upon completion, the changes that were observed at Clinic A could be adapted and applied to the model for Clinic B. Other potential changes proposed for redesign could also be simulated to estimate the impact.

One of the common impacts of ICTs is the automation of a process. For example, the implementation of the automated appointment reminder process automated the process of making reminder calls to patients. This type of change is implemented in the model by changing the service time to zero. Before implementation of the automated appointment reminder system, the service time for process type 8 (appointment reminder) is modeled as a Weibull distribution. After implementation, the service time for process type 8 is modeled as a discrete distribution with one possible value of zero. Further discussion regarding the impacts of the implementation of the automated appointment reminder process, including a cost-benefit analysis and process optimization is the subject of the next section.

Other impacts of ICTs or BPR might include changing the sequence of processes or rearranging processes. This type of impact could be implemented in the model by changing priority attributes of the affected processes. Other changes may impact the service times of processes, which can be modeled as theoretical or empirical distributions in a similar manner as presented above in Section 5.5. These changes can be simulated to estimate the effect on the system utilization. Changes in the demand for service can also be modeled by modifying the arrival patterns specified in the model in a similar manner as described above in Section 5.4.

5.9 Conclusion

The discrete-event simulation of the patient care process at the PCN examines the impact of the implementation of three ICTs - electronic medical records, appointment reminder systems, and a patient self-check in application. This model considers the actual prioritization and preemption of tasks and the relationships between processes in patient care. Entities representing the various processes in patient care and their service times are specified in the model based on quantitative data collected through observation at the PCN. The simulation results suggest a significant reduction in utilization of the patient care coordinator at both clinics after implementation of ICTs.

6 Feasibility Study of Appointment Reminder Process

Appointment reminders that were previously made by patient care coordinators during office hours have been changed to an automated appointment reminder system. The impact of the automated appointment reminder system on the patient care process was examined in the model and simulation in the previous chapter. Research on workflow impacts of appointment reminder systems often centers around the effects on attendance of appointments. Methods of reducing nonattendance are critical as missed appointments are lost income in fee-for-service clinics and artificially increase demand on the system.

This chapter further examines the impacts on the appointment reminder process by considering the costs avoided in manual labour and reduction in nonattendance against the cost of the system. Records are reviewed for nonattendance and level of success in the automated system. Factors affecting financial viability are explored and recommendations to optimise system performance are identified.

Section 6.1 provides a description of the appointment reminder processes. Section 6.2 proposes a financial viability model and describes method of data collection and statistical analysis. Section 6.3 provides results collected and financial viability. Section 6.4 provides a sensitivity analysis of the process and further analysis for process optimization. Conclusions and future work are presented in Section 6.5.

6.1 Appointment Reminder Process Overview

6.1.1 Manual Appointment Reminder Process

Appointment reminders were previously made one day prior to the appointment by patient care coordinators during office hours (0800 to 1600). The study period started after the transition from the manual process so data describing the process is limited. An overview of the manual appointment reminder process is shown in Figure 6-1.

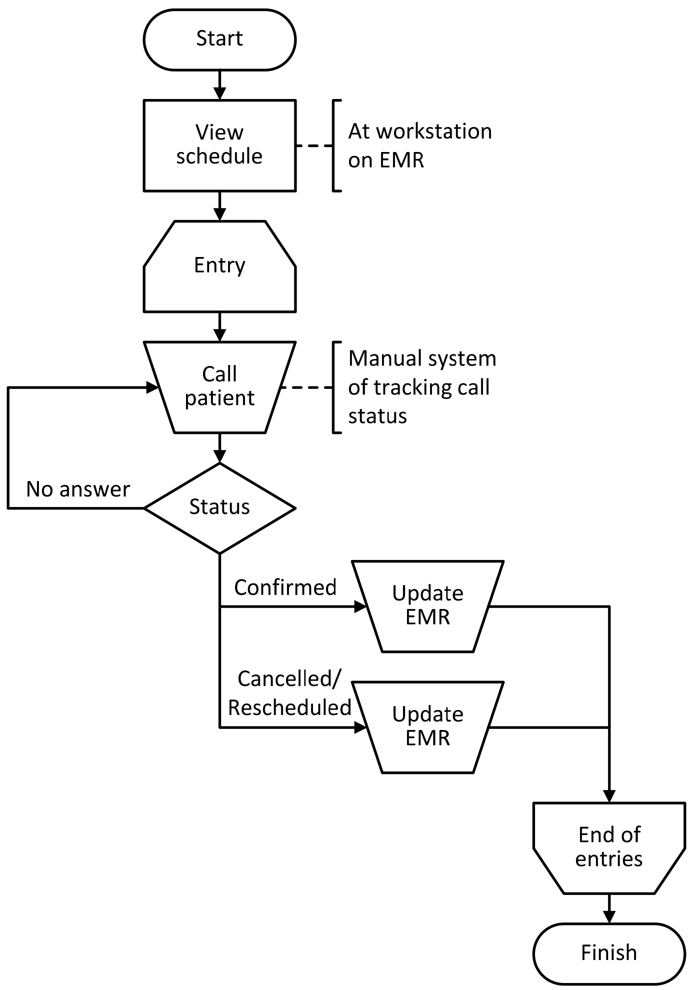


Figure 6-1: Manual appointment reminder process

The patient care coordinator viewed the scheduled appointments from their workstations and telephoned the patient for each schedule entry to remind them of their appointment. The outcome of the call, such as confirmation, cancellation, or reschedule, was updated in the EMR. Anecdotal data collected from the patient care coordinators indicate that the process took approximately one to two hours each day and that many appointments were often not confirmed since patients were unavailable to answer calls during office hours. As a result, most reminders were left as messages on answering machines or voicemail, and the patient care coordinators had to manage a manual system of tracking which appointments had been confirmed and which had still to be called.

Sometimes patient care coordinators tried to improve the success rate of reaching patients by making calls in the evening, but this required extended work hours. The reminder calls also affected their workflow due to an increase in interruptions and multi-tasking since the calls were often made between other tasks whenever they could be fit in.

6.1.2 Automated Appointment Reminder Process

Appointment reminders are now made with an automated reminder system, two days prior to the appointment during the evening (starting at 1800). Patients confirm their appointments by following prompts and entering selections using their phone keypads.

The experience of the patient care coordinators informed the system setup options. Reminders are made two days prior to give more time for patients to make arrangements (for work, childcare, etc.) as experience found that one day was often not enough time. Evening calls were also expected to better match the availability of the patients. These changes are expected to increase the success rate of reaching and confirming appointments and reduce nonattendance in comparison to the manual reminder process.

The automated reminder system has an initial $1450 setup fee and a monthly charge of $500 (Ludwick, 2012).

Each day the automated reminder system sends a calling report via email to the patient care coordinators with the status of the reminders. During the automated reminder call, patients also have the option to leave a message for the clinic, which is then sent as an audio attachment via email to the patient care coordinators. The patient care coordinators no longer make reminder phone calls, and spend minimal time, if any, to review the reminder outcomes in the daily calling reports.

6.2 Model Development

6.2.1 Financial Viability Model

The automated appointment reminder process is a financially viable option over the manual appointment reminder process if the costs avoided exceeds the costs of the automated system.

The costs avoided when implementing the automated reminder system are the labour costs for manual appointment reminders and the costs avoided due to a reduction in nonattendance.

The labour cost for the manual appointment reminder process per patient is $W_m t_m n$ where W_m is the wage of the patient care coordinator making reminder calls and t_m is the average length of each reminder call and n is the number of patients (reminders).

The costs avoided due to a reduction in nonattendance is $C_e n[P_m(N) - P_a(N)]$ where C_e is the average fee for a patient encounter, n is the number of patients (reminders), and $P_m(N)$ and $P_a(N)$ is the probability of nonattendance in the manual and automated appointment reminder process, respectively.

Let C_a be the cost of the automated appointment reminder system per specified time period. Then the automated appointment reminder process is financially viable if the balance of costs avoided from manual labor and the reduction of nonattendance minus the cost of the system is greater than zero.

$$balance = W_m t_m n + C_e n[P_m(N) - P_a(N)] - C_a > 0$$

6.2.2 Data Collection

Appointment attendance data were obtained from reports exported from the clinic's electronic medical record for Clinic A and Clinic B from a sample period when manual appointment reminders were made and a period after the implementation of the automated appointment reminder system.

For the sample after the implementation of the automated reminder system, reminder outcome data were obtained from the daily calling reports generated by the automated reminder system. Reminder outcome data and appointment attendance data that met the inclusion and exclusion criteria were cross tabulated to produce daily, weekly and summary contingency tables.

Inclusion criteria are appointment reminders presented in the automated reminder calling reports between June 6, 2011 and December 23, 2011 for Clinic A and between November 14, 2011 and December 23, 2011 for Clinic B. The sample for manual appointment reminders was taken from the same period one year prior.

Exclusion criteria are appointment reminders from the automated system reports that could not be cross-referenced to appointments in the electronic medical record, test calls/emails to PCN staff, and reminder outcomes of 'Call Number Unreachable.'

6.2.3 Statistical Methods

Large sample hypothesis testing and large sample confidence intervals were used to make statistical inference about sample proportions. Pearson's chi-square test for independence was used to demonstrate association of reminder and attendance outcomes and the results were verified with IBM SPSS Statistics software. These methods can be found in most statistical textbooks; Wackerly, Mendenhall and Scheaffer (2008) is one such text. A brief summary of statistical methods is given below.

Point Estimator, Standard Error, and Confidence Interval

An unbiased point estimator for the population proportion π is the sample proportion p of sample size n. The standard error of the point estimator p is $\sqrt{\frac{p(1-p)}{n}}$.

An unbiased point estimator for the difference in population proportions $\pi_1 - \pi_2$ is the difference in sample proportions $p_1 - p_2$ of samples sizes n_1 and n_2. The standard error of the point estimator $p_1 - p_2$ is $\sqrt{\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}}$.

A $100(1-\alpha)\%$ confidence interval for proportion π is $p \pm z_{\alpha/2}\sqrt{\frac{p(1-p)}{n}}$.

Hypothesis Testing

The components of a large-sample α-level hypothesis test for a proportion π with its point estimator p, standard error of the point estimator $\sqrt{\frac{p(1-p)}{n}}$, and a specific value for the proportion π_0 are: null hypothesis, $H_0: p = p_0$; alternative hypothesis, $H_a: \begin{cases} p > p_0 \\ p < p_0 \\ p \neq p_0 \end{cases}$; test statistic, $Z = \frac{p-p_0}{\sqrt{\frac{p(1-p)}{n}}}$; and rejection region, $RR: \begin{cases} \{z > z_\alpha\} \\ \{z < -z_\alpha\} \\ \{|z| > z_{\alpha/2}\} \end{cases}$.

The components of a large-sample α-level hypothesis test for comparing two sample proportions, p_1 of sample size n_1 and p_2 of sample size n_2, are: null hypothesis, $H_0: p_1 = p_2$; alternative hypothesis, $H_a: \begin{cases} p_1 > p_2 \\ p_1 < p_2 \\ p_1 \neq p_2 \end{cases}$; test statistic, $Z = \frac{p_1 - p_2}{\sqrt{\frac{p_1(1-p_1)}{n_1}+\frac{p_2(1-p_2)}{n_2}}}$; and rejection region, $RR: \begin{cases} \{z > z_\alpha\} \\ \{z < -z_\alpha\} \\ \{|z| > z_{\alpha/2}\} \end{cases}$.

Pearson Chi-Square Test of Independence

For an $I \; x \; J$ contingency table, the Pearson chi-square statistic for testing independence is $X^2 = \sum \frac{(O_{ij}-E_{ij})^2}{E_{ij}}$, where O_{ij} is the observed value of cell ij and E_{ij} is the expected value of cell ij under the null hypothesis of independence and is given by $E_{ij} = \frac{n_{i+}n_{+j}}{n}$. For α-level hypothesis testing, the rejection region is $RR: \{\chi^2 > \chi^2_{\alpha,(I-1)(J-1)}\}$. The standardised residual for cell ij is given by $r_{ij} = \frac{O_{ij}-E_{ij}}{\sqrt{E_{ij}\left(1-\frac{n_{i+}}{n}\right)\left(1-\frac{n_{+j}}{n}\right)}}$. Since the Pearson chi-square test for independence can be sensitive to small cell frequencies, results were verified using Exact tests using IBM SPSS.

6.3 Results

This section presents the attendance and reminder outcomes from the data collected and the cost benefit model. Section 6.4 provides discussion of these results and examines process optimization.

6.3.1 Attendance and Reminder Outcomes

Clinic A

The appointment attendance outcomes for the manual and automated appointment reminder processes at Clinic A are shown in Figure 6-2.

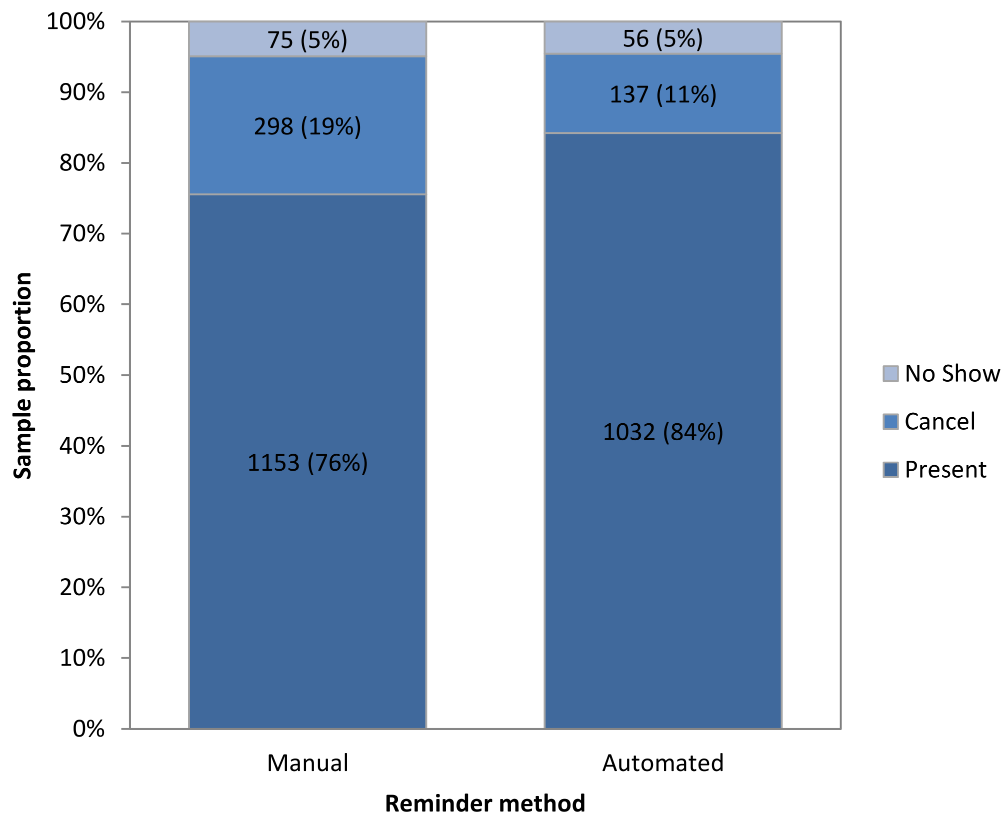


Figure 6-2: Comparison of attendance outcomes for manual and automated appointment reminder methods at Clinic A

The study period for the manual appointment reminders included 1526 scheduled appointments, of which 1153 (76%) were present for the appointment, 298 (19%) cancelled the appointment, and 75 (5%) did not attend the appointment. The study period for the automated appointment reminders included 1225 scheduled appointments, of which 1032 (84%) were present for the appointment, 137 (11%) cancelled the appointment, and 56 (5%) did not attend the appointment.

There are eleven observed reminder outcomes for the automated reminder system, which were grouped into eight categories for this analysis. These groups are shown in Table 6-1, along with the code used to abbreviate the outcome in the remainder of the discussion.

Table 6-1: Reminder outcomes

Code	Reminder Outcome	Includes
CR	Confirmed by recipient	• Confirmed by recipient
CF	Confirmed by family member	• Confirmed by family member
MSG	Message delivered to answering machine	• Message delivered to answering machine
VM	Voice message sent to office by email	• Voice message sent to office by email
CH	Call hangup	• Not confirmed – calling complete (Call hangup) • Further calls scheduled (Call hangup)
NA	No answer	• Not confirmed – calling complete (No answer) • Further calls scheduled (No answer)
DNR	Call was answered but the recipient did not respond to prompts	• Not Confirmed – calling complete (Call was answered but the recipient did not respond to prompts) • Further calls scheduled (Call was answered but the recipient did not respond to prompts)
CBL	User requested to be called back later	• Further calls scheduled (Call answered – User requested to be called back later)

The distribution of the eight reminder outcomes from the automated appointment reminder system is shown in Figure 6-3. The distribution of attendance outcomes within each reminder outcome is also shown.

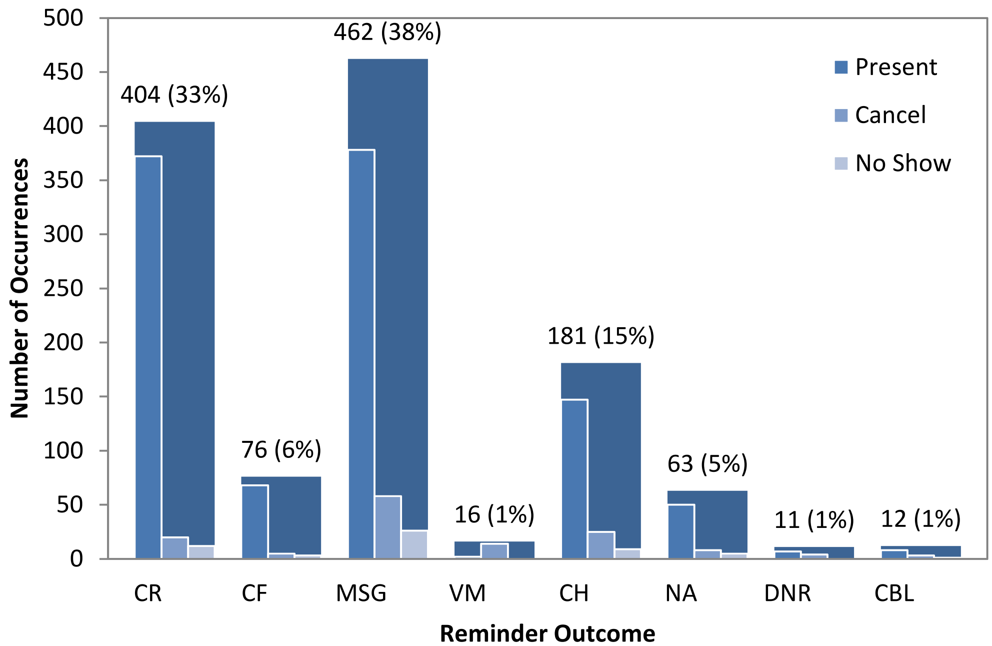


Figure 6-3: Distribution of reminder outcomes from automated appointment reminder system at Clinic A

The most frequent appointment reminder outcomes is a message is left by the automated system to the patient's answering machine (MSG, 38 percent) or the recipient receives the reminder and confirms their appointment (CR, 33 percent). A family member may also confirm the appointment (CFR, 6 percent). The reminder system sometimes does not get a response as the recipient hangs up (CH, 15 percent) or there is no answer (NA, 6 percent).

Clinic B

The appointment attendance outcomes for the manual and automated appointment reminder processes at Clinic B are shown in Figure 6-4.

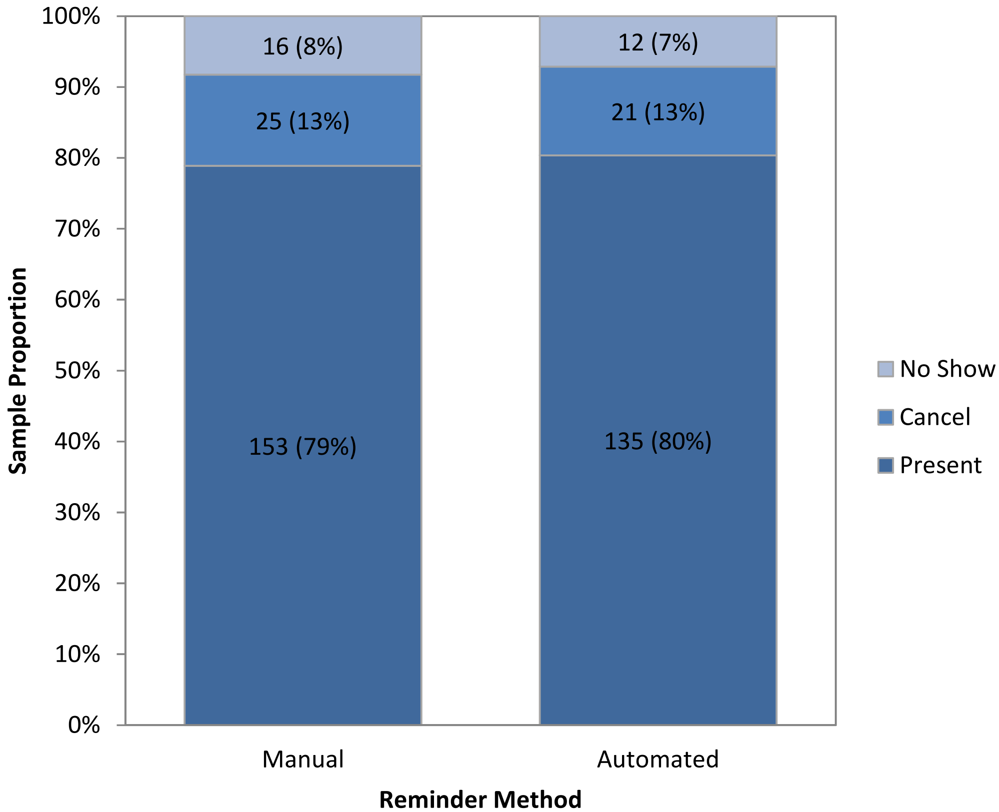


Figure 6-4: Comparison of attendance outcomes for manual and automated appointment reminder methods at Clinic B

The study period for the manual appointment reminders included 194 scheduled appointments, of which 153 (79%) were present for the appointment, 25 (13%) cancelled the appointment, and 16 (8%) did not attend the appointment. The study period for the automated appointment reminders included 168 scheduled appointments, of which 135 (80%) were present for the appointment, 21 (13%) cancelled the appointment, and 12 (7%) did not attend the appointment.

The distribution of the eight reminder outcomes from the automated appointment reminder system is shown in Figure 6-5. The distribution of attendance outcomes within each reminder outcome is also shown.

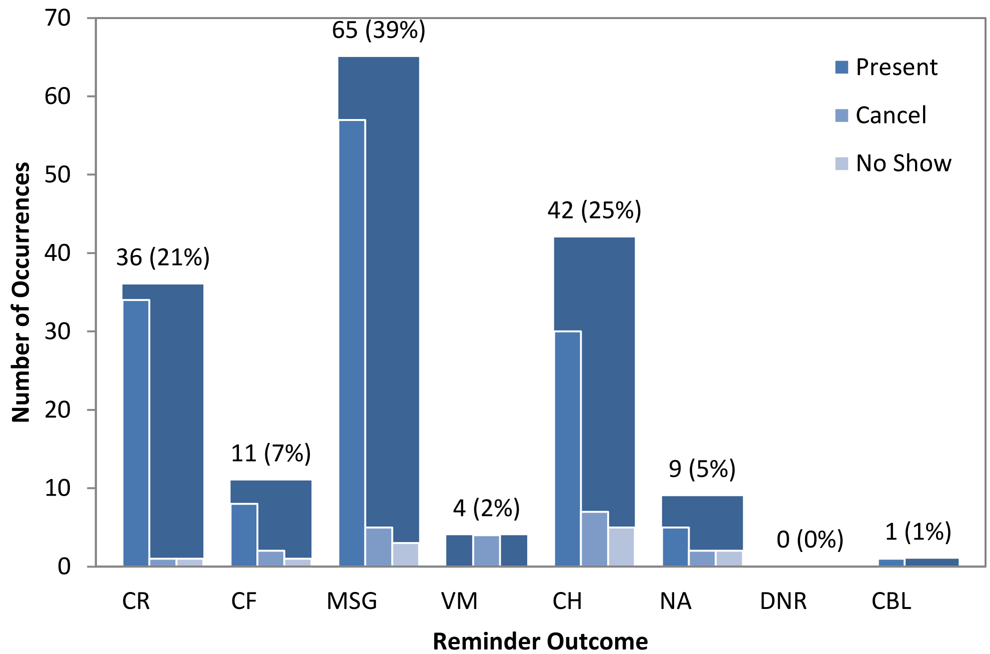


Figure 6-5: Distribution of reminder outcomes from automated appointment reminder system at Clinic B

The distribution of appointment reminder outcomes at Clinic B is similar to that observed at Clinic A. The most frequent outcome is a message is left by the automated system to the patient's answering machine (MSG, 39 percent). The confirmation by the recipient (CR, 21 percent) occurs less frequently than at Clinic A and call hang ups (CH, 25 percent) occur more frequently.

6.3.2 Cost Benefit Analysis

Recall that the automated appointment reminder process is financially viable if the balance of costs avoided from manual labor and the reduction of nonattendance minus the cost of the system is greater than zero.

$$balance = W_m t_m n + C_e n[P_m(N) - P_a(N)] - C_a > 0$$

The monthly cost for the automated reminder system is \$500. Assume the wage for a patient care coordinator is \$25 per hour and an average reminder call is 3 minutes, or 0.05 hours, in length. Assume the average cost of a patient encounter is \$50.

Clinic A

The proportions of nonattendance observed at Clinic A for the manual and automated appointment reminder process are

$$p_m(N) = (298 + 75) / 1526 = 0.244$$

$$p_a(N) = (137 + 56) / 1225 = 0.158$$

A summary of model parameters for Clinic A is shown in Table 6-2.

Table 6-2: Summary of model parameters for Clinic A

Model Parameter	Value
Wage for manual labor	W_m = \$25/hr
Length of reminder call	t_m = 5 min = 0.05 hr
Number of appointment reminders in study period	n = 1225
Cost of encounter	C_e = \$50
Sample proportion of nonattendance – manual process	$p_m(N)$ = 0.244
Sample proportion of nonattendance – automated process	$p_a(N)$ = 0.158
Cost of automated system	C_a = \$500/mth

The balance of costs avoided minus the cost of the system during the study period is $1903. The automated appointment reminder system is financially viable for Clinic A.

The appointment reminder volume for each month of the study period at Clinic A is shown in Table 6-3.

Table 6-3: Monthly appointment reminder volume at Clinic A

Month	2011-06	2011-07	2011-08	2011-09	2011-10	2011-11	2011-12
Volume	168	185	142	165	184	236	145

Evaluating the balance after each month in the study period, with costs and savings calculated from monthly appointment reminder volumes and the sample proportions of nonattendance calculated above, we can see that simple payback is achieved in four months, as shown in Figure 6-6.

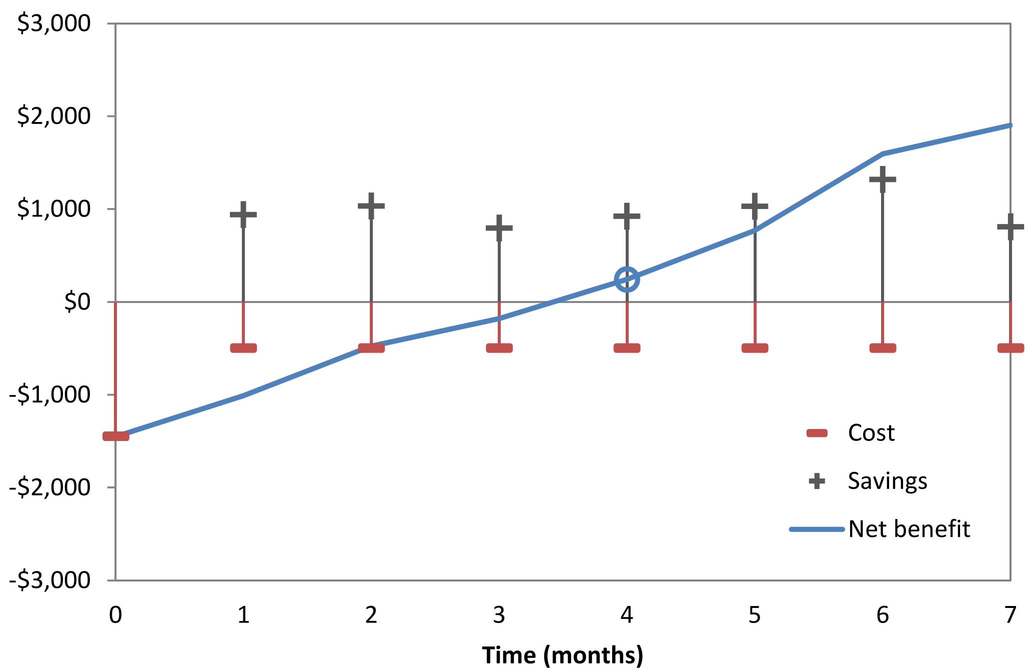


Figure 6-6: Simple payback of automated appointment system in the fourth month

The net benefit for the PCN increases further once the system is implemented for Clinic B. No additional system costs are associated with the implementation and the reminder call volume does not increase beyond the current monthly rate.

6.4 Discussion

This section contains a sensitivity analysis of the financial viability model and further analysis to support recommendations for process optimization. This discussion is based on the results obtained for Clinic A as there are limited results for Clinic B.

6.4.1 Sensitivity Analysis

The results in the previous section show that the automated appointment reminder system is financially viable for the PCN. This section examines how that conclusion may be affected by changes to model parameters, such as reminder call volume, system cost, and wages. The analysis assumes simple payback has been achieved and only the monthly system cost, and not the initial system cost, is included in the subsequent analysis.

Reminder Volume

The minimum number of patients (reminders) in a given time period for the automated reminder system to be financially viable is given by

$$n > \frac{C_a}{W_m t_m + C_e [P_m(N) - P_a(N)]}$$

The automated reminder system is financially viable if the monthly volume exceeds 90. For reminder volumes less than this, the savings in manual labour is not offset by the cost of the automated system and is not financially viable.

System Cost

The maximum cost of the automated reminder system to be financially viable is given by

$$C_a < W_m \, t_m \, n + C_e \, n \, [P_m(N) - P_a(N)]$$

If the monthly cost of the automated system exceeds $979, then it is no longer financially viable as it exceeds the cost of the manual reminder process and costs of nonattendance.

Patient Care Coordinator Wage

The minimum wage for the automated reminder system to be financially viable is given by

$$W_m > \frac{C_a - C_e\, n\, [P_m(N) - P_a(N)]}{n\, t_m}$$

In this case, the automated reminder system is financially viable regardless of the wage paid for manual labor due to the reminder volume and costs avoided due to reduction in nonattendance.

Summary of Sensitivity Analysis

A summary of the sensitivity analysis is shown in Table 6-4.

Table 6-4: Sensitivity analysis of model parameters

Model Parameter	Boundary Condition
Reminder volume [per month]	$n > 90$
System cost [per month]	$C_a < \$979$
Wage for manual labor [per hour]	$W_m \geq \$0$

Other Considerations

The cost-benefit analysis does not include the labour cost for time to deal with cancellations. However, the proportion of cancellations has decreased from the sample of manual reminders to the sample of automated reminders, so inclusion of this cost would be more in favour of the financial viability of the automated system.

The cost-benefit analysis also does not capture other benefits which can be more difficult to quantify. These benefits include the ability to focus on more meaningful work in patient care and less interruptions to this work which can improve the quality of job satisfaction leading to increased efficiency.

6.4.2 Process Optimization

The preceding results and sensitivity analysis demonstrate that the automated reminder system is a financially viable process for the PCN and will be for a range of system parameters.

The remainder of the discussion looks at how to maximise the benefits of the automated reminder system to increase the return on investment. By optimizing system setup options, the automated reminder process may be optimised to increase the success rate in confirming appointments to further reduce nonattendance to increase the return on investment.

Increase Success Rate

The vendor of the automated reminder system claims they have "a 97% success rate in reaching and confirming patient appointments" (Patient Prompt, 2012). Has this success rate been achieved at the PCN?

The distribution of reminder outcomes is shown in Figure 6-7.

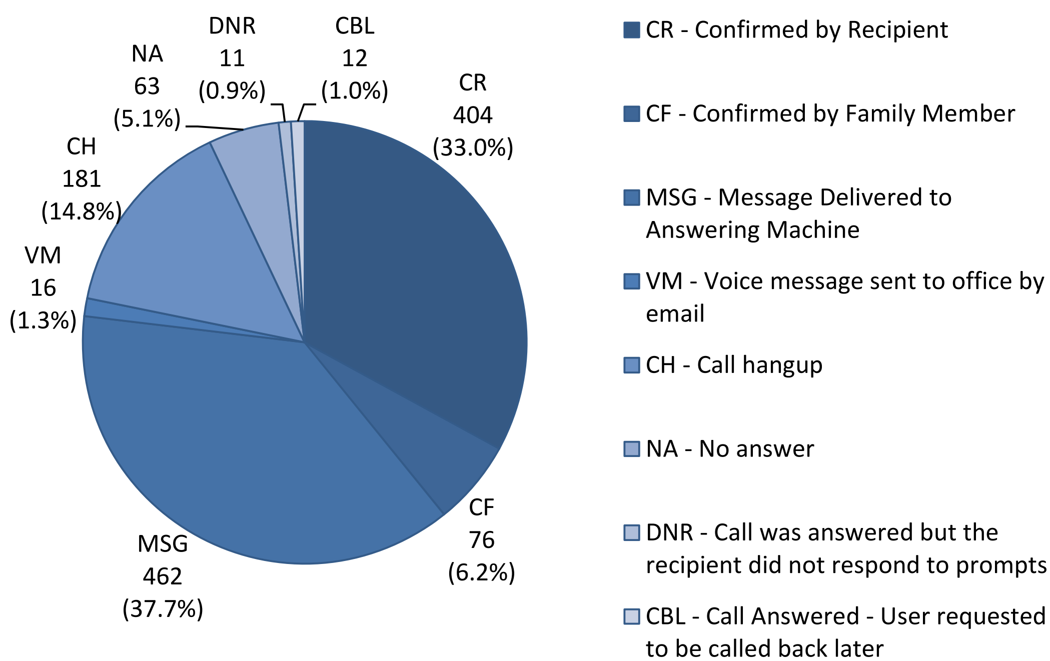


Figure 6-7: Distribution of automated appointment reminder outcomes at Clinic A

What reminder outcomes are considered as a success in "reaching and confirming patient appointments?" Consider the interpretation where success includes the CR, CR, MSG, and VM outcomes and the other outcomes (CH, NA, DNR, and CBL) are considered unsuccessful.

Based on this interpretation of successful and unsuccessful reminder outcomes, the observed number of successes and the sample success rate p(S) from sample size n are given in Table 6-5.

Table 6-5: Observed success rate of reaching and confirming patient appointments at Clinic A

Sample size (n)	Number of Successes	Success Rate (p(S))
1225	958	0.782

The claim that the automated reminder system has "a 97% success rate in reaching and confirming patient appointments" was tested as the null hypothesis against the alternative hypothesis that the success rate was less than 97%. At a significance level of $\alpha = 0.05$, the null hypothesis is rejected in favour of the alternative hypothesis. There is strong evidence to indicate the success rate achieved is less than the 97% claimed by the vendor of the automated reminder system (p-value < 0.0001).

The 95% two-sided confidence intervals for the actual success rate in "reaching and confirming patient appointments" is 0.782 ± 0.023 or (0.759, 0.805). Note that this interval excludes the claimed rate of 97%, as expected given the results of hypothesis testing.

Also note that alternate interpretations of success may lead to alternate conclusions. Although the success rate is less than 97%, perhaps a modification to the system will increase the success rate.

Reduction in Nonattendance

The vendor of the automated reminder system claims their "advanced patient communication technology can reduce no-show rates and cancellations by as much as 80%" (Patient Prompt, 2012). Has this reduction in nonattendance been achieved at the PCN?

The observed sample attendance and nonattendance rates for the manual and automated reminder processes are shown in Table 6-6.

Table 6-6: Comparison of attendance outcomes for manual and automated appointment reminder methods at Clinic A

Attendance Outcome	Manual Reminder Process (2010-W24 to 2010-W52)		Automated Reminder Process (2011-W24 to 2011-W52)	
	Frequency	Proportion	Frequency	Proportion
Attendance	1153	0.756	1032	0.842
Nonattendance	373	0.244	193	0.158
Total	**1526**		**1225**	

The weekly nonattendance rates from the manual and automated reminder process are shown in Figure 6-8.

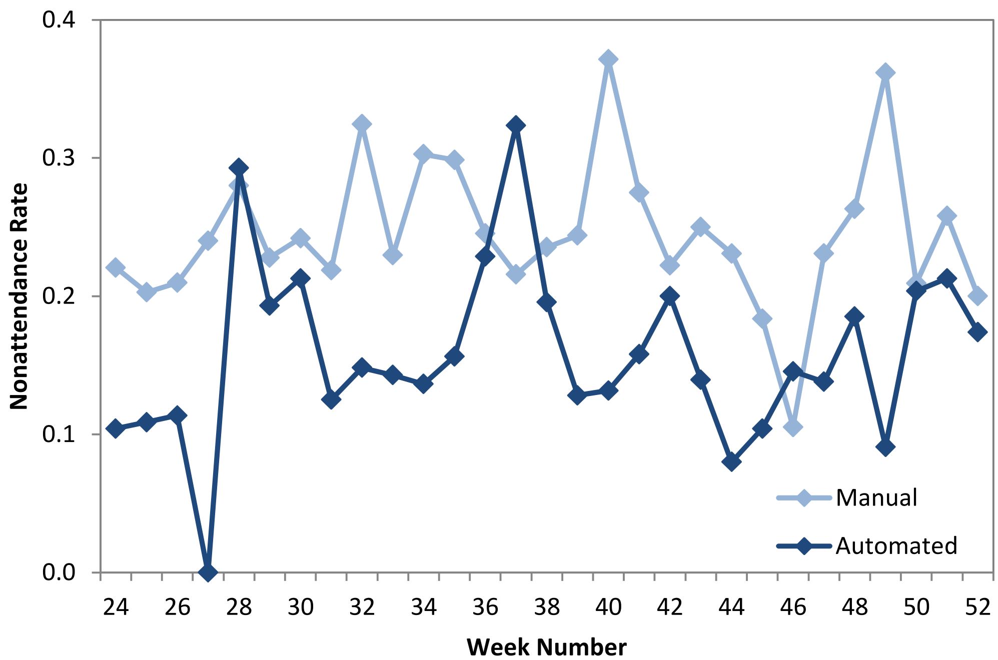


Figure 6-8: Comparison of weekly nonattendance rates for manual and automated appointment reminder methods at Clinic A

To show there has been a reduction in nonattendance rates since the implementation of the automated reminder system, we form the null hypothesis that there is no change in nonattendance ($P_m(N) - P_a(N) = 0$). The null hypothesis was tested against the alternative hypothesis that there was a reduction in nonattendance rates ($P_m(N) - P_a(N) > 0$).

At a significance level of α = 0.05, the null hypothesis is rejected in favour of the alternative hypothesis. There is strong evidence to indicate a reduction in nonattendance rate since the implementation of the automated reminder system (p-value < 0.0001). Note that this does not imply a causal relationship between the implementation of the automated reminder system and the reduction in nonattendance rates. However, there were no other changes that can be attributed to this change in nonattendance. The 95% two-sided confidence interval for the reduction in nonattendance rates is 0.087 ± 0.030, or (0.057, 0.117).

Recall the vendor's claim that their "advanced patient communication technology can reduce no-show rates and cancellations by as much as 80%." An 80% reduction in nonattendance rates would imply a reduction of 0.196 using the pre-implementation nonattendance rate estimate as a baseline. This value is not included in the 95% confidence interval for the reduction in nonattendance rates. Again, we propose that a modification to system options may further reduce nonattendance perhaps by increasing the success rate discussed in the section above.

Association between Reminder and Appointment Outcomes

If the reminder outcome results in a confirmation by the recipient (CR), does the patient actually attend the appointment? In this section, we explore the relationship between reminder outcomes and attendance outcomes; that is, we will show there is an association between reminder and attendance outcomes.

The reminder and attendance outcome results presented in the previous section are shown in Table 6-7.

Table 6-7: Sample frequencies of reminder and attendance outcomes at Clinic A

Reminder Outcome	Attendance Outcome		
	Attendance	Nonattendance	Total
CR	372	32	404
CF	68	8	76
MSG	378	84	462
VM	2	14	16
CH	147	34	181
NA	50	13	63
DNR	7	4	11
CBL	8	4	12
Total	1032	193	**1225**

The distribution of these outcomes is shown in Figure 6-9. The width of each bar represents the distribution of reminder outcomes and the height of the bars within each column represents the distribution of attendance outcomes for a given reminder outcome. The sample marginal probabilities and the sample conditional probabilities for attendance outcomes given the reminder outcome are shown. The sample marginal probability for attendance outcomes is indicated by the red dotted line.

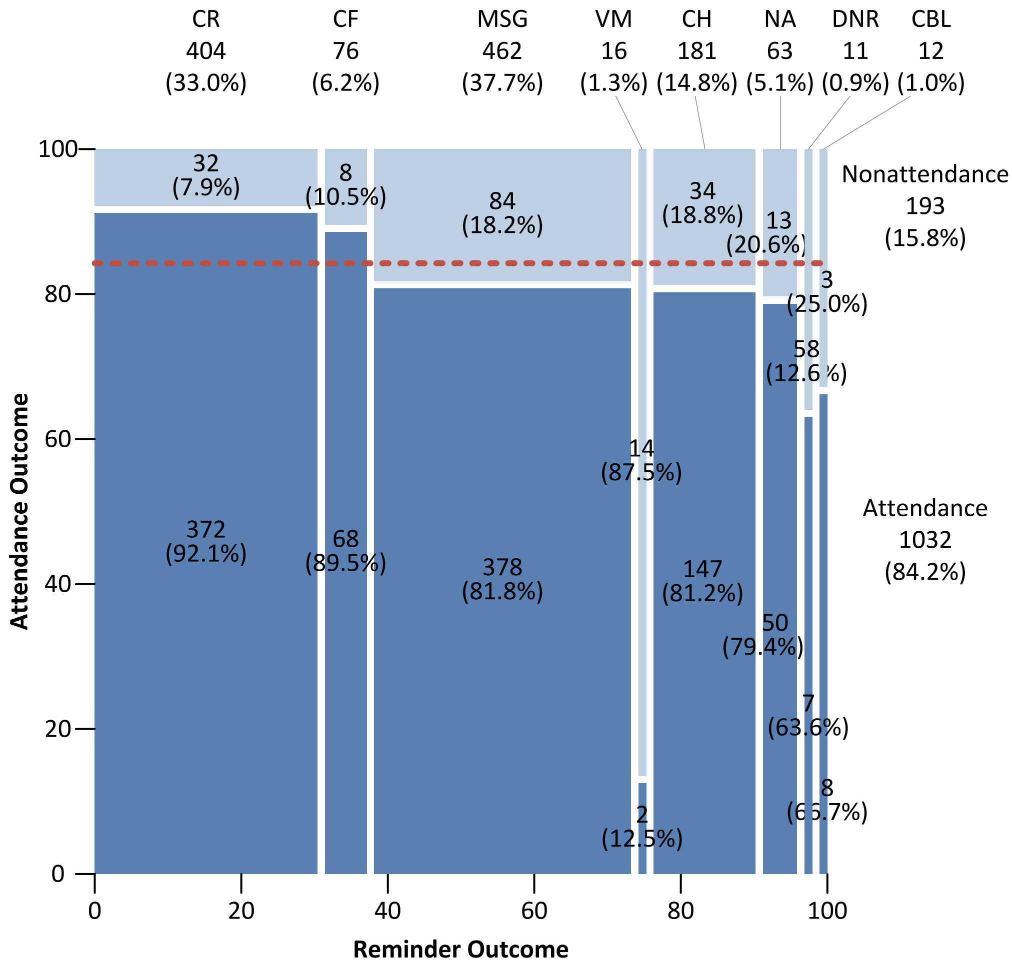


Figure 6-9: Mosaic plot of reminder and attendance outcomes at Clinic A

This plot visually confirms the intuitive notion that attendance outcomes are dependent on reminder outcomes. If the attendance outcomes were independent of the reminder outcomes, then the distribution of attendance outcomes would be the same regardless of the reminder outcome; that is, the height of each bar would be the same in each column.

The observed values, expected values under the null hypothesis, standardised residuals, and contributions to the chi-square statistic for reminder and attendance outcomes are shown in Table 6-8.

Table 6-8: Observed values (in bold), expected values, standardised residuals (in parenthesis), and contributions to the chi-square statistic (in italics) of reminder and attendance outcomes at Clinic A

Reminder Outcome	Attendance Outcome		
	Attendance	Nonattendance	Total
CR	**372** 340.349 (5.280) *2.943*	**32** 63.651 (-5.280) *15.738*	404
CF	**68** 64.026 (1.292) *0.247*	**8** 11.974 (-1.292) *1.319*	76
MSG	**378** 389.211 (-1.814) *0.323*	**84** 72.789 (1.814) *1.727*	462
VM	**2** 13.479 (-7.929) *9.776*	**14** 2.521 (7.929) *52.273*	16
CH	**147** 152.483 (-1.212) *0.197*	**34** 28.517 (1.212) *1.054*	181
NA	**50** 53.074 (-1.092) *0.178*	**13** 9.926 (1.092) *0.952*	63
DNR	**7** 9.267 (-1.885) *0.555*	**4** 1.733 (1.885) *2.965*	11
CBL	**8** 10.109 (-1.680) *0.440*	**4** 1.891 (1.680) *2.353*	12
Total	1032	193	**1225**

The standardised residuals are approximately standard normal, and we draw our attention to the largest residuals. Although it may be difficult to alter the behaviour of the call recipient to not hang up or request to be called back later, we may potentially alter system options. For example, we can explore setup options such as whether the system should leave a message if it reaches a machine (MSG) or if it should continue calling in an attempt to reach a confirmed by recipient (CR) outcome? How can the system setup be modified to reduce the number of calls not answered or call hang-ups?

Answering Machines – Leave a Message or Try Again?

First, we will show that the sample conditional probability for a nonattendance outcome given an observed CR reminder outcome is less than the sample conditional probability for a nonattendance outcome given an MSG reminder outcome.

The following discussion will use the notation for observed frequencies shown in Table 6-9.

Table 6-9: Notation for observed frequencies of reminder and attendance outcomes

Reminder Outcome	Attendance Outcome		
	Attendance	**Nonattendance**	**Total**
CR	n(CR, A)	n(CR,N)	n(CR,+)
CF	n(CF,A)	n(CF,N)	n(CF,+)
MSG	n(MSG,A)	n(MSG,N)	n(MSG,+)
VM	n(VM,A)	n(VM,N)	n(VM,+)
CH	n(CH,A)	n(CH,N)	n(CH,+)
NA	n(NA,A)	n(NA,N)	n(NA,+)
DNR	n(DNR,+)	n(DNR,N)	n(DNR,+)
CBL	n(CBL,A)	n(CBL,N)	n(CBL,+)
Total	n(+,A)	n(+,N)	**n**

Let the conditional probability for a nonattendance outcome given a CR reminder outcome be the sample conditional probability given by

$$P(N|CR) = \frac{n(CR, N)}{n(CR, +)}$$

Then $P(N|CR)$, the conditional probability for a nonattendance outcome given a CR reminder outcome is 0.079.

Let the conditional probability for a nonattendance outcome given a MSG reminder outcome be the sample conditional probability given by

$$P(N|MSG) = \frac{n(MSG, N)}{n(MSG, +)}$$

Then $P(N|MSG)$, the conditional probability for a nonattendance appointment outcome given a MSG reminder outcome is 0.182.

To show that $P(N|CR)$ is less than $P(N|MSG)$, we form the null hypothesis that the conditional probabilities are equal ($P(N|CR) - P(N|MSG) = 0$). The null hypothesis was tested against the alternative hypothesis that $P(N|CR)$ is less than $P(N|MSG)$, or ($P(N|CR) - P(N|MSG) < 0$).

At a significance level of α = 0.05, the null hypothesis is rejected in favour of the alternative hypothesis. There is strong evidence to indicate that $P(N|CR)$ is less than $P(N|MSG)$ (p-value < 0.0001).

Furthermore, we can show that the odds of a patient not attending an appointment where the reminder outcome was a message delivered to an answering machine (MSG) is 2.58 times the odds of not attending if the reminder outcome was confirmed by recipient (CR). This is given by the odds ratio

$$\frac{n(MSG, N)\, n(CR, A)}{n(MSG, A)\, n(CR, N)}$$

Assume that by modifying system setup to attempt the reminder a number of times prior to delivering a message on an answering machine, we can reduce the proportion of MSG reminder outcomes by a proportion x and instead increase the proportion of CR reminder outcomes by the corresponding number. Also assume that the conditional probabilities of nonattendance for a given reminder outcome (i.e., $P(N|CR)$ and $P(N|MSG)$) remain unchanged. Then the nonattendance rate for the modified system is given by

$$P'(+,N) = \frac{1}{n}\left[\frac{n(CR,N)\,n(MSG,+)}{n(CR,+)} - n(MSG,N)\right] x + \frac{n(+,N)}{n}$$

For the observed sample frequencies, the projected nonattendance rate is given by

$$P'(+,N) = -0.039\,x + 0.158$$

The projected nonattendance rate for various values of x, reduction in MSG reminder outcomes in favour of CR outcomes, is shown in Figure 6-10.

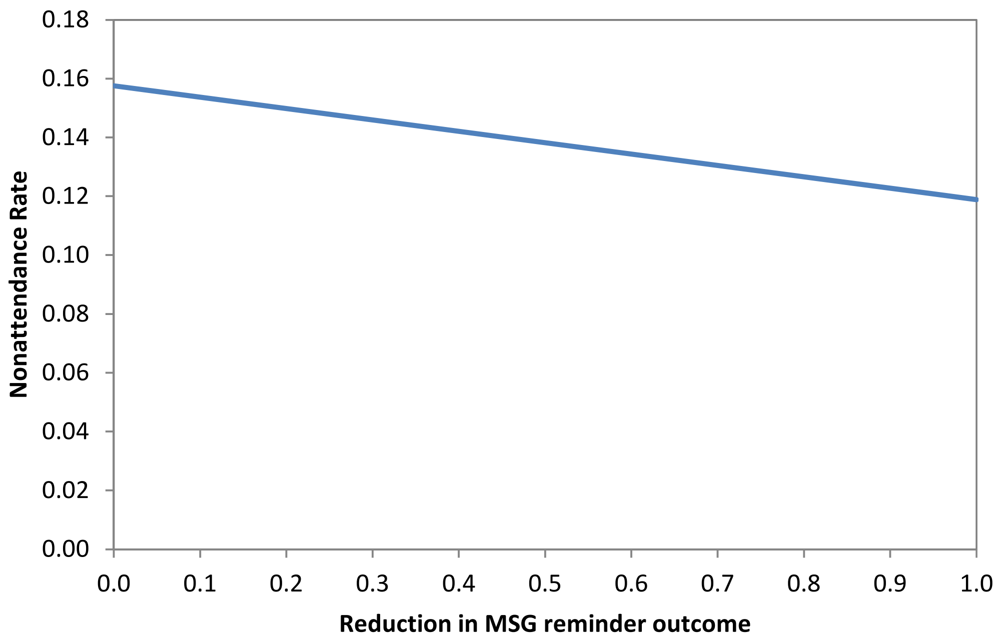


Figure 6-10: Projected nonattendance rates following reduction in MSG reminder outcomes

Is this worth pursuing? Let's say we achieve a 20% reduction in MSG outcomes by modifying system setup. For this sample size of n = 1225, this would translate to approximately 92 fewer MSG reminder outcomes and 92 more CR reminder outcomes. Assuming the conditional probabilities for nonattendance given a reminder outcome remain unchanged, then we can expect a nonattendance rate of 0.150. Again for this sample size, this nonattendance rate translates to approximately nine more attendances (or equivalently, nine fewer nonattendances). For an average encounter cost of $50, this reduction in nonattendance is equivalent to an avoided cost of $450. Although this may not be a substantial cost savings, there is also no cost associated with setup modifications.

No Answer and Call Hangups

If there is no answer, the automated system tries again in half an hour. Although the time of day for reminder calls was selected for the availability of most patients, perhaps some would be more likely to take calls at other times. What are the system options for trying again in more than half an hour or the next day?

Anecdotal evidence suggests that the automated system is prone to system glitches that do not allow the call recipient to make a selection and end the call. In these calls, the prompts replay continuously despite selections and call recipients have no other choice than to hang up.

6.5 Conclusion

The cost benefit analysis of the automated appointment reminder system using sample data of attendance outcomes demonstrates that the system is financially viable and simple payback is achieved in four months.

The sensitivity analysis shows that this automated appointment reminder system is financially viable for a wide range of model parameters including the reminder call volume, monthly system cost, wages and effect on nonattendance.

The automated system has not achieved the success rate in reaching and confirming appointments and has not reduced the nonattendance rate that is claimed by the vendor. Analysis of the association between reminder and attendance outcomes indicates that the system may be optimised for increased return on investment by modifying system setup options. This modification may lead to a further reduction in nonattendance by increasing the success rate for reaching and confirming appointments.

In future work, the sample size could be expanded by including reminder and attendance data from 2012, especially for Clinic B, for which only limited data was available and was therefore excluded from analysis.

The system setup could be modified based on the conclusions of this analysis and the subsequent reminder and attendance outcomes could be analysed to verify the projected decrease in nonattendance.

7 Concluding Discussion

A multifaceted approach was taken to examine the impacts of information and communication technology on processes in primary health care. Chapter 4 presented a discrete-event model and simulation of a simplified patient scheduling process and the impact of a hypothetical online scheduling option, demonstrating model development, experimental design and sensitivity analysis. The simulation examined the impact on the key performance measures in various scenarios including an increase in the supply of service by increasing manual labor and a decrease in the demand for service by introducing a self-service option.

Chapter 5 presented the patient care process model at the PCN and the impacts of several ICTs: electronic medical records, an automated appointment reminder system, and a patient self-service check-in and registration tablet application. The patient care process model expanded the scope from the appointment scheduling process examined in the previous chapter to the entire administrative process. The relationships and interactions between processes and the input models describing demand and service times were developed based on data observed at the PCN. The simulation demonstrated a reduction in utilization after the implementation of ICTs and could be used to examine other potential scenarios including process redesign.

Chapter 6 presented the appointment reminder process at the PCN and the impacts of an automated reminder system. In addition to the elimination of a manual process, which was explored in the discrete-event model and simulation in the previous chapter, the cost avoided in manual labor and reduction in nonattendance were considered and demonstrate the feasibility of the automated system. Relationships between the reminder outcomes and appointment attendance were examined to optimise system performance.

This chapter assembles the learnings from these approaches on the impacts of ICTs in primary care and how business processes in primary care can be reengineered to accommodate the integration of ICTs into the workflow; the discussion will be framed by the ICT capability topology suggested by Davenport (1993).

The most common capability of ICTs is automational, the ability to eliminate, replace, or reduce human labor and produce a more structured process (Davenport and Short, 1990; Davenport, 1993). We see this capability in the appointment reminder process where an automated reminder system has eliminated the manual process of making and tracking phone calls to patients. The transition to a paperless clinic through the use of EMRs has eliminated the creation and filing of paper charts; charts are automatically available to the clinicians through the EMR and the opportunity for charts to be misplaced or lost is eliminated. The use of a tablet computer for self-service check-in and registration has reduced the manual labor required to obtain and transcribe patient information and eliminated the possibility of transcription error. The patient intake process may also be redesigned by leveraging the automational capability of ICTs in electronic referrals, so that referrals would be sent electronically to the clinic PCC, which would eliminate the manual labor required to retrieve and distribute faxed referrals. Similar automational redesigns in primary care include the electronic submission of prescriptions and lab requisitions directly to the pharmacy or lab.

The informational capability of ICTs captures vast amounts of detailed information about process performance, which can then be analysed to understand and optimise the process (Davenport and Short, 1990; Davenport, 1993). While the PCN gathered information to support their operations prior to the implementation of ICTs, the amount of information that can be captured with the use of ICTs has increased and the manual labor previously spent to gather the data is now better spent making use of the information. The study and optimization of the appointment reminder process in the previous chapter was enabled by the attendance and reminder outcome information captured by the EMR and automated reminder system. Process redesigns can use the wealth of information to support or test potential changes in the design phase.

The sequential capability of ICTs enables changes in the sequences of processes, often enabling parallelism, or simultaneous process execution (Davenport, 1993). Through the use of EMRs, patient charts can be reviewed by several clinicians in the patient care team simultaneously rather than passing along paper charts for sequential review (which also reduces the opportunity for misplaced charts).

The tracking capability of ICTs closely monitors and tracks process or task status and objects (Davenport and Short, 1990; Davenport, 1993). The use of the EMR has greatly reduced the effort required to track the status of patients through the care process. To determine whether a referral had been received, whether a care plan had been developed, whether the patient had been successfully contacted, and if an appointment had been scheduled required searching for a paper referral or chart in various places depending upon the status. If a referral had been received, but had not been reviewed to develop a care plan, the paper referral was likely in one particular folder. If the care plan was developed, but the patient had not yet been contacted, the paper referral was likely in another folder, and if the PCC had attempted to contact the patient, there was yet another folder. Using the EMR, the patient's status is readily accessible; the referral, care plan, contact history, and scheduled appointments are all available in one place and the process no longer relies upon the location of a paper chart for tracking patient status.

The analytical capability of ICTs improves the analysis of information for decision making (Davenport and Short, 1990; Davenport, 1993). In the advanced access model used in the Alberta AIM program, metrics, such as the number of referrals received and the wait time for appointments, are used to track and manage operations. These metrics, which had previously been analysed manually, can now be called upon at any time through the EMR.

The geographical capability of ICTs coordinates processes and transfers information with rapidity and ease across distances, making processes independent of geography (Davenport and Short, 1990; Davenport, 1993). The use of EMRs allows clinicians at geographically separate clinics to access a patient's electronic chart. This capability of ICTs has also been used to implement various telehealth applications.

The integrative capability of ICTs coordinates between tasks and processes to transform unstructured processes into routinised transactions (Davenport and Short, 1990; Davenport, 1993). The use of the EMR enabled the integration of processes from various tasks that were often performed in batches to an integrated process focused on each patient. Certain tasks that required specific materials or equipment, such as the creation of patient charts or mailing and faxing letters, were performed in batches for efficiency; rather than continuously moving from one workstation to another, the PCCs would perform these tasks in batches, for a number of patients. The EMR enabled the integration of tasks into processes by allowing more tasks to be performed directly from one workstation rather than moving from one location to another. This enabled the PCCs to complete the entire process for each patient before moving on to the next instead of breaking up processes into disparate tasks. This integration eliminates the need to keep track of tasks for each patient as all tasks are completed for each patient in an integrated process.

The knowledge management or intellectual capability of ICTs captures and disseminates intellectual assets, knowledge and expertise to improve the process (Davenport and Short, 1990; Davenport, 1993). The use of templates within the EMR allows for structured process to be followed in the patient care process.

The disintermediating capability of ICTs eliminates intermediaries from a process by connecting parties within a process that would otherwise communicate through an (internal or external) intermediary (Davenport and Short, 1990; Davenport, 1993). In the patient registration process, the patient provides information for the clinician. The PCC acted as an intermediary by obtaining the information on a paper form and then attaching the form to the patient's paper chart or transcribing the information in the patient's electronic chart. With the use of the tablet computer for self-service check-in and registration, the information provided by the patient is automatically attached to the patient's electronic chart eliminating the need for the PCC to facilitate the transfer of information. The patient intake process could also be redesigned in a similar manner by eliminating the intermediary through the use of an electronic referral system; referrals would no longer be transferred internally within the PCN.

These ICT capabilities and their impacts on processes in primary care were examined in this work. Discrete-event modeling and simulation showed the impacts of selected ICTs on the workflows in the patient care process. In addition to demonstrating a reduction in the utilization of administrative resources, the models were also used for sensitivity analysis and testing what-if scenarios. A cost-benefit analysis also demonstrated the feasibility of the selected ICTs and process optimization techniques were presented from further analysis. Understanding the impacts of ICTs on workflow is critical for successful integration and leveraging the capabilities of ICTs to redesign processes will increase ICT adoption and contribute to improvements in the quality of health care.

As is often the case with ethnographic research, this work developed an in-depth understanding of the processes studied, but may be limited in generalisability to all primary care clinics (Savage, 2000). Some findings may be more applicable to other primary care clinics that have similar characteristics, while other findings may not. The model that was developed from this detailed understanding describes the situation at specific points in time and enables the simulation of various scenarios. Simulation of other what-if scenarios would require further model validation to accurately describe the processes in future states.

There was limited data collected at the second clinic to examine the impacts of the ICTs as implementation was not yet complete at the time of this study. Further research should be conducted to assess the impacts at this clinic and compared with the results from the first clinic. The impact of the ICTs studied here and other ICTs should be examined in other health care organizations and compared with these results. The scope should be expanded to include larger health care organizations that are more geographically dispersed and involve a greater number of functional departments. This comparison could support the generalisability of these findings.

Successful integration of ICTs needs to fully leverage all ICT capabilities to reengineer entire processes in whole systems. Measurement frameworks need to be developed to assess the impacts of ICTs in health care. This work used the ICT capability topology suggested by Davenport (1993). Further research should look at whether these capabilities are widely applicable in health care and if there are other ICT capabilities unique to the health care sector. The research should also look at which ICT capabilities are most often capitalised upon in health care and which may be underutilized or underrealized.

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Appendix A Model Development of Patient Scheduling Process

This section presents the model development of the patient scheduling process in SimEvents and MATLAB. The SimEvents model of the patient scheduling process is shown in Figure A-1. The development of the model is described in detail below. Colors of the blocks in the model are coded to facilitate this discussion, where:

- model components related to the generation, attribute assignment, and flow of appointment requests (q) are pink,
- model components related to the generation, attribute assignment, and flow of appointment reminders (m) are blue,
- model components related to both appointment requests and appointment reminders, or where their flows merge are purple,
- random number generators used in Monte Carlo sampling are grey, and
- outputs to the MATLAB workspace are green.

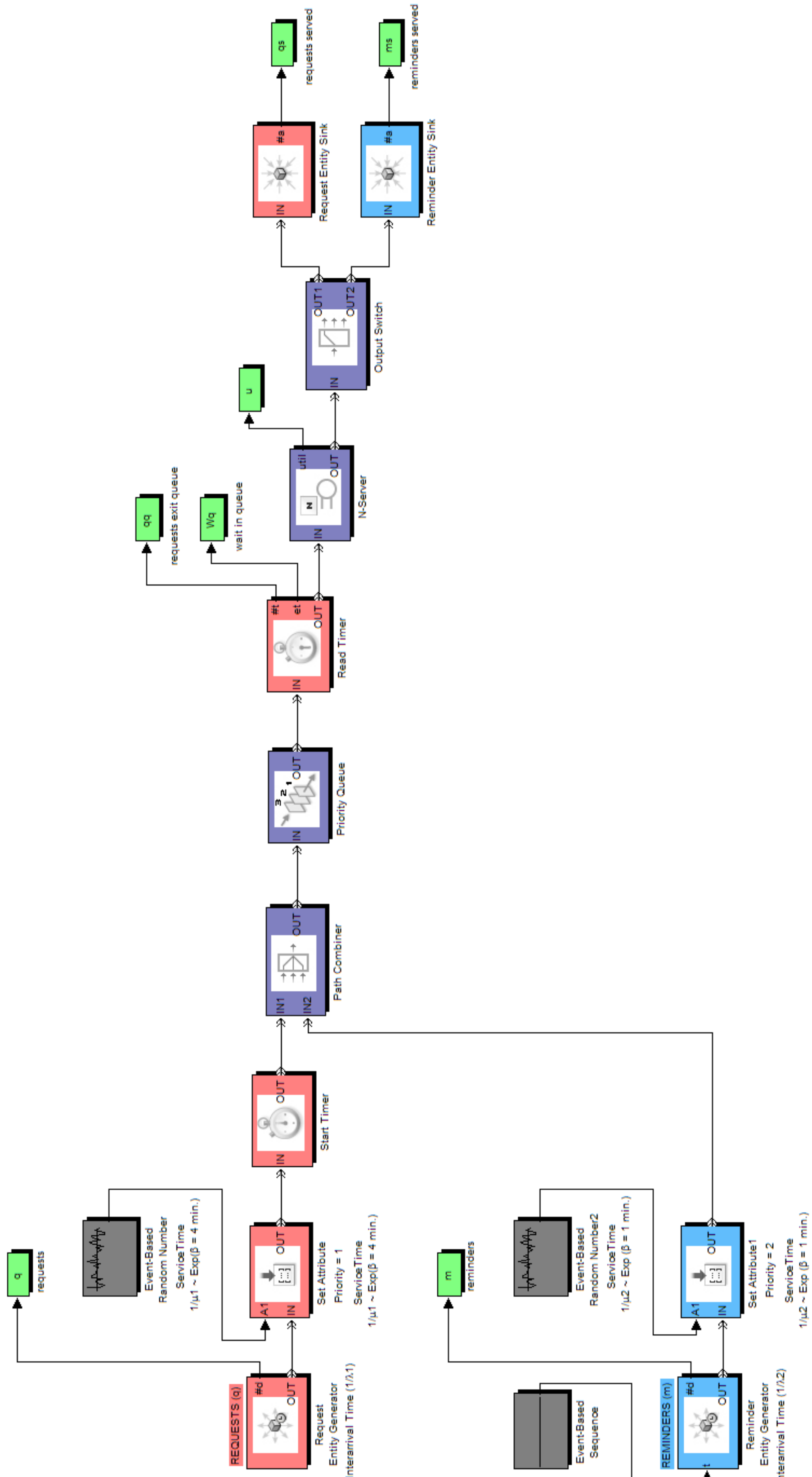


Figure A-1: SimEvents model of the patient scheduling process

A.1 Appointment Request Entity Generation and Attribute Assignment

Appointment request entities are generated and assigned attributes with the portion of the SimEvents model shown in Figure A-2. The various blocks will be discussed in detail below.

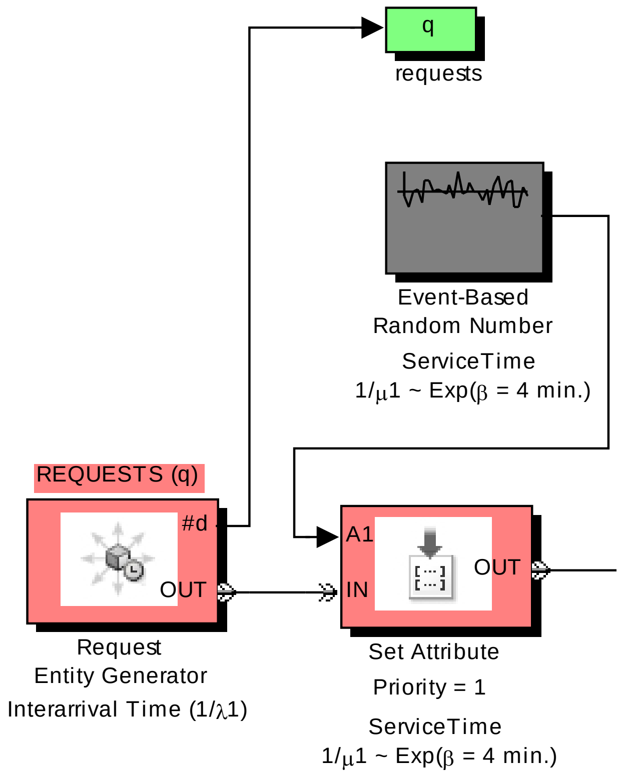


Figure A-2: Blocks used to generate appointment request entities and assign attributes

Appointment request entities are generated with a Time-Based Entity Generator block, as shown in Figure A-3. The Time-Based Entity Generator block is found in the SimEvents block library, in the Generators / Entity Generators sublibrary.

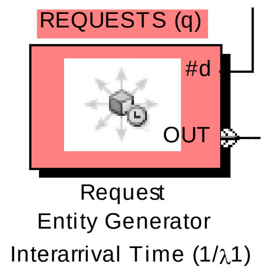


Figure A-3: Time-based entity generator for appointment requests

The interarrival (or intergeneration) time is specified to be exponentially distributed in the Entity Generation tab of the Time-Based Entity Generator dialog box, as shown in Figure A-4. The mean value of the distribution is calculated and set within the MATLAB function simPS.

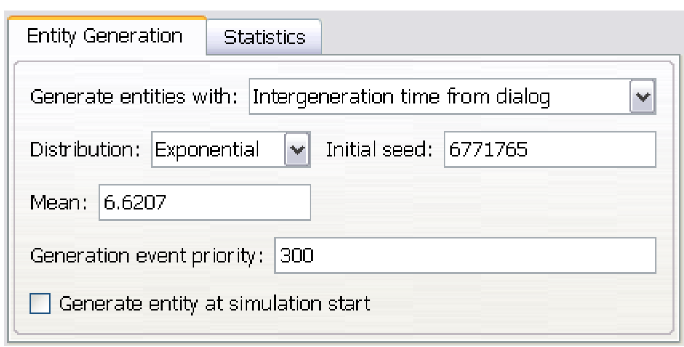


Figure A-4: Entity generation tab in the time-based entity generator dialog box

The signal output port #d is selected in the Statistics tab of the Time-Based Entity Generator dialog box, as shown in Figure A-5, and outputs the number of entities that have departed from the block since the start of the simulation.

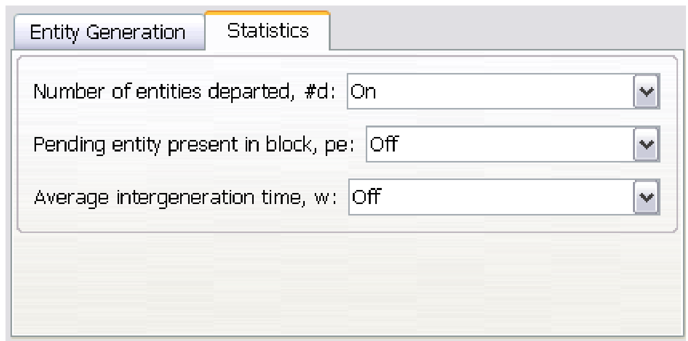


Figure A-5: Statistics tab in the time-based entity generator dialog box

The number of entities (appointment requests) that have departed from the time-based entity generator is output to a Discrete Event Signal to Workspace sink, as shown in Figure A-6. The Discrete Event Signal to Workspace block is found in the SimEvents block library, in the SimEvents sink sublibrary.

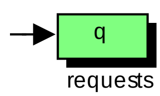


Figure A-6: Discrete event signal to workspace sink for appointment requests

The number of appointment requests is assigned a variable name of q and is output to the MATLAB workspace as a structure with time with an infinite number of data points, in the Discrete Event Signal to Workspace dialog box, as shown in Figure A-7. This data format indicates when the signal assumes each value which can subsequently be used to visualise the entity generation.

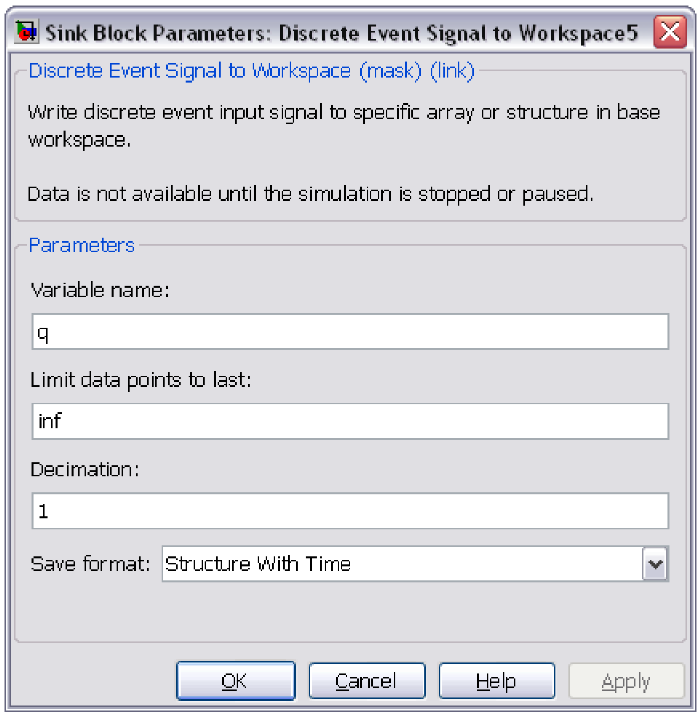


Figure A-7: Discrete event signal to workspace dialog box

The appointment request entities generated by the time-based entity generator are assigned two attributes using the Set Attribute block, as shown in Figure A-8. The Set Attribute block is found in the SimEvents block library, in the Attributes sublibrary.

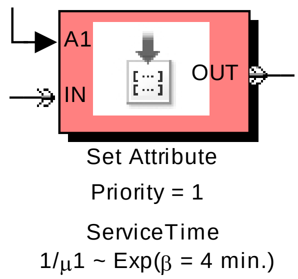


Figure A-8: Set attribute block for appointment request entities

Appointment requests entities are assigned a Service Time attribute in the Set Attribute dialog box, as shown in Figure A-9.

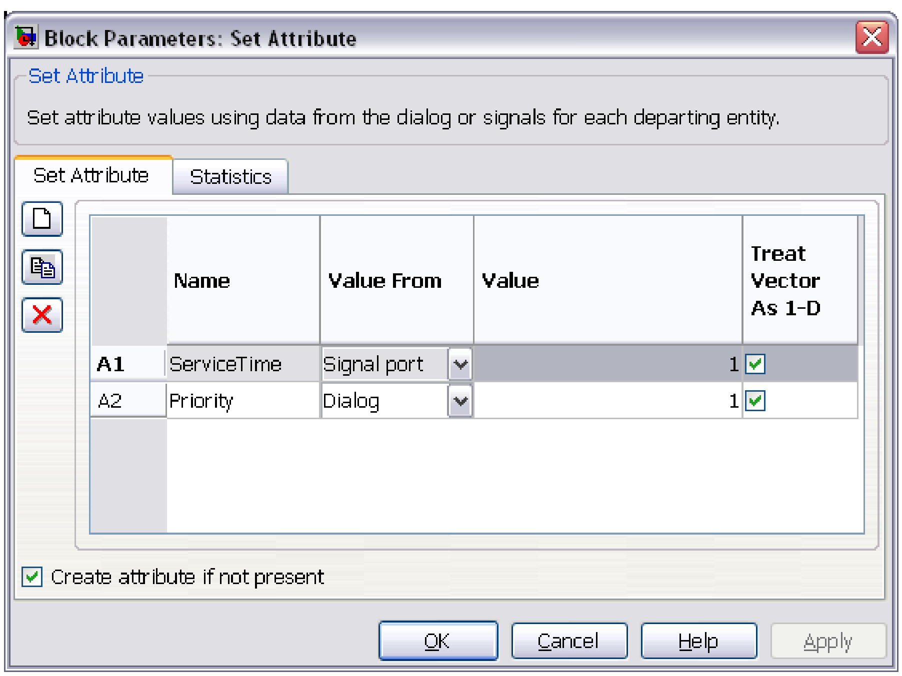


Figure A-9: Set attribute dialog box

Recall the service times for appointment requests are assumed to be exponentially distributed with a mean service time of four minutes. The service time for Monte Carlo sampling is generated using an Event-Based Random Number block, as shown in Figure A-10. The Event-Based Random Number block is found in the SimEvents library, in the Generators / Signal Generators sublibrary.

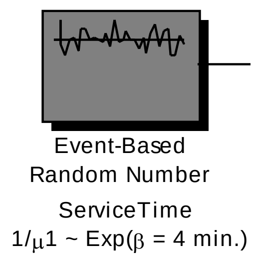


Figure A-10: Event-based random number block for appointment request service time

Each time an entity arrives at the Set Attribute block, the Event-Based Random Number block will generate a random number from the distribution specified in the Event-Based Random Number dialog box, as shown in Figure A-11.

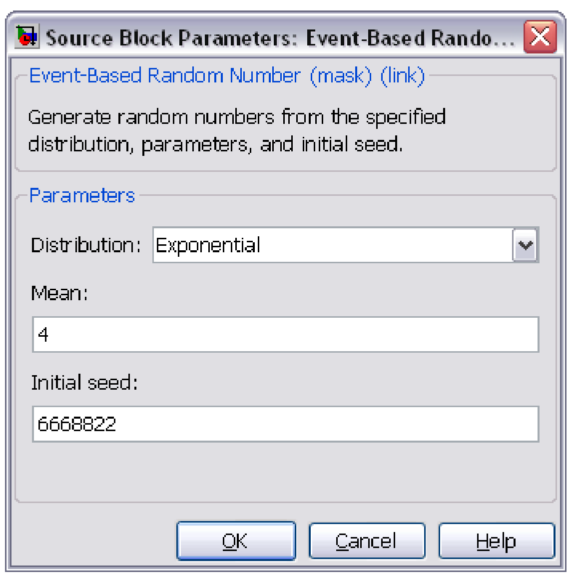


Figure A-11: Event-based random number dialog box

Appointment request entities are also assigned a Priority attribute of 1, as shown above in Figure A-9. This Priority attribute will be used to give the appointment requests priority service over reminder calls by the PCC (server) in the priority queue.

A.2 Appointment Reminder Entity Generation and Attribute Assignment

Appointment reminder entities are generated and assigned attributes with the portion of the SimEvents model shown in Figure A-12. The various blocks will be discussed in detail below.

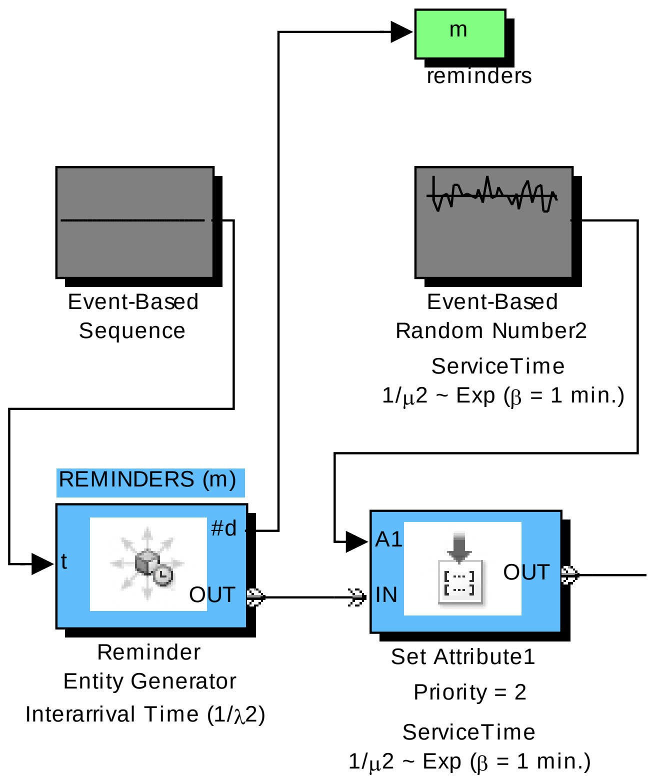


Figure A-12: Blocks used to generate appointment reminder entities and assign attributes

Appointment reminder entities are also generated with a Time-Based Entity Generator block, as shown in Figure A-13.

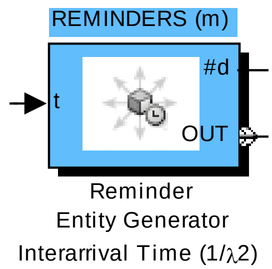


Figure A-13: Time-based entity generator for appointment reminders

Recall that the list of appointment reminders that the PCC must make is available at the start of each day and the number of appointment reminders (m) that must be made each day is a normally distributed random number. The reminder entity interarrival times can then be generated as sequence of m values all equal to one (minute) divided by the number of entities, which is a random number. This entity generation can be interpreted as the PCC turning on the computer first thing in the morning and the appointment scheduling software generating the list of reminders within one minute.

The Event-Based Sequence block, as shown in Figure A-14, is used to specify the intergeneration times for the Time-Based Entity Generator for appointment reminder entities.

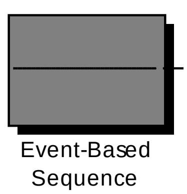


Figure A-14: Event-based sequence block for appointment reminder intergeneration times

The intergeneration times are specified in the Event-Based Sequence dialog box, as shown in Figure A-15. The intergeneration times are calculated and set within the MATLAB function simPS. To ensure that no further reminder entities are generated after the specified number, the 'Form output after final data value by:' parameter is set to 'Setting to infinity'.

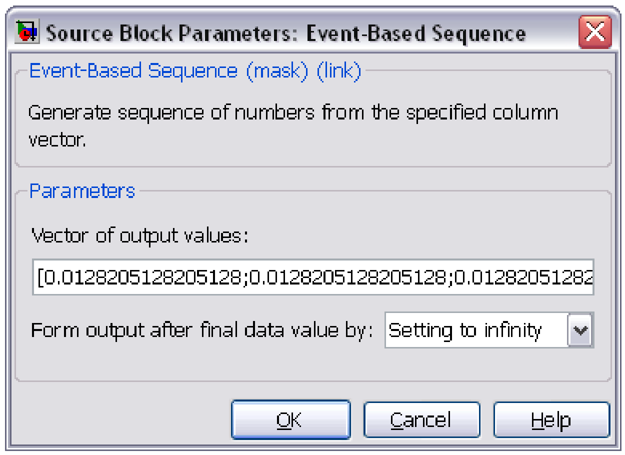


Figure A-15: Event-based sequence dialog box

The number of appointment request entities that have departed from the time-based entity generator is output to a Discrete Event Signal to Workspace sink, as shown in Figure A-16.

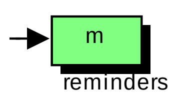


Figure A-16: Discrete event signal to workspace sink for appointment reminders

The number of appointment reminders is assigned a variable name of m and is output to the MATLAB workspace as an array with one data point, in the Discrete Event Signal to Workspace dialog box, as shown in Figure A-17. This data format is sufficient as the engineer has specified the generation time and only needs to confirm the total number generated.

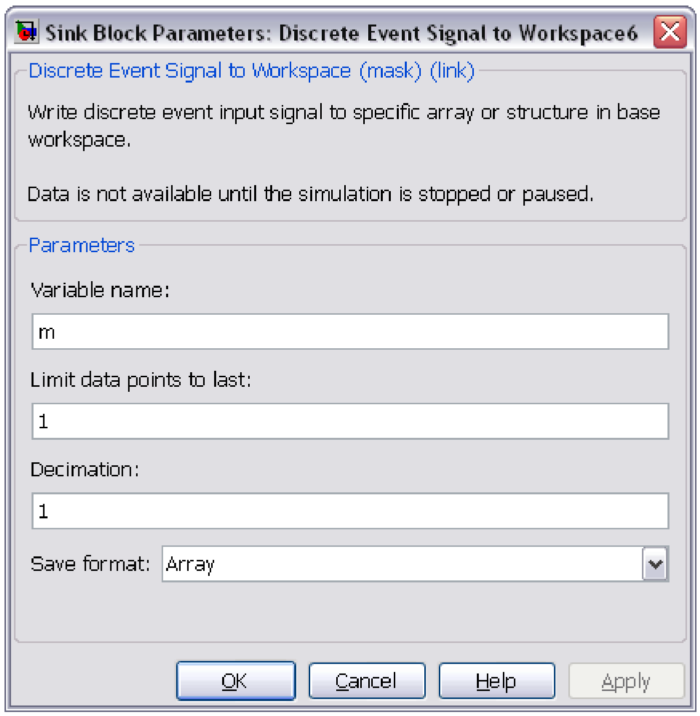


Figure A-17: Discrete event signal to workspace dialog box

Similar to the appointment request entities, the appointment reminder entities are assigned two attributes using the Set Attribute block, as shown in Figure A-18.

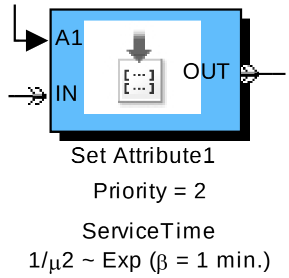


Figure A-18: Set attribute block for appointment reminder entities

Appointment reminder entities are assigned a Service Time attribute in the Set Attribute dialog box, as shown in Figure A-19.

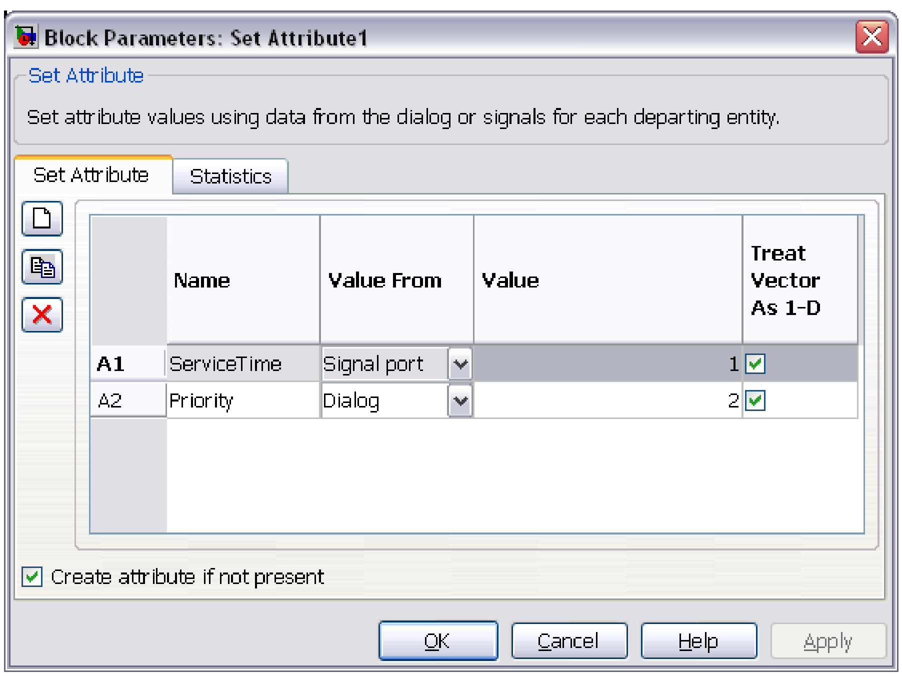


Figure A-19: Set attribute dialog box

Recall the service times for appointment reminders are assumed to be exponentially distributed with a mean service time of 1 minute. Again, the service time is generated using an Event-Based Random Number block, as shown in Figure A-20.

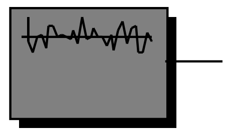


Figure A-20: Event-based random number block for appointment reminder service time

The probability distribution for the appointment reminder service times is specified in the Event-Based Random Number dialog box, as shown in Figure A-21.

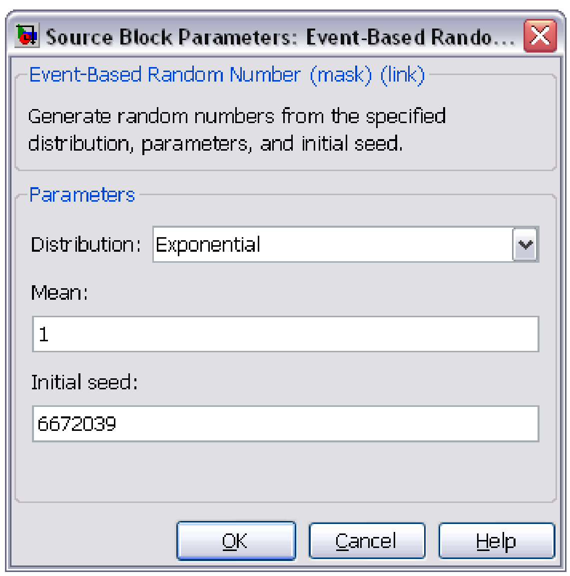


Figure A-21: Event-based random number block for appointment reminder service time

Similar to appointment request entities, the appointment reminder entities are also assigned a Priority attribute, as shown above in Figure A-19. However, the appointment reminder entities are assigned a priority of 2, to give the appointment requests priority service over reminder calls by the PCC (server) in the priority queue.

A.3 Entities Enter a Queue to Wait for Service

The appointment request and appointment reminder entities then merge paths and enter a queue where they wait to receive service from the patient care coordinator. This portion of the SimEvents model is shown in Figure A-25. The various blocks will be discussed in detail below.

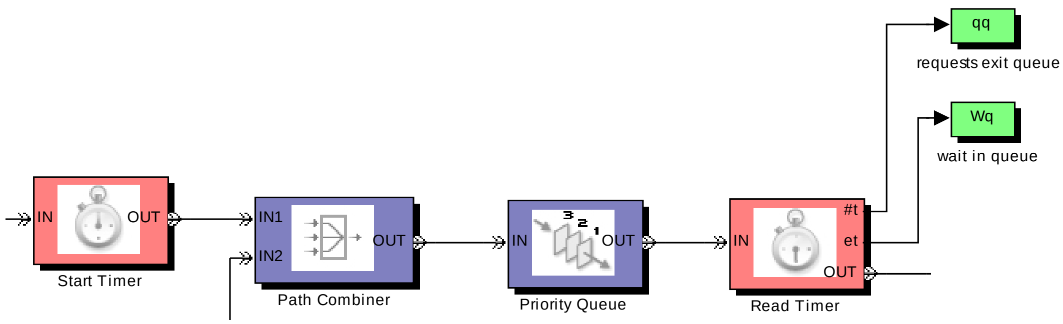


Figure A-22: Appointment request and reminder entities merge paths and enter a queue for service

Recall that one of the key performance measures is the amount of time the patient spends waiting on hold to speak with the patient care coordinator to request an appointment. To do this, a timer a started for every appointment request entity that is generated and enters the queue, using a Start Timer block, as shown in Figure A-23. The Start Timer block is found in the SimEvents library, in the Timing sublibrary.

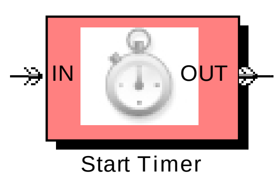


Figure A-23: Start timer block for appointment request entities

The timer is given a name (tag) in the Start Timer tab of the Start Timer dialog box, as shown in Figure A-29.

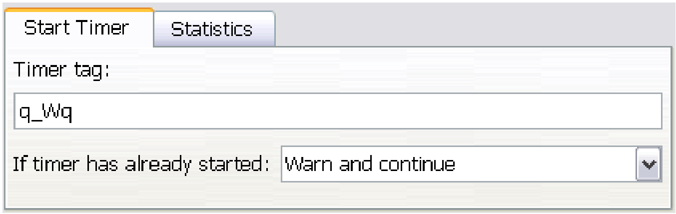


Figure A-24: Start timer tab in the start timer dialog box

The appointment request and appointment reminder entities then merge paths using the Path Combiner block, as shown in Figure A-25. The Path Combiner block is found in the SimEvents library, in the Routing sublibrary.

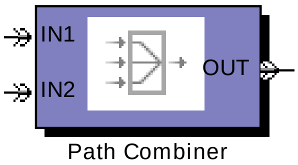


Figure A-25: Path combiner block to merge appointment request and appointment reminder paths

The number of input ports is specified in the Path Combiner tab of the Path Combiner dialog box, as shown in Figure A-26. There are two entity paths merging, the appointment requests and the appointment reminders, and two entity input ports are specified.

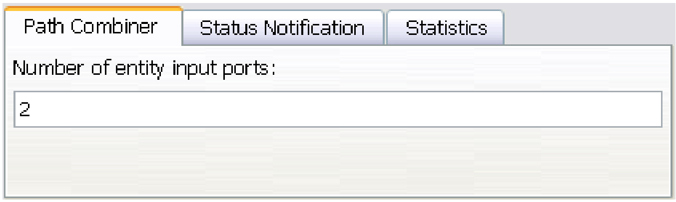


Figure A-26: Path combiner tab in the path combiner dialog box

The appointment request entities and appointment reminder entities, now in a merged path, enter the queue for service. A Priority Queue block, as shown in Figure A-27, is used to store these entities until the server (patient care coordinator) is available to serve them. The Priority Queue block is found in the SimEvents library, in the Queues sublibrary.

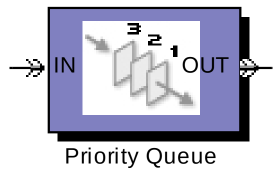


Figure A-27: Priority queue block for appointment request and appointment reminder entities

The priority sequence is specified in the Priority Queue tab of the Priority Queue dialog box, as shown in Figure A-28. The Priority attribute, previously assigned to the appointment request entities and the appointment reminder entities, is specified in this dialog box. The order in which the priorities are served is also specified, which in this case, is in ascending order. That is, the appointment request entities with priority attribute 1 are served before the appointment reminder entities with priority attribute 2. The queue capacity is also specified as infinity.

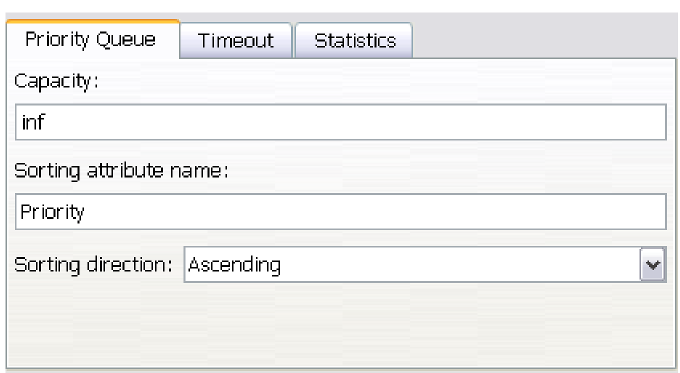


Figure A-28: Priority queue tab in the priority queue dialog box

Entities will depart from the Priority Queue block in the order in which they arrived (first-come, first-served) when the server is available to serve them. The PCC will serve a patient (appointment request) if one is present in the queue prior to serving a reminder call. The priority service is, however, non-preemptive. That is, if the PCC is currently busy making a reminder call when an appointment request arrives in the queue, the PCC will finish the reminder call and then attend to the next patient in the queue.

As appointment request entities leave the queue to be served by the PCC, the timer associated with that entity is read by the Read Timer block, as shown in Figure A-29. The Read Timer block is found in the SimEvents library, in the Timing sublibrary.

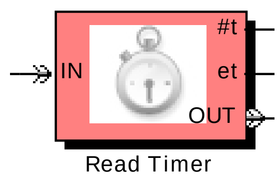


Figure A-29: Read timer block for appointment request entities

The timer tag is specified in the Read Timer tab of the Read Timer dialog box, as shown in Figure A-30.

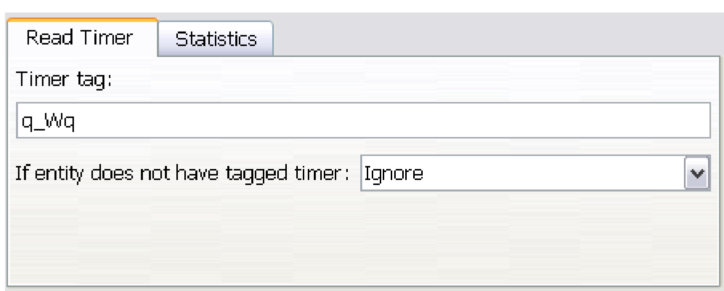


Figure A-30: Read timer tab in the read timer dialog box

The number of request entities that have exited the queue to enter service, #t, and the amount of time that the entity has spent waiting for in the queue, et, is generated with the statistics selected in the Statistics tab of the Read Timer dialog box, as shown in Figure A-31.

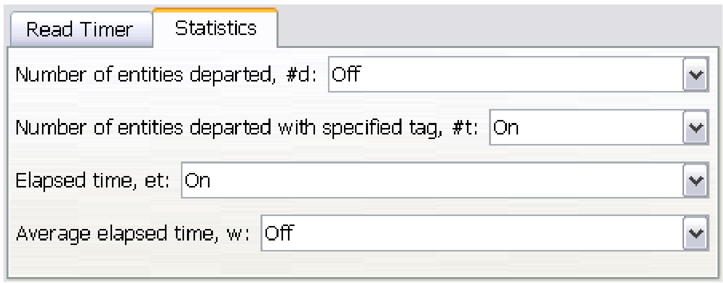


Figure A-31: Statistics tab in the read timer dialog box

The number of request entities that have exited the queue is output to a Discrete Event Signal to Workspace sink, as shown in Figure A-33.

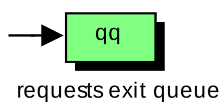


Figure A-32: Discrete event signal to workspace sink for request entities that have exited the queue

The output is assigned a variable name of qq and is output to the MATLAB workspace as a structure with time with an infinite number of data points, in the Discrete Event Signal to Workspace dialog box. This data format indicates when each request entity exits the queue or begins service which can subsequently be used to visualise the flow of entities in the queue.

The amount of time each appointment request entity spends in the queue is output to a Discrete Event Signal to Workspace sink, as shown in Figure A-33.

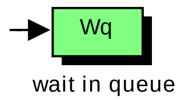


Figure A-33: Discrete event signal to workspace sink for appointment request wait time in queue

The output is assigned a variable name of Wq and is output to the MATLAB workspace as a structure with time with an infinite number of data points, in the Discrete Event Signal to Workspace dialog box. This data format allows each patient's waiting time to be stored as well as the time they exited the queue to receive service.

Note that if an appointment request entity enters the queue and there are no other request entities ahead in the queue and the PCC is not currently busy, the patient (entity) receives service immediately and the wait in queue time is zero. That is, no time is elapsed as the entity passes through the blocks.

Also note that the Priority Queue block has a statistic to output the average wait time. However, since two types of entities flow through the queue and since the engineer is only interested in how long appointment request entities wait to be served, and not the appointment reminder entities, the timer structure consisting of the Start Timer and Read Timer blocks is used. Furthermore, this timer structure provides more information because it records each patient's wait time, instead of just the average time, from which the average can be subsequently calculated.

A.4 Service of Appointment Request and Appointment Reminder Entities

Appointment request and appointment reminder entities are served as the patient care coordinator(s) is available using the N-Server block, as shown in Figure A-34. The N-Server block is found in the SimEvents library, in the Servers sublibrary.

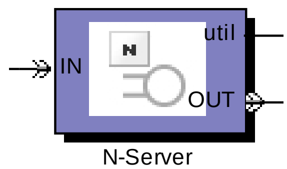


Figure A-34: N-Server block for PCC(s)

The number of servers (PCCs) is specified in the N-Server tab of the N-Server dialog box, as shown in Figure A-35. The service time is specified by the Service Time attribute previously assigned to the appointment request and appointment entities. This is the amount of simulation time that the entity will stay in the N-Server block to receive service.

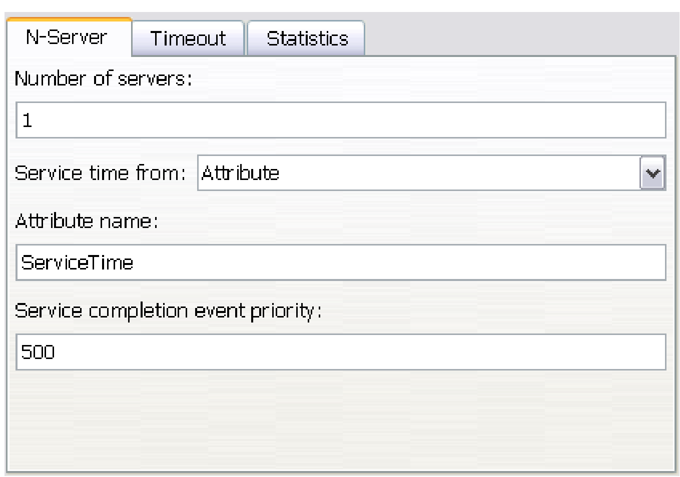


Figure A-35: N-Server tab in n-server dialog box

Recall that the other key performance measure that the engineer needs to estimate is how busy the PCC is, or the utilization of the server. This utilization, util, is selected from the Statistics tab of the N-Server dialog box, as shown in Figure A-36, which outputs the proportion of simulation time spent serving an entity.

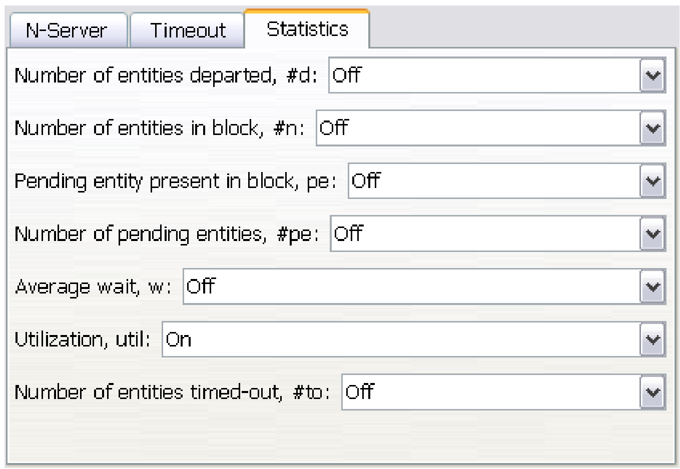


Figure A-36: Statistics tab in the N- dialog box

Since the simulation run length is set equivalent to one day, the utilization is interpreted as the proportion of the day that the PCC is busy. This value is output to a Discrete Event Signal to Workspace sink, as shown in Figure A-37.

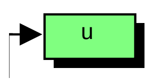


Figure A-37: Discrete event signal to workspace sink for server utilization

The utilization is assigned a variable name of u and is output to the MATLAB workspace as an array with one data point, in the Discrete Event Signal to Workspace dialog box, as shown in Figure A-38. This data format outputs one value, the daily average utilization, for each simulation run.

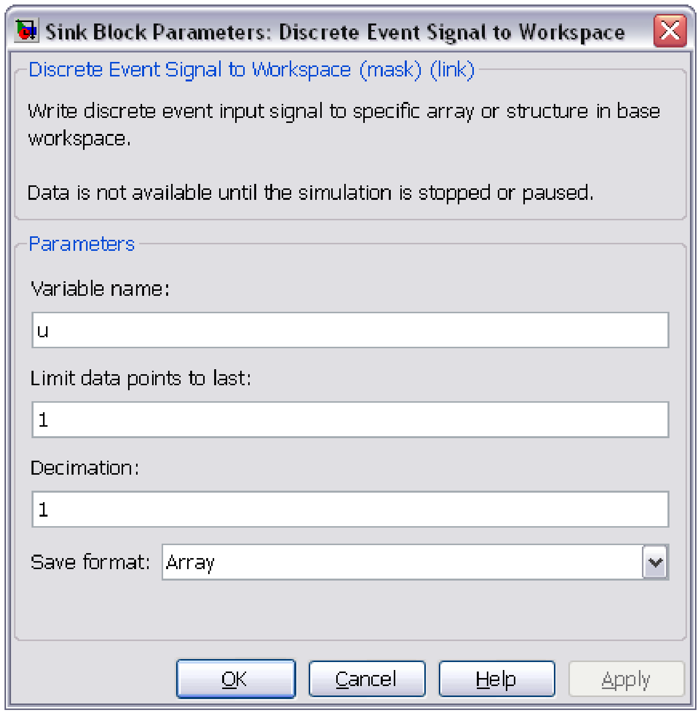


Figure A-38: Discrete event signal to workspace dialog box for server utilization

After the entities have received service, their paths are split to separate entity sinks so that the number of each type of entity served can be recorded. The entity paths are split using an Output Switch block, as shown in Figure A-39. The Output Switch block is found in the SimEvents library, in the Routing sublibrary.

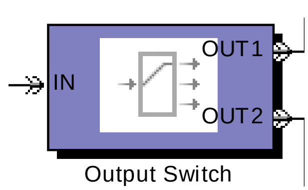


Figure A-39: Output switch block

The number of output ports is specified in the Output Switch tab of the Output Switch dialog box, as shown in Figure A-40. The switch is to split two types of entities, the appointment requests and the appointment reminders, and two entity output ports are specified. Entities are split based on the Priority attribute that was previously assigned, which uniquely distinguishes appointment request entities from appointment reminder entities.

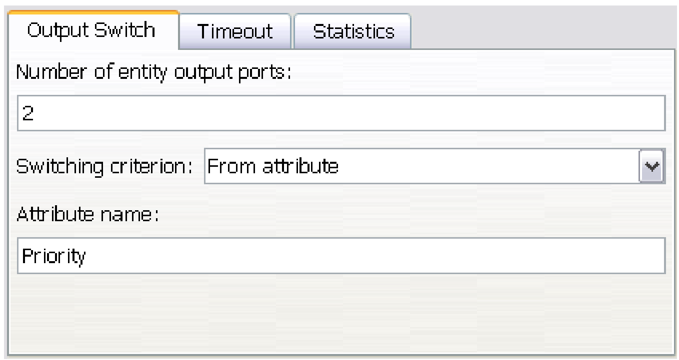


Figure A-40: Output switch tab in the output switch dialog box

Once the appointment request entity and the appointment reminder entity paths are split, each type of entity flows into its respective entity sink. The appointment request entities flow into the request entity sink block, as shown in Figure A-41. The Entity Sink block is found in the SimEvents library, in the SimEvents Sinks sublibrary.

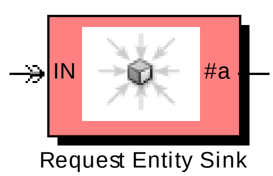


Figure A-41: Entity sink block for appointment request entities with service completed

The number of appointment request entities that have received service and arrived at the sink, #a, is selected in the Entity Sink dialog box, as shown in Figure A-42.

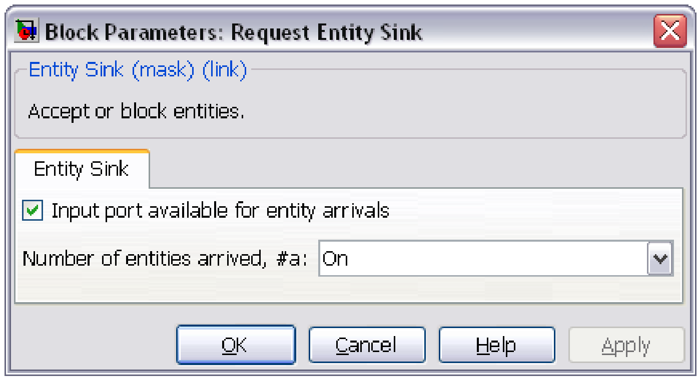


Figure A-42: Request entity sink dialog box

The number of appointment requests served is output to a Discrete Event Signal to Workspace sink, as shown in Figure A-43.

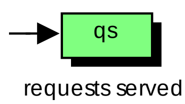


Figure A-43: Discrete event signal to workspace for request entities with service completed

The output is assigned a variable name of qs and is output to the MATLAB workspace as a structure with time with an infinite number of data points, in the Discrete Event Signal to Workspace dialog box, as shown in Figure A-44. This data format indicates when the each entity completes service which can subsequently be used to visualise the service completion.

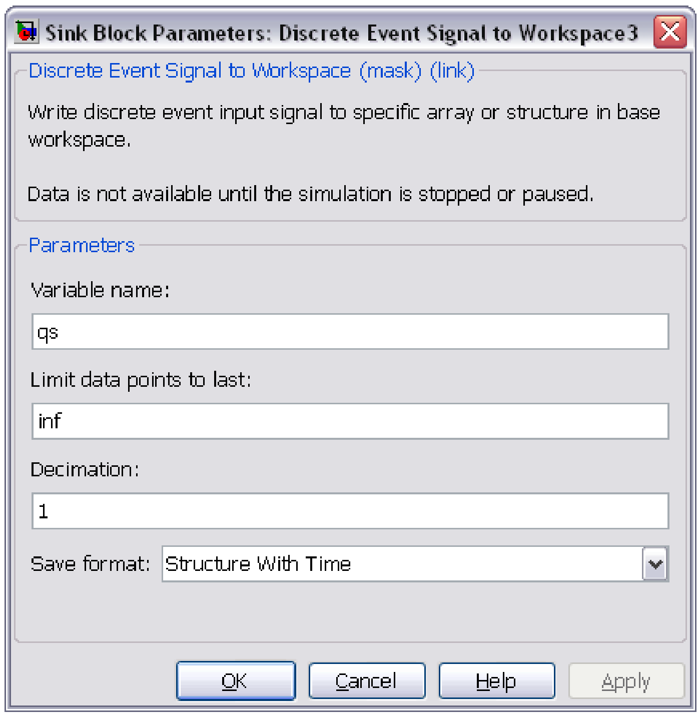


Figure A-44: Discrete event signal to workspace dialog box for request entities with service completed

Similarly, the appointment reminder entities flow into the reminder entity sink block, as shown in Figure A-45. Likewise, the number of appointment reminder entities that have received service and arrived at the sink, #a, is selected in the Entity Sink dialog box.

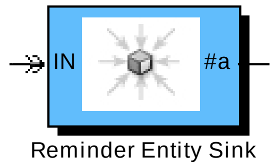


Figure A-45: Entity sink block for appointment reminder entities with service completed

The number of appointment reminders served is output to a Discrete Event Signal to Workspace sink, as shown in Figure A-46. The data format is a single entry array to record the total number of reminders served in the day.

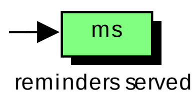


Figure A-46: Discrete event signal to workspace for reminder entities with service completed

A.5 MATLAB Code for Patient Scheduling Process

```
function simPS(n, s, p)
% Simulates patient scheduling process.
% simPS(n, s, p) performs n simulation runs,
% with s number of PCCs (servers), and
% p percentage of online usage (reduction in demand).
% Outputs selected summary statistics,
% a sample patient chart and a histogram of wait times.

nruns = n;
nservers = s;
ponline = p/100;

% Calculate daily demand (requests and reminders)
numberOfPhysicians = 3;
patientsPerPhysician = 1000;
consultationsPerYearPerCapita = 5.8;
workingDaysPerYear = 12 * 20;
demand = numberOfPhysicians * patientsPerPhysician * ...
    consultationsPerYearPerCapita / workingDaysPerYear;

% Declare vectors to store results:
% daily request volume (q),
requests = zeros(nruns,1);
% daily reminder volume (m),
reminders = zeros(nruns,1);
% daily average wait in queue (Wq);
waitInQueue = zeros(nruns,1);
% daily average utilization (u),
utilization = zeros(nruns,1);
% daily number of requests served (qs) and not served,
requestsServed = zeros(nruns,1);
requestsNotServed = zeros(nruns,1);
% daily number of reminders served (ms) and not served,
remindersServed = zeros(nruns,1);
remindersNotServed = zeros(nruns,1);
% Intialize index and vector for Wq_log
k0 = 0;
Wq_log = [];

% Run simulation
for i = 1:nruns
    se_randomizeseeds('PS');

    % Generate mean intergeneration time
    % for appointment requests.
    % Base demand is specified as constant
    % Reduce demand based on proportion of online users p
    % If there are no requests, set to mean to infinity
    nRequests = (1 - ponline) * demand;
    if (nRequests == 0)
        qmean = inf;
    else
```

```
        qmean = 480 / nRequests;
    end

    % Set appointment request mean intergeneration time
    set_param('PS/Request Entity Generator','mean',...
    num2str(qmean));

    % Generate number of reminder calls to be made from a
    % normally distributed random number with mean equal to base
    % demand  and standard deviation 2.5.
    % Reduce demand based on proportion of online users p
    % Round result to nearest integer.
    nRemind = round(((1 - ponline) * demand) + 2.5 * randn);

    % Generate intergeneration times so that all reminder
    % entities are present in the first minute of simulation.
    % If there are no reminders,
    % set intergeneration time to infinity
    if (nRemind == 0)
        mintergentimes = inf;
    else
        mintergentimes = zeros(nRemind,1);
        for j = 1:nRemind
            mintergentimes(j) = 1/nRemind;
        end
    end

    % Set reminder calls intergeneration times
    set_param('PS/Event-Based Sequence','VectorOutputValues', ...
        mat2str(mintergentimes));

    % Set number of servers
    set_param('PS/N-Server','NumberOfServers', ...
        num2str(nservers));

    % Run simulation and record daily results
    sim('PS',[]);

    % daily request volume (q),
    if isempty(q.signals.values)
        requests(i) = 0;
    else
        requests(i) = q.signals.values(length(q.signals.values));
    end

    % daily reminder volume (m),
    if isempty(m)
        reminders(i) = 0;
    else
        reminders(i) = m;
    end

    % daily average wait in queue (Wq);
    if isempty(Wq.signals.values)
```

```
        waitInQueue(i) = 0;
    else
        waitInQueue(i) = mean(Wq.signals.values);
    end

    % daily average utilization (u),
    if isempty(u)
        utilization(i) = 0;
    else
        utilization(i) = u;
    end

    % daily number of requests served (qs),
    if isempty(qs.signals.values)
        requestsServed(i) = 0;
    else
        requestsServed(i) = ...
            qs.signals.values(length(qs.signals.values));
    end

    % daily number of requests not served (q - qs),
    requestsNotServed(i) = requests(i) - requestsServed(i);

    % daily number of reminders served (ms),
    if isempty(ms)
        remindersServed(i) = 0;
    else
        remindersServed(i) = ms;
    end

    % daily number of requests not served,
    remindersNotServed(i) = reminders(i) - remindersServed(i);

    % Keep log of every wait time in queue
    for k = 1:length(Wq.signals.values)
        Wq_log(k0 + k) = Wq.signals.values(k);
    end
    k0 = k0 + length(Wq.signals.values);
end

% Calculate simulation summary (mean, variance, min, max)
% daily request volume (q),
mean_requests = mean(requests);
var_requests = var(requests);
min_requests = min(requests);
max_requests = max(requests);

% daily reminder volume (m),
mean_reminders = mean(reminders);
var_reminders = var(reminders);
min_reminders = min(reminders);
max_reminders = max(reminders);

% daily average wait in queue (Wq);
```

```
mean_waitInQueue = mean(waitInQueue);
var_waitInQueue = var(waitInQueue);
min_waitInQueue = min(waitInQueue);
max_waitInQueue = max(waitInQueue);

% daily average utilization (u),
mean_utilization = mean(utilization);
var_utilization = var(utilization);
min_utilization = min(utilization);
max_utilization = max(utilization);

% daily number of requests served (qs),
mean_requestsServed = mean(requestsServed);
var_requestsServed = var(requestsServed);
min_requestsServed = min(requestsServed);
max_requestsServed = max(requestsServed);

% daily number of requests not served (q - qs),
mean_requestsNotServed = mean(requestsNotServed);
var_requestsNotServed = var(requestsNotServed);
min_requestsNotServed = min(requestsNotServed);
max_requestsNotServed = max(requestsNotServed);

% daily number of reminders served (ms),
mean_remindersServed = mean(remindersServed);
var_remindersServed = var(remindersServed);
min_remindersServed = min(remindersServed);
max_remindersServed = max(remindersServed);

% daily number of reminders not served (m - ms),
mean_remindersNotServed = mean(remindersNotServed);
var_remindersNotServed = var(remindersNotServed);
min_remindersNotServed = min(remindersNotServed);
max_remindersNotServed = max(remindersNotServed);

% Display simulation summary
str =
sprintf('*******************************************************
**************');
disp(str);

str = sprintf('*  Patient Scheduling Simulation
*');
disp(str);

str = sprintf('*  Number of simulation runs: %-9.0f
*',...
    nruns); disp(str);

str = sprintf('*  Number of servers: %-9u
*',...
    nservers); disp(str);
```

```
str = sprintf('*  Online usage rate: %-3.0f%%
*',...
    ponline*100); disp(str);

str = sprintf('*
*');
disp(str);

str = sprintf('*  Simulation statistics
*');
disp(str);
str = sprintf('*                        mean     variance
minimum     maximum   *');
disp(str);

str = sprintf('*  utilization            %-5.3f    %-5.3f
%-5.3f       %-5.3f     *',...
    mean_utilization, var_utilization, min_utilization,
max_utilization);

disp(str);

str = sprintf('*  wait in queue          %-5.2f    %-5.2f
%-5.2f       %-5.2f     *',...
    mean_waitInQueue, var_waitInQueue, min_waitInQueue,
max_waitInQueue);
disp(str);

str = sprintf('*
*');
disp(str);

str = sprintf('*  requests               %-5.1f    %-5.0f
%-5.0f       %-5.0f     *',...
    mean_requests, var_requests, min_requests, max_requests);
disp(str);

str = sprintf('*  requests served        %-5.1f    %-5.0f
%-5.0f       %-5.0f     *',...
    mean_requestsServed, var_requestsServed,
min_requestsServed,...
    max_requestsServed);
disp(str);

str = sprintf('*  requests not served    %-5.1f    %-5.0f
%-5.0f       %-5.0f     *',...
    mean_requestsNotServed, var_requestsNotServed,
min_requestsNotServed,...
    max_requestsNotServed);
disp(str);

str = sprintf('*
*');
```

```
disp(str);

str = sprintf('*  reminders              %-5.1f    %-5.0f
%-5.0f        %-5.0f     *',...
    mean_reminders, var_reminders, min_reminders, max_reminders);
disp(str);

str = sprintf('*  reminders served       %-5.1f    %-5.0f
%-5.0f        %-5.0f     *',...
    mean_remindersServed, var_remindersServed,
min_remindersServed,...
    max_remindersServed);
disp(str);

str = sprintf('*  reminders not served   %-5.1f    %-5.0f
%-5.0f        %-5.0f     *',...
    mean_remindersNotServed, var_remindersNotServed,...
    min_remindersNotServed,max_remindersNotServed);
disp(str);

str =
sprintf('*****************************************************************
**************');
disp(str);

% Extract data from structure for the last simulation run

% Request enters queue
q_t = q.time;
q_v = q.signals.values;

% Request exits queue
qq_t = qq.time;
qq_v = qq.signals.values;

% Request served
qs_t = qs.time;
qs_v = qs.signals.values;

% Display sample customer chart from last simulation run
% (if there were any customers)
if isempty(q_t)
else
    figure; hold on;
    stairs(qs_t, qs_v, 'LineWidth',2, 'Color', 'b');
    stairs(qq_t, qq_v, 'LineWidth',2, 'Color', 'g');
    stairs(q_t, q_v, 'LineWidth',2, 'Color', 'r');
    xlim([0 480]); set(gca,'XTick',[0:60:480]); grid on;
    leg = legend('Patient served','Patient enters service',...
        'Patient enters queue');
    set(leg, 'FontSize',14);
    set(leg, 'Location', 'NorthWest');
    title('Sample Patient Chart',...
        'FontSize',14);
```

```
    xlabel('Time [minutes]','FontSize',14);
    ylabel('Number of patients','FontSize',14);
    hold off;
end

% Display histogram of wait time log
% (if there are entries in log)
if isempty(Wq_log)
else
    figure; hold on;
    hist(Wq_log,max(Wq_log));
    h = findobj(gca,'Type','patch'); grid on;
    set(h,'EdgeColor','w')
    title('Histogram of wait in queue', 'FontSize', 14);
    xlabel('Time [minutes]','FontSize',14);
    ylabel('Number of patients','FontSize',14);
    hold off;
end
```

Appendix B Model Development of Patient Care in the PCN

Sections B.1 and B.2 present the development of the input models for the arrival patterns and service times of the thirteen process types for Clinic A and Clinic B. The general method for specifying input models, described in Section 3.2.1, will be followed.

In this and the next section, the first instance of each step in the process will be shown in detail and the results will be verified using SPSS and ExpertFit software programs. Subsequently, only the resulting input models will be presented and the detailed analysis and will be omitted.

The MATLAB code for function simPCC is given in Section B.3.

B.1 Entity Generation

A summary of the arrival patterns for each of the process types for the two clinics studied at the PCN was presented in Section 5.4. The detailed development of those patterns is shown in this section. The arrival pattern for process type 1 at Clinic A was presented previously and is repeated here for completeness.

Process Type 1 (S1.1 Create record and S1.2 Develop care plan)

Clinic A

The patient intake process begins when a referral is received by the PCN from the patient's physician. Referrals are received throughout the day at the administrative office and are delivered to the PCC twice daily, in the morning and afternoon. To model the arrival of referrals, or the arrival of entities representing process type 1, we estimate the number of referrals received each week, and assume an equiprobable distribution of in each of the twice daily deliveries.

The number of new referrals received at Clinic A each week over the last 100 weeks, was obtained from the PCN's records. As the techniques used in the subsequent steps of the input modeling process assume that the sample set is independent, we will first verify this assumption.

Let $X_1, X_2, \dots, X_{100}$ be the number of new referrals received in week 1, 2,…, 100, respectively, and form the null hypothesis that the X_i's are independent. We qualitatively assess the impendence of the data points by inspection of the scatter plot of the empirical data with x-y pairs given by (X_i, X_{i+1}) for i = 1, 2,…, 99, as shown in Figure B-1, and note that the data does not appear to be correlated.

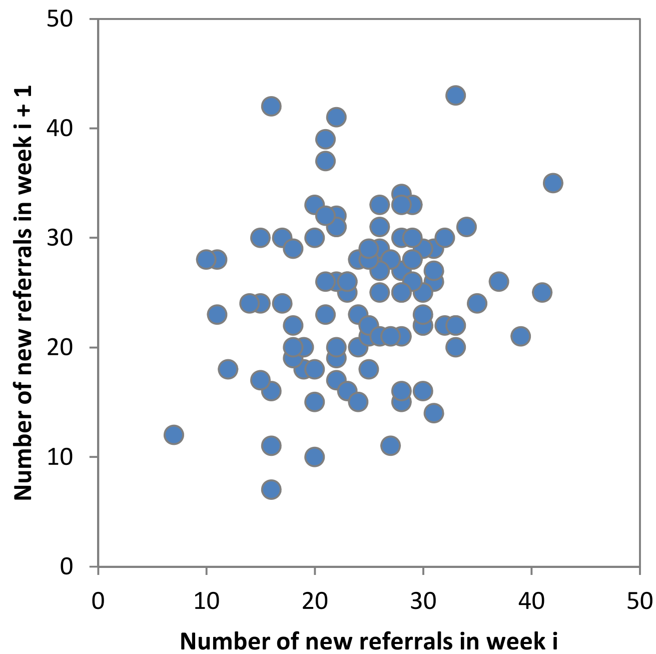


Figure B-1: Scatter plot of empirical data for number of new referrals at Clinic A

We quantitatively confirm the assumption of independence using the runs test, which is represented graphically in Figure B-2.

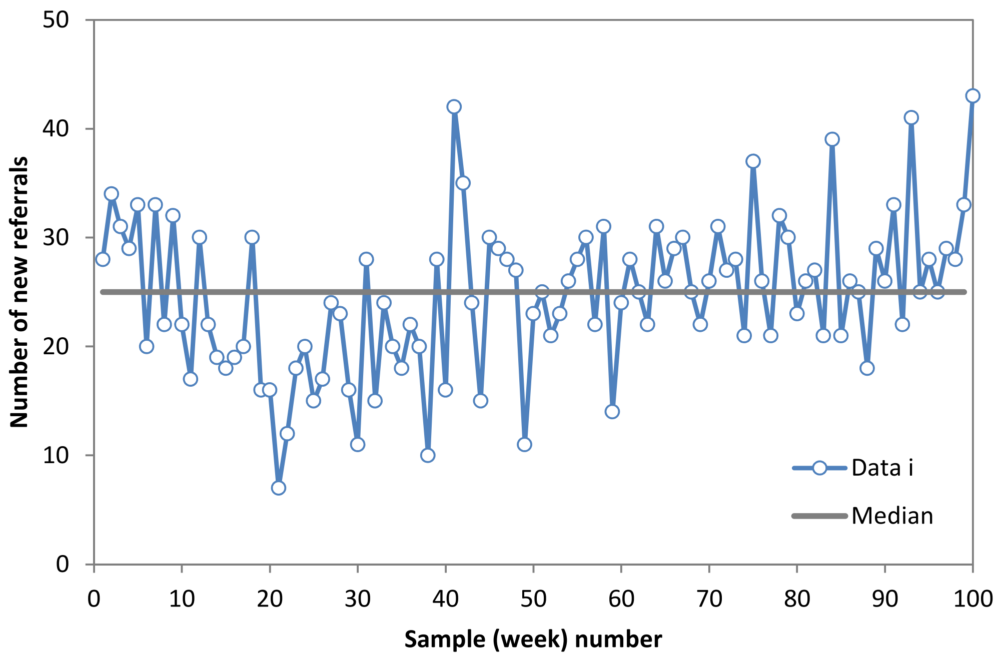


Figure B-2: Runs test of empirical data for number of new referrals at Clinic A

From Figure B-2, we can see that of the 100 samples with a median of 25, there are 53 samples greater than (or equal) to the median, there are 47 samples less than the median and there are 43 runs. The test statistic is -1.578 and at a significance level of $\alpha = 0.05$, we retain the null hypothesis of independence. The test result was confirmed using the runs test algorithm in SPSS.

With the assumption of independence verified, we can proceed to fit a distribution to the data. The number of new referrals received each week, over the last 100 weeks, is summarised by the statistics given Table B-1 and the distribution is shown in Figure B-3.

Table B-1: Summary statistics for number of new referrals received weekly at Clinic A

Sample Size n	Mean $\bar{X}(n)$	Median $\hat{x}_{0.5}(n)$	Standard Deviation $s(n)$	Minimum $X_{(1)}$	Maximum $X_{(n)}$
100	24.7	25	6.9	7	43

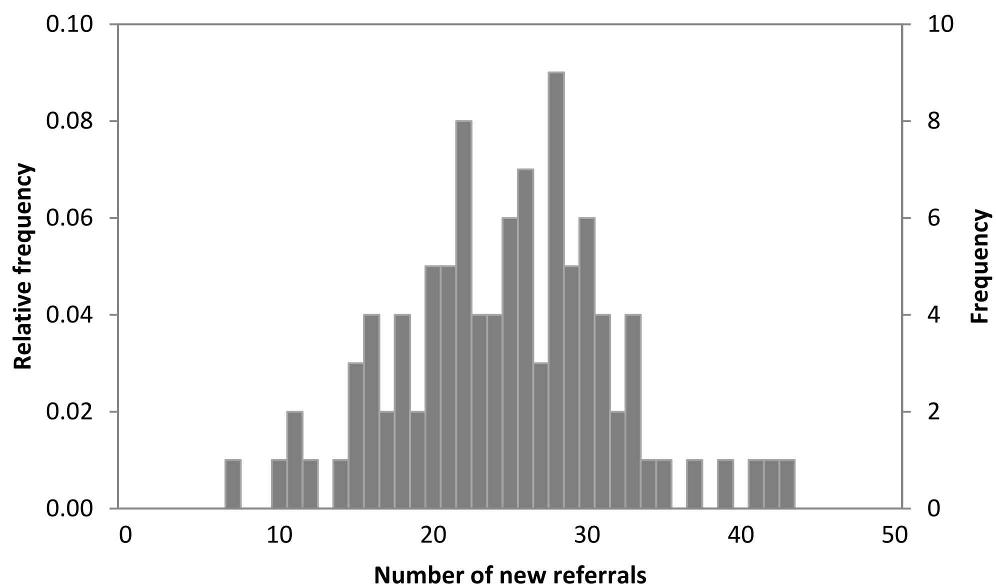


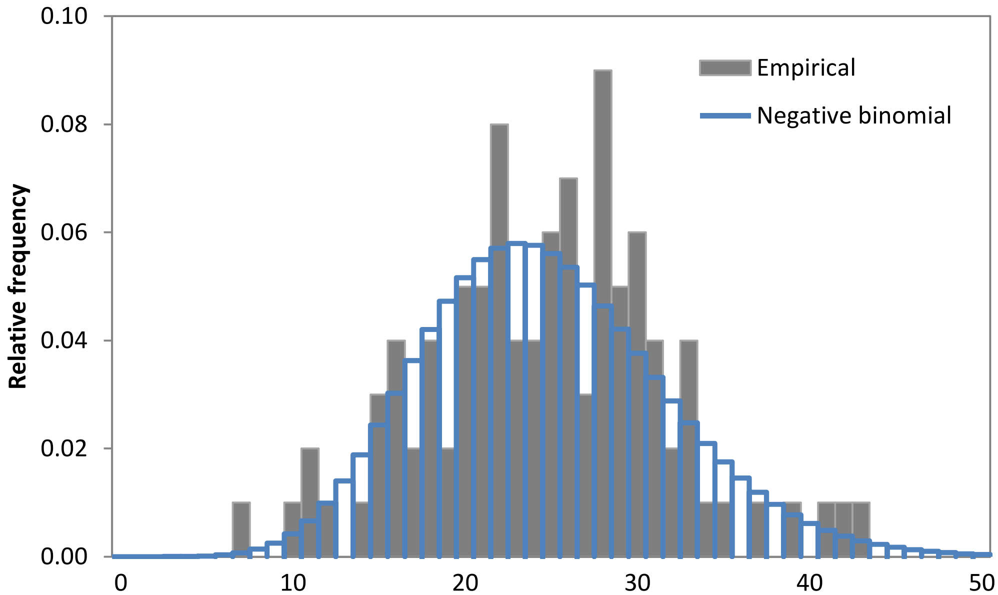
Figure B-3: Distribution of number of new referrals at Clinic A

By examining the summary statistics and distribution of the data, we expect that the number of new referrals follows a discrete distribution with non-negative values. Visual inspection of the empirical distribution suggests that the negative binomial, Poisson, and binomial families of distributions may be appropriate. The range of the negative binomial and Poisson families of distributions support the range of the possible numbers of new referrals. The binomial distribution has a finite range but may be suitable if parameters are selected appropriately.

We will estimate the parameters for the three potential discrete distributions using the MLEs presented in Law (2007, p. 302-309). The first candidate distribution is the negative binomial distribution with 25 successes and a probability of success of 0.503. The second candidate distribution is the Poisson distribution with mean of 24.680. Estimators for the binomial distribution do not exist for this data set. The distribution parameters are verified using ExpertFit software.

A frequency comparison of the empirical data and the two fitted distributions is shown in Figure B-4. The empirical data is shown in grey bars; the fitted negative binomial distribution is shown in blue in Figure B-4a and the fitted Poisson distribution is shown in blue in Figure B-4b.

A



B

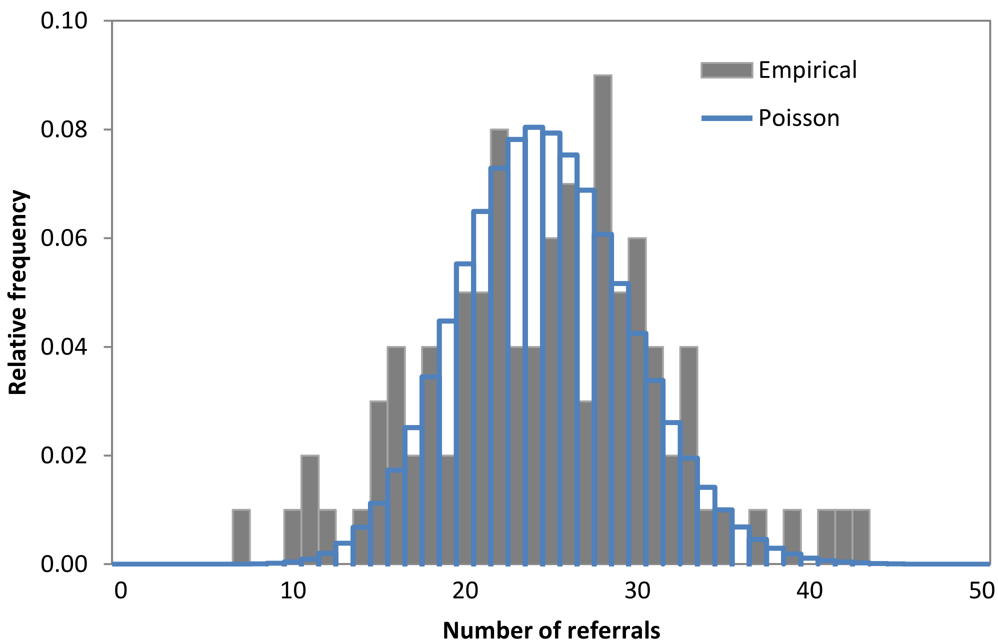


Figure B-4: Frequency comparison of empirical data and the fitted (A) negative binomial and (B) Poisson distributions for the number of new referrals at Clinic A

A qualitative assessment of the frequency comparisons in Figure B-4 suggests that the negative binomial distribution may be a better fit than the Poisson distribution.

The chi-square goodness-of-fit test is used to quantitatively assess the two potential distributions where the null hypothesis is the empirical data are independent, identically distributed random variables from the theoretical distribution. The intervals are selected to minimise the variance in the expected values in each interval while ensuring each interval has at least five expected values.

The chi-square goodness-of-fit test for the negative binomial and Poisson distributions is shown in Table B-2.

Table B-2: Chi-square goodness-of-fit test for negative binomial and Poisson distributions for the number of new referrals at Clinic A

Negative binomial (s = 25, p = 0.503)				
j	Interval	N_j	np_j	$\frac{(N_j - np_j)^2}{np_j}$
1	{0, 1, …, 18}	19	19.154	0.001
2	{19, 20, …, 22}	20	21.097	0.057
3	{23, 24, 25}	14	17.164	0.583
4	{26, 27, …, 30}	30	22.999	2.131
5	{31, 32, … }	17	19.585	0.341
			Test statistic, χ^2 =	3.114
			Significance level, α =	0.05
			Rejection region, RR: χ^2 >	9.488
			Decision:	Do not reject

Poisson (λ = 24.680)				
j	Interval	N_j	np_j	$\frac{(N_j - np_j)^2}{np_j}$
1	{0, 1,…, 20}	26	20.264	1.624
2	{21, 22, 23}	17	21.597	0.978
3	{24, 25}	10	15.975	2.235
4	{26, 27, 28}	19	20.488	0.108
5	{29, 30, … }	28	21.677	1.844
			Test statistic, χ^2 =	6.789
			Significance level, α =	0.05
			Rejection region, RR: χ^2 >	9.488
			Decision:	Do not reject

The results of the chi-square goodness-of fit test confirm the qualitative assessment of fit from inspection of the frequency comparisons in Figure B-4. Both distributions are acceptable, but the negative binomial distribution is a better fit for the data. This assessment is verified with ExpertFit software.

The distribution of the number of new referrals received in a week is modeled as a negative binomial distribution.

$$r_{w,A} \sim Negative\ binomial\ (s = 25,\ \ p = 0.503)$$

A frequency comparison of the empirical data and simulated data to the fitted negative binomial distributions is shown in Figure B-5 to verify the input model describes the empirical data. The simulated data is the result of 10000 trials.

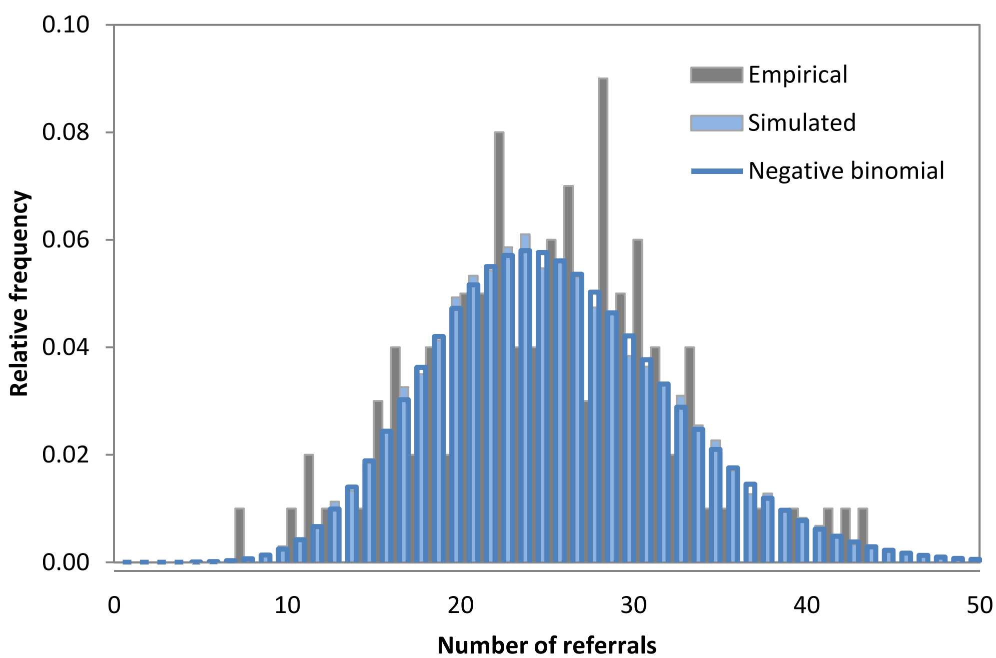


Figure B-5: Frequency comparison of empirical data and simulated data to fitted negative binomial distribution for number of new referrals at Clinic A

Referrals are received throughout the day at the administrative office and are delivered to the PCC twice daily, in the morning and afternoon, or ten times per week. We assume an equiprobable distribution of weekly referrals in the ten weekly deliveries, or a binomial distribution with $r_{w,A}$ trials and probability of 0.1.

$$r_{am,A} \sim Binomial\left(n = r_{w,A},\ \ p = 0.1\right)$$

$$r_{pm,A} \sim Binomial\left(n = r_{w,A},\ \ p = 0.1\right)$$

Referrals are delivered from the administrative office to the PCC at approximately 10 am and 2 pm. We model the arrival time as a uniformly distributed random variable within 30 minutes of 10 am and 2 pm.

$$t_{am} \sim Uniform\ (a = 09{:}45,\ \ b = 10{:}15)$$

$$t_{pm} \sim Uniform\ (a = 13{:}45,\ \ b = 14{:}15)$$

Clinic B

The number of new referrals received at Clinic B each week over the last 100 weeks, was obtained from the PCN's records. Following the same method as above for Clinic A, we use the runs test in SPSS to verify the assumption that the sample set is independent.

Summary statistics for the number of new referrals received at Clinic B is given in Table B-3.

Table B-3: Summary statistics for number of new referrals received weekly at Clinic B

Sample Size n	Mean $\bar{X}(n)$	Median $\hat{x}_{0.5}(n)$	Standard Deviation $s(n)$	Minimum $X_{(1)}$	Maximum $X_{(n)}$
100	19.9	20	6.0	9	34

ExpertFit software is used to fit a theoretical distribution to the data and test the goodness-of-fit. The distribution of the number of new referrals received in a week is modeled as a negative binomial distribution.

$$r_{w,B} \sim Negative\ binomial\ (s = 25,\ \ p = 0.557)$$

A frequency comparison of the empirical data and simulated data to the fitted negative binomial distributions is shown in Figure B-6.

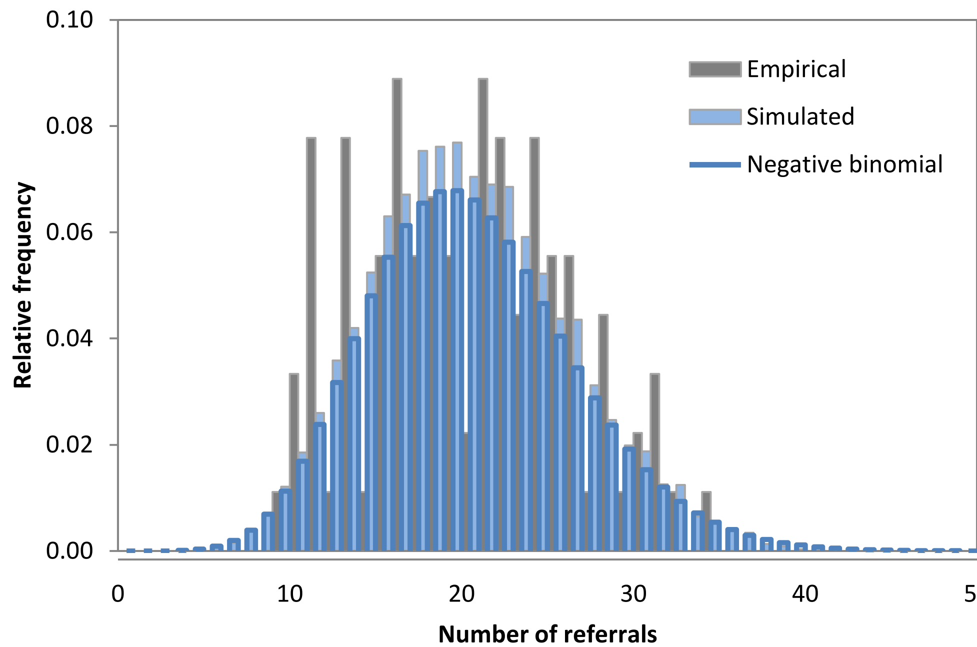


Figure B-6: Frequency comparison of empirical data and simulated data to fitted negative binomial distributions for the number of new referrals at Clinic B

Then we assume an equiprobable distribution of referrals over five days

$$r_{d,B} \sim Binomial\left(n = r_{w,B},\;\; p = 0.2\right)$$

Referrals at Clinic B are received throughout the day, but only begin the process after triage by clinicians that meet daily. We model the arrival time as a uniformly distributed random variable within 10 minutes of 1:30 pm.

$$t_{pm} \sim Uniform\;(a = 13{:}25,\;\; b = 13{:}35)$$

$$t_{pm} \sim Uniform\;(a = 13{:}45,\;\; b = 14{:}15)$$

Process Types 2, 3, and 4 (S1.3 Schedule appointment)

Three process types are defined for the schedule appointment (S1.3) process to model their different arrival patterns, service times and priority levels. The first attempt to schedule an appointment is represented by process type 2 which is triggered by the completion of process type 1 (create record and develop care plan).

The observed success rate of reaching a patient and scheduling an appointment is 0.356 at Clinic A and 0.260 at Clinic B. For the patients that could not be reached on the first attempt, the PCC may leave a message. The proportion of calls where the patient could not be reached and an appointment was not scheduled is considered the failure rate: 0.64 at Clinic A and 0.74 at Clinic B.

Patients that call back are represented with process type 3 and those that require a subsequent attempt by process type 4. Of the first attempts that were unsuccessful, we assume that 1 in 3 patients will return the phone call (process type 3) and that 2 in 3 will require a subsequent attempt (process type 4).

For the arrival of process type 3, first, the number of new referrals received in a week is modeled as a negative binomial distribution as described in the previous section. Second, the expected number of return calls per day is modeled as a binomial distribution with probability of success equal to one-third of the failure rate distributed over five days. Finally, the arrival pattern is modeled as an exponential distribution with the expected number of return calls.

The arrival of process type 4 is modeled in a similar manner. First, the number of new referrals received in a week is modeled as a negative binomial distribution as described in the previous section. Then, the expected number of second attempts is modeled as a binomial distribution with probability of success equal to two-thirds of the failure rate distributed over five days. Since the referrals requiring a second attempt to contact are known, the arrival time is not modeled as a distribution as in the case of process type 3, and is present at the start of simulation.

Process Types 5, 6 and 7 (S2.1 Patient mailout, S2.2 Notify referring physician, and S2.3 Create chart)

The appointment preparation process begins once the appointment has been scheduled with the patient. The PCC prepares a patient mailout, notifies the referring physician and creates a chart for the patient, represented by process types 5, 6, and 7, respectively. These processes are triggered by the completion of the schedule appointment process (process types 2, 3, or 4) when the result is a success (an appointment is made).

Process Type 8 (S2.4 Appointment reminder)

Appointment reminders are made by the PCC prior to the scheduled appointment and are represented by process type 8.

Clinic A

The number of scheduled appointments each month over the last 27 months, was obtained from the PCN's records. The assumption of independence is verified using the runs test in SPSS software.

The number of appointments scheduled each month over the last 27 months is summarised in Table B-4 and the distribution is shown in Figure B-7.

Table B-4: Summary statistics for number of appointments scheduled monthly at Clinic A

Sample Size n	Mean $\bar{X}(n)$	Median $\hat{x}_{0.5}(n)$	Standard Deviation $s(n)$	Minimum $X_{(1)}$	Maximum $X_{(n)}$
27	232	225	58	137	382

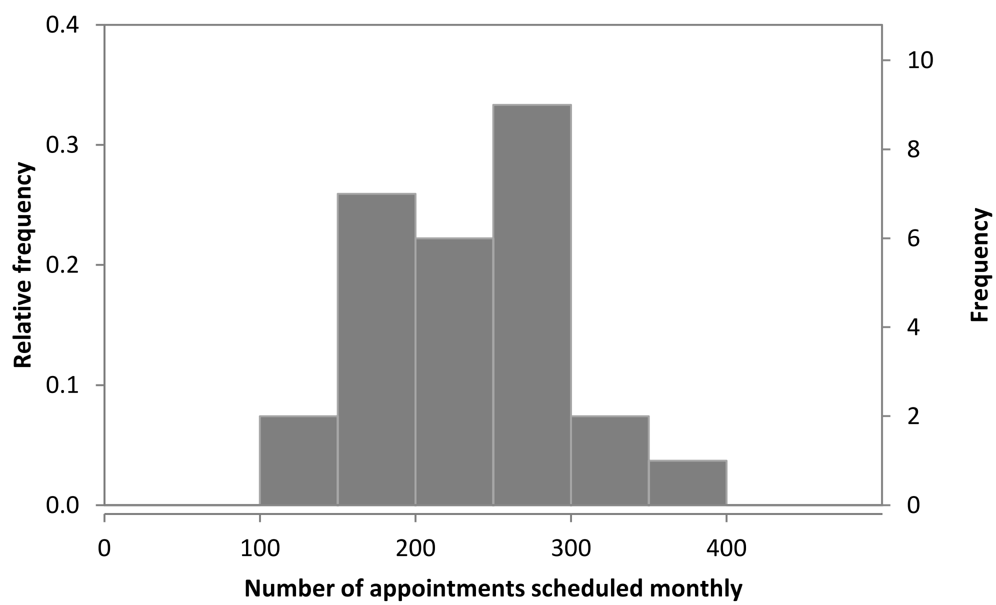


Figure B-7: Distribution of number of scheduled appointments at Clinic A

We again expect that the number of scheduled appointments follows a discrete distribution with non-negative values and use ExpertFit software to estimate parameters for three candidate discrete distributions – negative binomial, Poisson, and binomial. The first candidate distribution is the negative binomial distribution with 18 successes and a probability of success of 0.072. The second candidate distribution is the Poisson distribution with mean of 232.333. The data does not support a binomial distribution. A frequency comparison of the empirical data and the two fitted distributions is shown in Figure B-8.

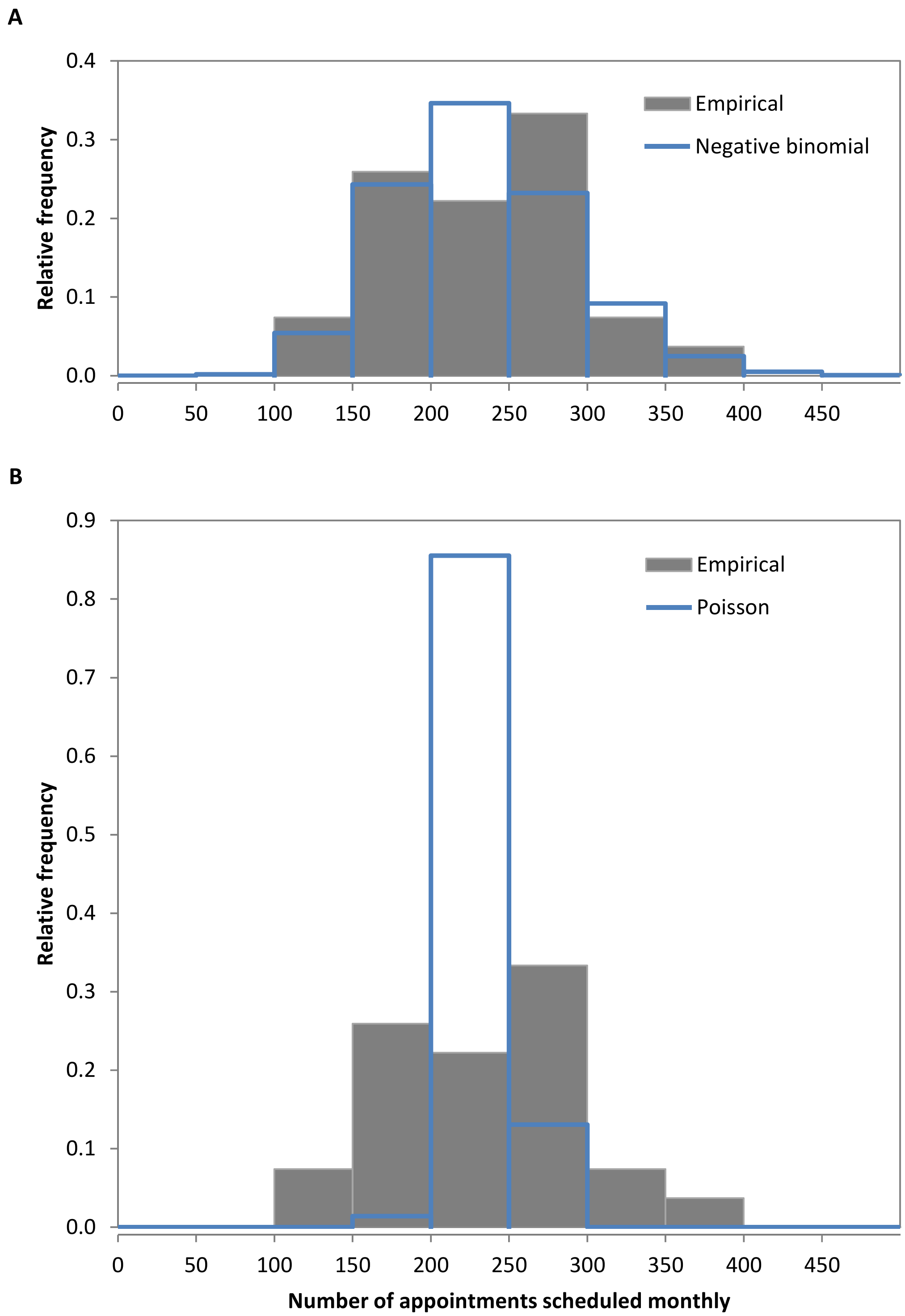


Figure B-8: Frequency comparison of empirical data and the fitted (A) negative binomial and (B) Poisson distributions for the number of scheduled appointments at Clinic A

A qualitative assessment of the frequency comparisons in Figure B-8 suggests that the negative binomial distribution may be a good fit for the data and the Poisson distribution is not. The chi-square goodness-of-fit test with ExpertFit software for the negative binomial and Poisson distributions confirm the qualitative assessment of fit. The negative binomial distribution is an acceptable fit for the data but the Poisson distribution is not.

The distribution of the number of appointments scheduled in a month is modeled as a negative binomial distribution.

$$a_{m,A} \sim Negative\ binomial\ (s = 18,\ \ p = 0.072)$$

A frequency comparison of the empirical data and simulated data to the fitted negative binomial distributions is shown in Figure B-9.

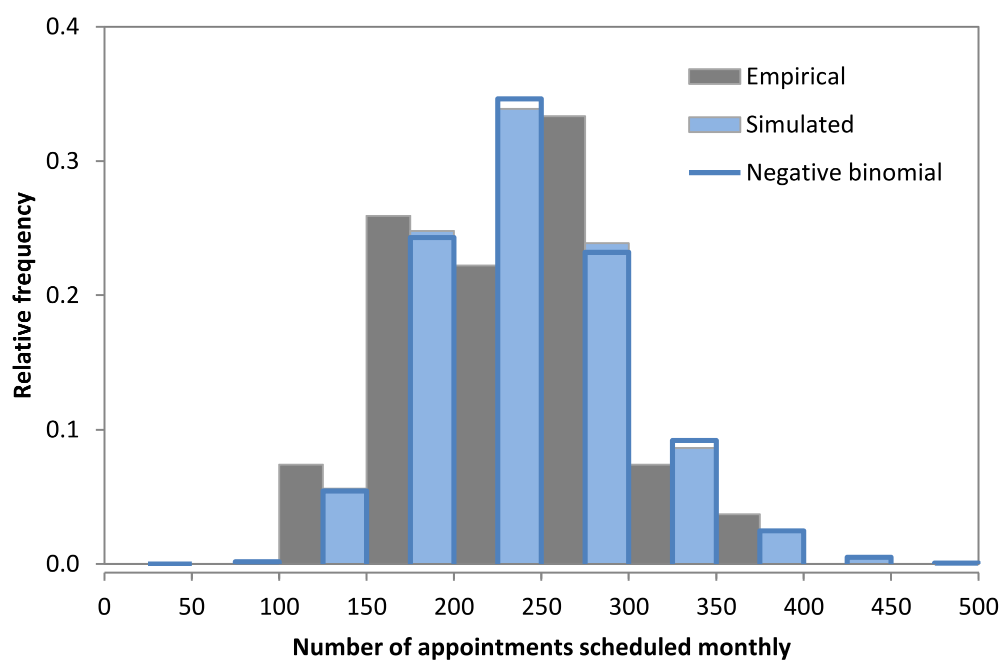


Figure B-9: Frequency comparison of empirical data and simulated data to fitted negative binomial distributions for the number of scheduled appointments at Clinic A

We assume there are on average 20 working days in each month and assume an equiprobable distribution of appointments scheduled in each working day of the month and model the number of scheduled appointments each day as a binomial distribution with $a_{m,A}$ trials and probability of 0.05.

$$a_{d,A} \sim Binomial\left(n = a_{m,A},\ \ p = 0.05\right)$$

The list of patients that the PCC will need to call at available at the start of each day, so we model the entities representing process type 8 to arrive at the start of the simulation.

Clinic B

The number of scheduled appointments each month over the last 27 months, was obtained from the PCN's records. The assumption of independence is verified using the runs test in SPSS software.

Summary statistics for the number of appointments scheduled monthly at Clinic B is given in Table B-5.

Table B-5: Summary statistics for number of appointments scheduled monthly at Clinic B

Sample Size n	Mean $\bar{X}(n)$	Median $\hat{x}_{0.5}(n)$	Standard Deviation $s(n)$	Minimum $X_{(1)}$	Maximum $X_{(n)}$
27	121	119	27	73	170

ExpertFit software was used to estimate parameters for and assess the fit of candidate distributions. The distribution of the number of appointments scheduled in a month is modeled as a negative binomial distribution.

$$a_{m,B} \sim Negative\ binomial\ (s = 25,\ \ p = 0.171)$$

A frequency comparison of the empirical data and simulated data to the fitted negative binomial distributions is shown in Figure B-10.

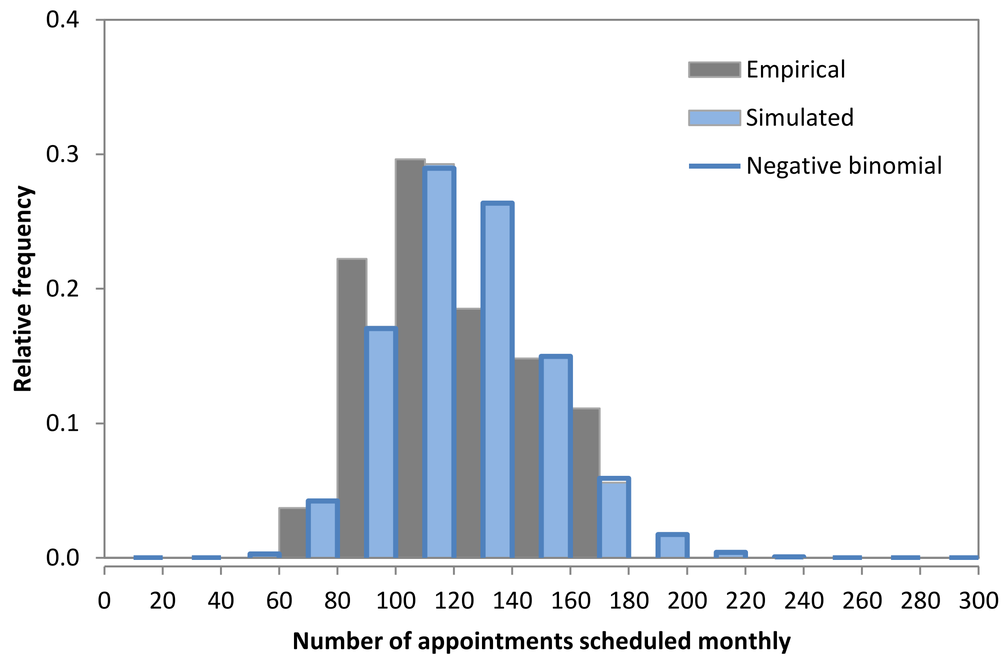


Figure B-10: Frequency comparison of empirical data and simulated data to fitted negative binomial distributions for the number of scheduled appointments at Clinic B

Again, we assume an equiprobable distribution of appointments in each month over 20 working days and model the number of scheduled appointments each day as a binomial distribution with $a_{m,B}$ trials and probability of 0.05.

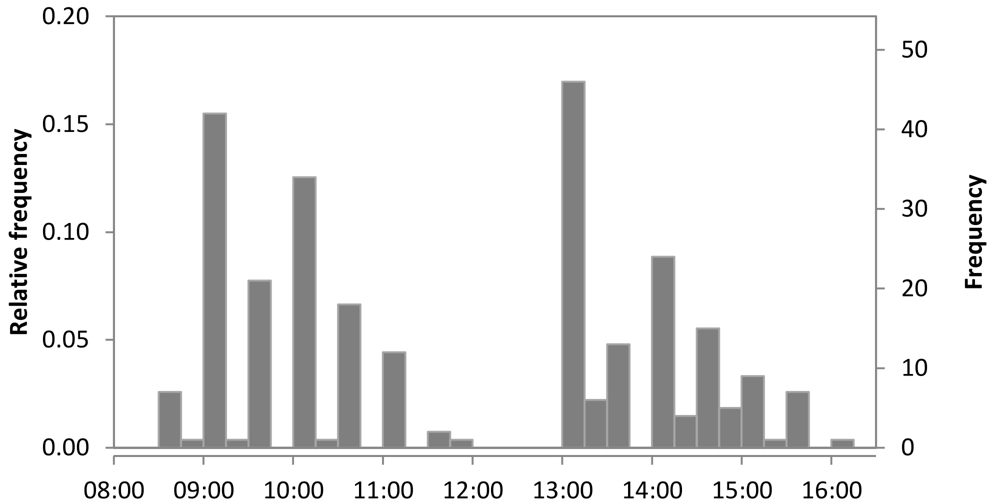
$$a_{d,B} \sim Binomial\left(n = a_{m,B},\ \ p = 0.05\right)$$

Process Type 9 (S3.1.1 Obtain patient data)

The patient registration process begins when a patient arrives for their scheduled appointment. The PCC estimates that 95% of patients arrive for their appointment within 10 minutes of their scheduled appointment time. We estimate the arrival time as a normally distributed random variable with mean y and standard deviation 300, where y is the scheduled appointment time.

From the automated appointment reminder system reports, we tally the distribution of schedule appointment times for one month (January 2012). The distribution of the 271 appointments at clinic A is shown in Figure B-11a and the 147 appointments at clinic B is shown in Figure B-11b.

A



B

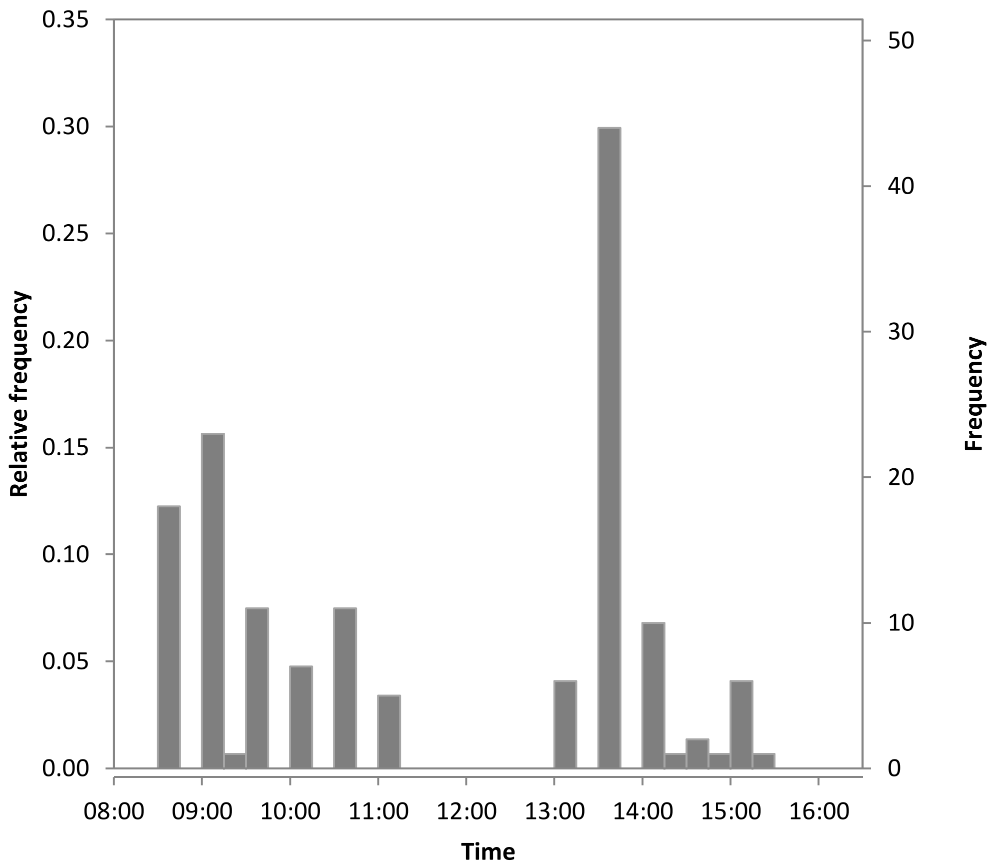


Figure B-11: Distribution of empirical data for scheduled appointment times at (A) clinic A and (B) clinic B

The empirical distribution of schedule appointment times will be used in the input model. We model the arrival of this process type in a similar manner as the previous type. The number of appointments scheduled in a month is modeled as a negative binomial distribution.

Then we assume an equiprobable distribution of scheduled appointments over the 20 working days in a month and model the number of scheduled appointments each day as a binomial distribution.

The daily scheduled appointments are then distributed as a multinomial probability distribution with the empirical distribution of relative frequencies shown in Figure B-11.

$$t_{schappt,A} \sim Multinomial\left(n = a_{d,A},\ \ Y_1 = 08{:}30, Y_2 = 08{:}45, \cdots, Y_{22} = 16{:}00,\\ p_1 = 0.026, p_2 = 0.004, \cdots, p_{22} = 0.004\right)$$

$$t_{schappt,B} \sim Multinomial\left(n = a_{d,B},\ \ Y_1 = 08{:}30, Y_2 = 09{:}00, \cdots, Y_{15} = 15{:}15,\\ p_1 = 0.122, p_2 = 0.156, \cdots, p_{15} = 0.007\right)$$

Finally, it is estimated that 95% of patients arrive within 10 minutes of their scheduled appointment time. The arrival time for each scheduled appointment is normally distributed with the mean given by the scheduled appointment time and a standard deviation of five minutes, or 300 seconds.

$$t_{appt} \sim Normal\left(\mu = t_{schappt},\ \ \sigma = 300\right)$$

Process Type 10 (S3.2.2 Notify clinician)

The PCC notifies the clinician, represented by process type 10, once the patient information has been obtained. Process type 10 is triggered by the completion of process type 9.

Process Type 11 (S3.3.1 Report to referring physician)

The report to the referring physician is prepared when the patient care is transferred back to the referring physician and the patient chart is closed.

The number of chart closures for each clinic in each month over the last 21 months, was obtained from the PCN's records. The assumption of independence is verified using the runs test in SPSS software.

Summary statistics for the number of chart closures at the two clinics is given in Table B-5.

Table B-6: Summary statistics for number of chart closures monthly

Clinic	Sample Size n	Mean $\bar{X}(n)$	Median $\hat{x}_{0.5}(n)$	Standard Deviation $s(n)$	Minimum $X_{(1)}$	Maximum $X_{(n)}$
A	21	194	172	109	66	498
B	21	82	83	23	26	135

ExpertFit software was used to estimate parameters for and assess the fit of candidate distributions. The distribution of the number of chart closures in a month is modeled as a negative binomial distribution for each clinic.

$$c_{m,A} \sim Negative\ binomial\ (s = 4,\ \ p = 0.020)$$

$$c_{m,B} \sim Negative\ binomial\ (s = 14,\ \ p = 0.146)$$

Frequency comparisons of the empirical data and simulated data to the fitted negative binomial distributions for Clinic A and Clinic B are shown in Figure B-12 and Figure B-13, respectively.

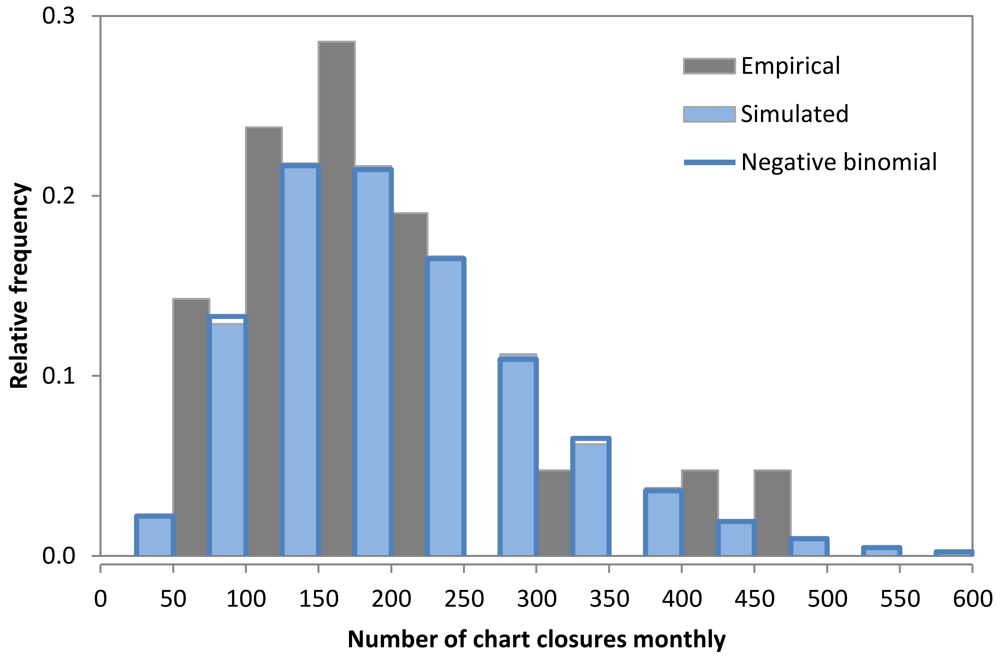


Figure B-12: Frequency comparison of empirical data and simulated data to fitted negative binomial distribution for the number of chart closures at Clinic A

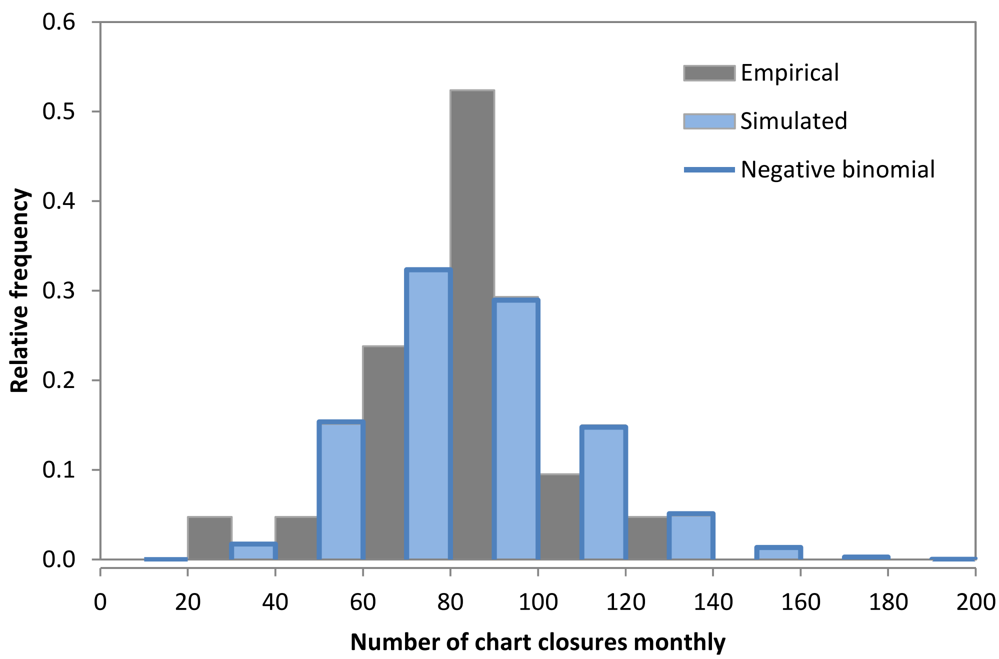


Figure B-13: Frequency comparison of empirical data and simulated data to fitted negative binomial distribution for the number of chart closures at Clinic B

Again, we assume an equiprobable distribution of chart closures in each month over 20 working days and model the number of chart closures each day as a binomial distribution with c_m trials and probability of 0.05.

$$c_{d,A} \sim Binomial\left(n = c_{m,A},\ \ p = 0.05\right)$$

$$c_{d,B} \sim Binomial\left(n = c_{m,B},\ \ p = 0.05\right)$$

Finally, the arrival pattern is modeled as an exponential distribution with the expected number of chart closures.

Process Type 12 (S3.3.2 Close chart)

The PCC closes the patient chart, represented by process type 11, once the report for the referring physician has been prepared. Process type 12 is triggered by the completion of process type 11.

Process Type 13 (Other interruptions)

There were 115 interruptions noted in the 36.5 hours of observation at clinic A and 48 interruptions noted in the 33 hours of observation at clinic B.

We model the arrival process for interruptions as a Poisson arrival process and the interarrival times are exponentially distributed with a mean interarrival time of 1143 seconds per interruption at clinic A and 2475 seconds per interruption at clinic B.

Reasons for difference in observed interruptions:

- Clinic A located in more prominent location, large signage, easily seen from the street, more walk in traffic. Clinic B less easy to see from the street, signage is less prominent
- Clinic A located where there was once a walk in clinic, still received patients looking for the clinic
- Clinic A has more clinicians and higher patient volume

B.2 Service Times

A summary of the service time distributions for each of the process types for the two clinics studied at the PCN was presented in Section 5.5. The service time distributions for each of the process types for the two clinics were developed in a similar manner. These distributions will be presented briefly in this section with density-histogram plots or probability distributions that show the empirical data, fitted theoretical distribution (where applicable), and the simulated data. The service times for Clinic A will be presented first, followed by those for Clinic B.

Clinic A

Process Type 1 (S1.1 Create record and S1.2 Develop care plan)

Summary statistics for the service time of process type 1 at Clinic A is given in Table B-7.

Table B-7: Summary statistics for service time of process type 1 at Clinic A

Task	Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
1.1	18	185	156	88	87	356
1.2	33	29	20	18	10	84

The service time distribution for process type 1 at Clinic A is described by

$$S \sim log\text{-}logistic\ (\alpha = 3.917, \beta = 164.554)$$
$$+\ gamma\ (\alpha = 1.130, \beta = 16.817, \gamma = 9.943)$$

Density-histograms plots of the empirical and simulated data and the fitted log-logistic distribution is shown in Figure B-14a and the fitted gamma distribution is shown in Figure B-14b.

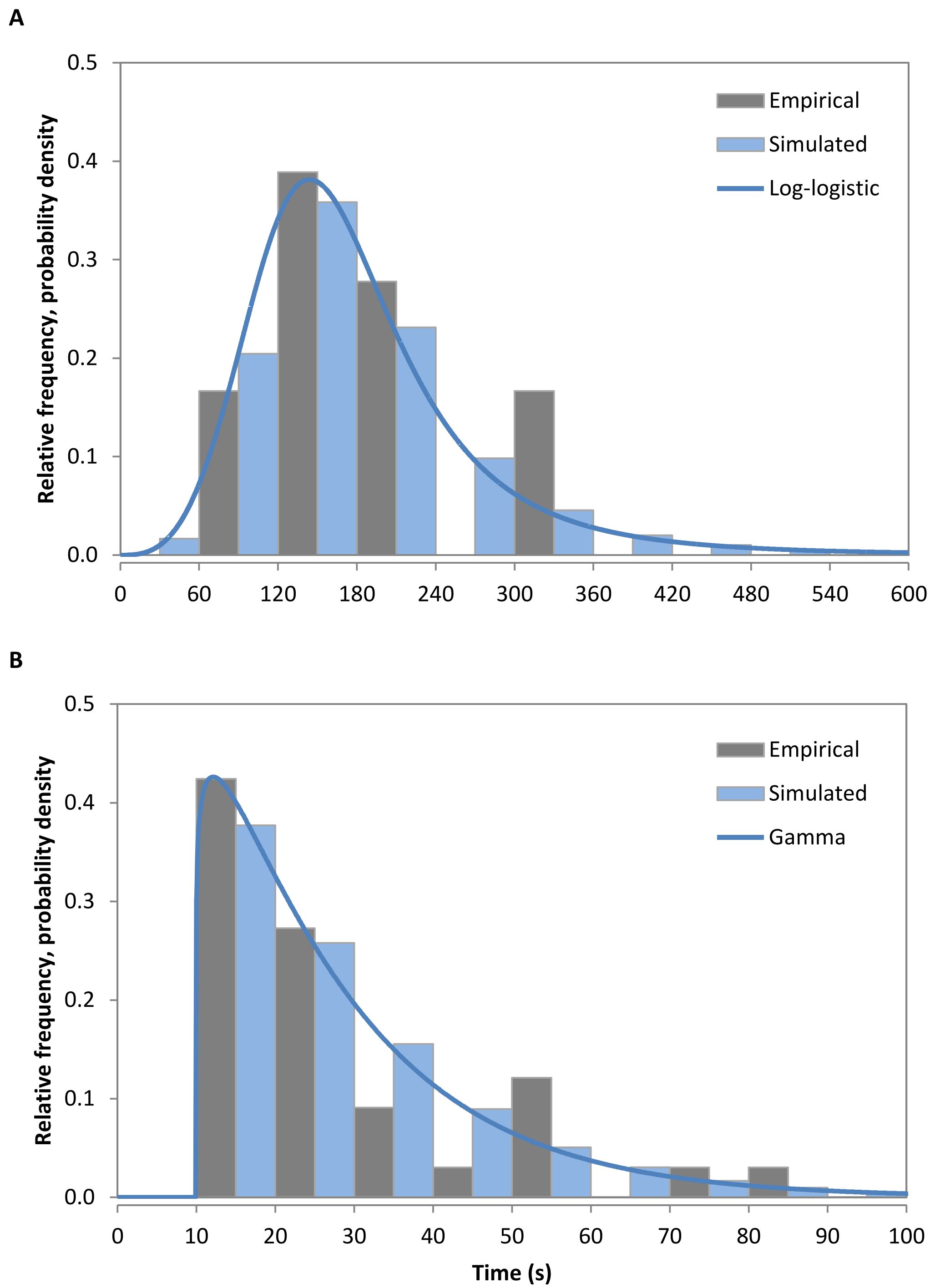


Figure B-14: Density-histogram plot of empirical and simulated data and fitted (A) log-logistic and (B) gamma distributions for service time of process type 1 at Clinic A

Process Type 2 (S1.3 Schedule appointment – First attempt)

The empirical distribution of outcomes observed over 45 attempts to contact patients at Clinic A is shown in Figure B-15.

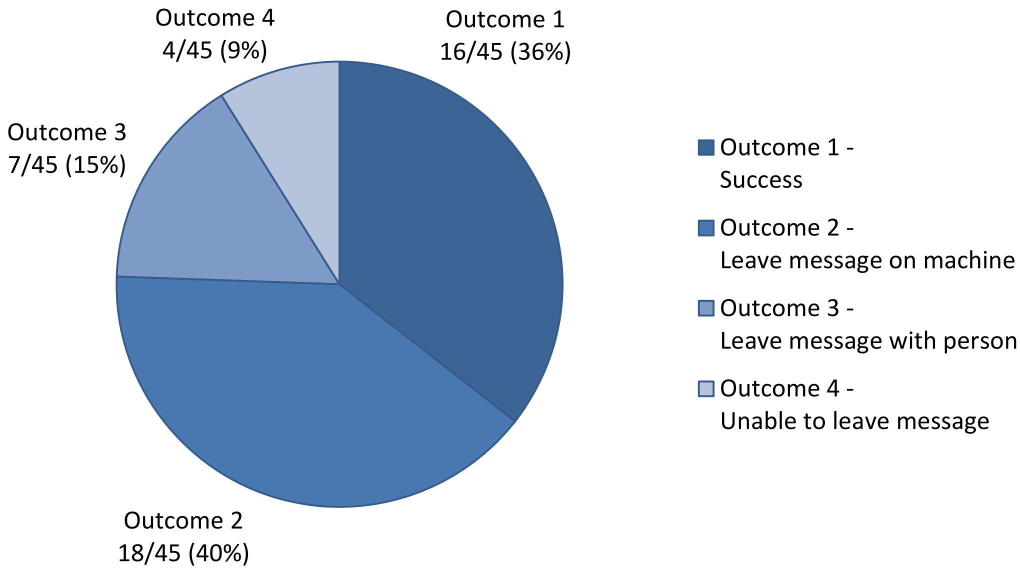


Figure B-15: Distribution of outcomes for process type 2 at Clinic A

Outcome 1

Summary statistics for the service time of outcome 1 for process type 2 at Clinic A is given in Table B-8.

Table B-8: Summary statistics for service time of outcome 1 for process type 2 at Clinic A

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
16	213	197	70	93	355

The service time distribution of outcome 1 for process type 2 at Clinic A is described by

$$log\text{-}logistic\ (\alpha = 5.439, \beta = 202.478)$$

A density-histogram plot of the empirical and simulated data and the fitted log-logistic distribution is shown in Figure B-16.

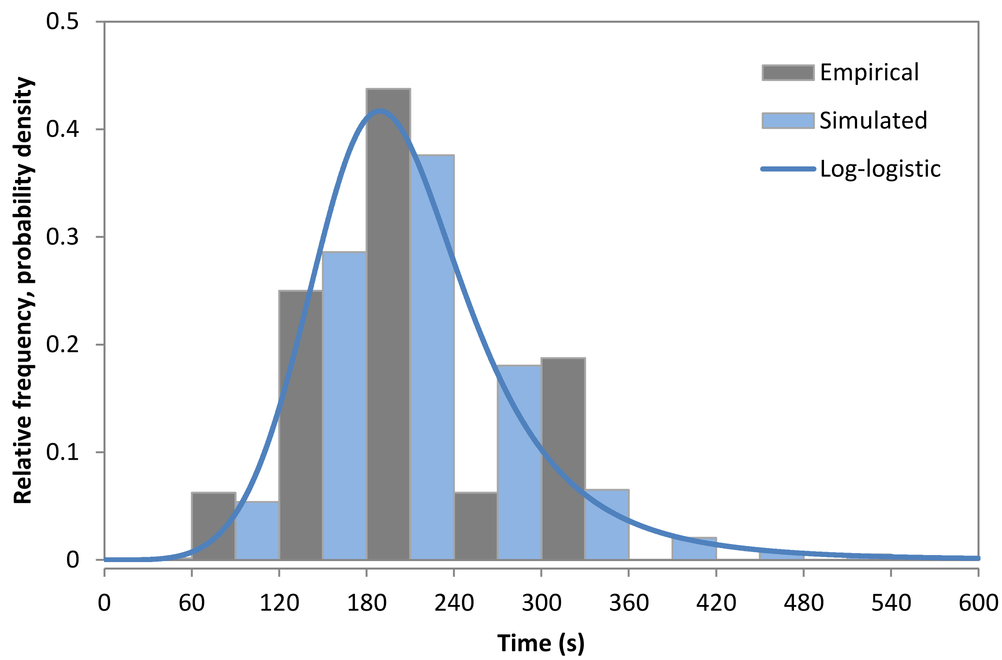


Figure B-16: Density-histogram plot of empirical and simulated data and fitted log-logistic distribution for service time of outcome 1 for process type 2 at Clinic A

Outcome 2

Summary statistics for the service time of outcome 2 for process type 2 at Clinic A is given in Table B-9.

Table B-9: Summary statistics for service time of outcome 2 for process type 2 at Clinic A

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
18	61	61	10	49	87

The service time distribution of outcome 2 for process type 2 at Clinic A is described by

$$log\text{-}logistic\ (\alpha = 11.580, \beta = 60.079)$$

A density-histogram plot of the empirical and simulated data and the fitted log-logistic distribution is shown in Figure B-17.

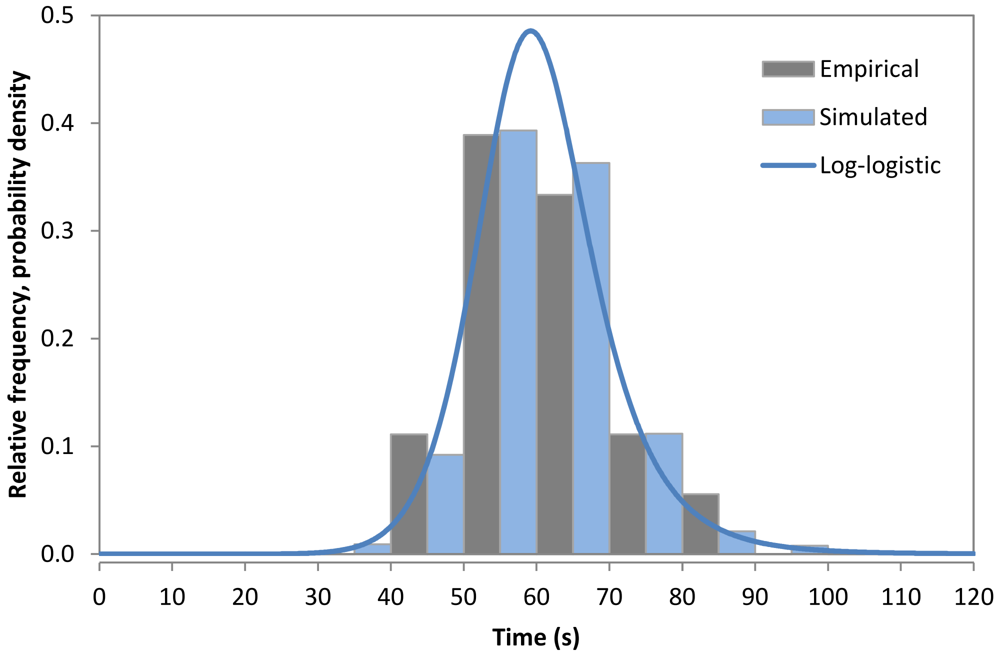


Figure B-17: Density-histogram plot of empirical and simulated data and fitted log-logistic distribution for service time of outcome 2 for process type 2 at Clinic A

Outcome 3

The data set observed for the service time of outcome 3 for process type 2 at Clinic A is

$$S \in \{70, 64, 84, 39, 97, 66, 108\}$$

The empirical distribution function specified from this data set is

$$F(s) = \begin{cases} 0 & , s < 39 \\ \dfrac{s-39}{6 \times 25} & , 39 \leq s < 64 \\ \dfrac{1}{6} + \dfrac{s-64}{6 \times 2} & , 64 \leq s < 66 \\ \dfrac{2}{6} + \dfrac{s-66}{6 \times 4} & , 66 \leq s < 70 \\ \dfrac{3}{6} + \dfrac{s-70}{6 \times 14} & , 70 \leq s < 84 \\ \dfrac{4}{6} + \dfrac{s-84}{6 \times 13} & , 84 \leq s < 97 \\ \dfrac{5}{6} + \dfrac{s-97}{6 \times 11} & , 97 \leq s < 108 \\ 1 & , s \geq 108 \end{cases}$$

The empirical and simulated probability distributions are shown in Figure B-18.

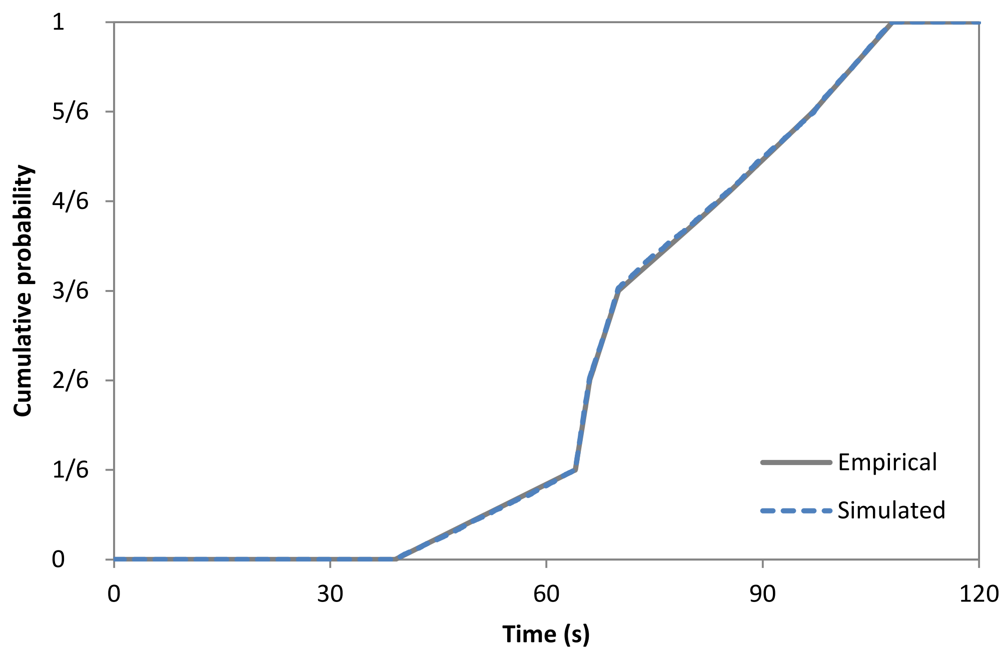


Figure B-18: Empirical and simulated probability distribution of service time of outcome 3 for process type 2 at Clinic A

Outcome 4

The data set observed for the service time of outcome 4 for process type 2 at Clinic A is

$$S \in \{70, 74, 94, 83\}$$

The empirical distribution function specified from this data set is

$$F(s) = \begin{cases} 0 & , s < 70 \\ \dfrac{s-70}{3 \times 4} & , 70 \le s < 74 \\ \dfrac{1}{3} + \dfrac{s-74}{3 \times 9} & , 74 \le s < 83 \\ \dfrac{2}{3} + \dfrac{s-83}{3 \times 11} & , 83 \le s < 94 \\ 1 & , s \ge 94 \end{cases}$$

The empirical and simulated probability distributions are shown in Figure B-19.

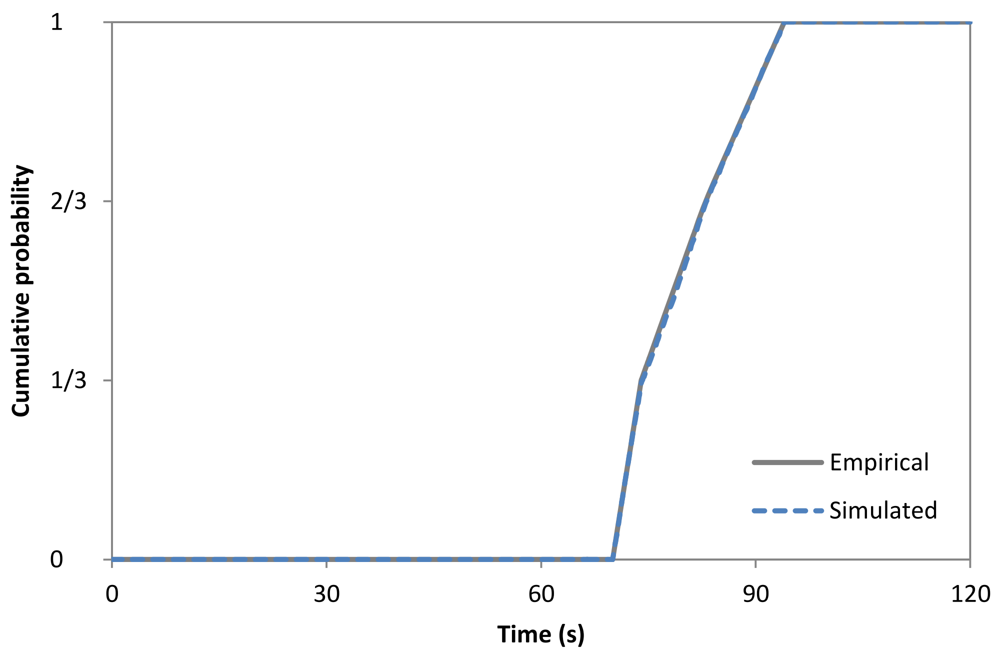


Figure B-19: Empirical and simulated probability distribution of service time of outcome 4 for process type 2 at Clinic A

Process Type 3 (S1.3 Schedule appointment – Patient call back)

The data set observed for the service time for process type 3 at Clinic A is

$$S \in \{145, 167, 333, 677, 205, 57, 161, 346, 117\}$$

The empirical distribution function specified from this data set is

$$F(s) = \begin{cases} 0 & , s < 57 \\ \dfrac{s-57}{8 \times 60} & , 57 \le s < 117 \\ \dfrac{1}{8} + \dfrac{s-117}{8 \times 28} & , 117 \le s < 145 \\ \dfrac{2}{8} + \dfrac{s-145}{8 \times 16} & , 145 \le s < 161 \\ \dfrac{3}{8} + \dfrac{s-161}{8 \times 6} & , 161 \le s < 167 \\ \dfrac{4}{8} + \dfrac{s-167}{8 \times 38} & , 167 \le s < 205 \\ \dfrac{5}{8} + \dfrac{s-205}{8 \times 128} & , 205 \le s < 333 \\ \dfrac{6}{8} + \dfrac{s-333}{8 \times 13} & , 333 \le s < 346 \\ \dfrac{7}{8} + \dfrac{s-346}{8 \times 331} & , 346 \le s < 677 \\ 1 & , s \ge 677 \end{cases}$$

The empirical and simulated probability distributions are shown in Figure B-20.

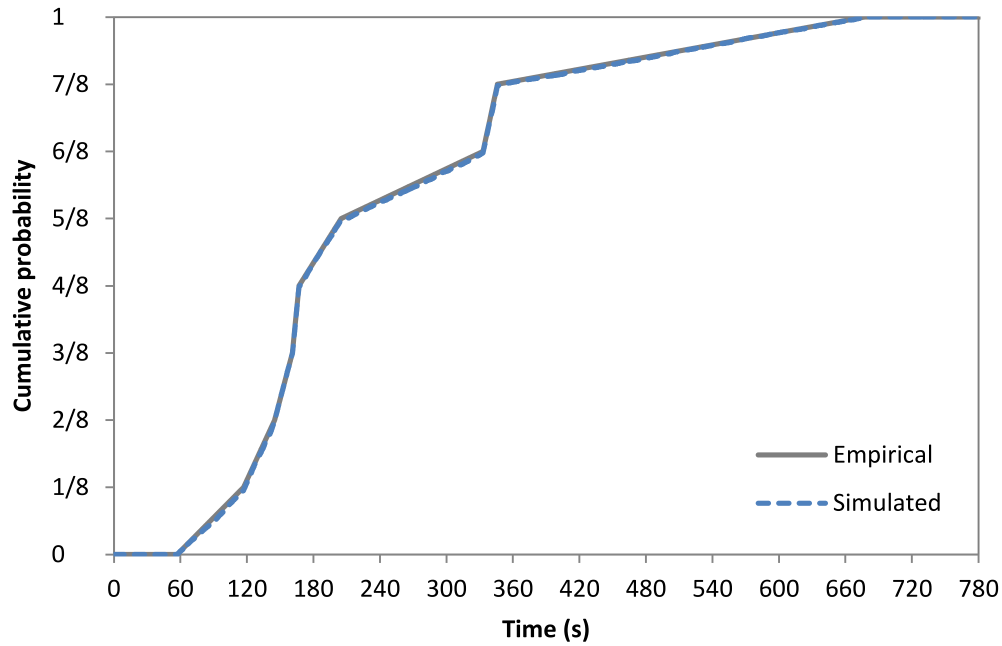


Figure B-20: Empirical and simulated probability distribution of service time of process type 3 at Clinic A

Process Type 4 (S1.3 Schedule appointment – Subsequent attempt)

The service time for process type 4 follows the same distributions as process type 2.

Process Type 5 (S2.1 Patient mailout)

The data set observed for the service time for process type 5 prior to ICT implementation at Clinic A is

$$S \in \{30, 50, 63\}$$

The empirical distribution function specified from this data set is

$$F(s) = \begin{cases} 0 & , s < 30 \\ \dfrac{s-30}{2 \times 20} & , 30 \leq s < 50 \\ \dfrac{1}{2} + \dfrac{s-50}{2 \times 13} & , 50 \leq s < 63 \\ 1 & , s \geq 63 \end{cases}$$

The empirical and simulated probability distributions are shown in Figure B-21.

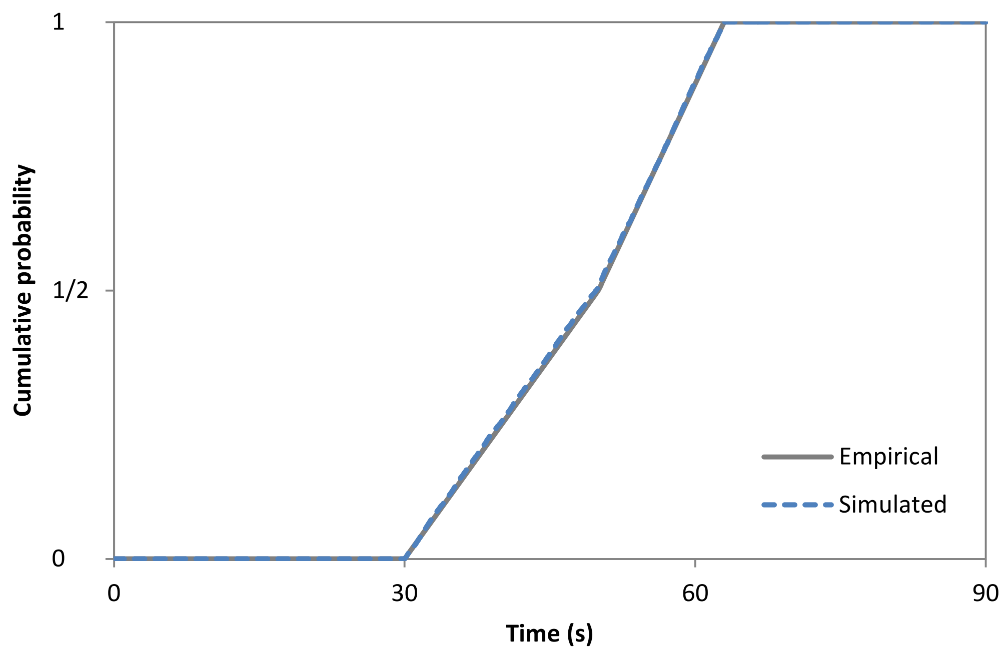


Figure B-21: Empirical and simulated probability distribution of service time of process type 5 prior to ICT implementation at Clinic A

The data set observed for the service time for process type 5 after ICT implementation at Clinic A is

$$S \in \{48, 170, 157, 78, 64, 110\}$$

The empirical distribution function specified from this data set is

$$F(s) = \begin{cases} 0 & , s < 48 \\ \dfrac{s-48}{5 \times 16} & , 48 \le s < 64 \\ \dfrac{1}{5} + \dfrac{s-64}{5 \times 14} & , 64 \le s < 78 \\ \dfrac{2}{5} + \dfrac{s-78}{5 \times 32} & , 78 \le s < 110 \\ \dfrac{3}{5} + \dfrac{s-110}{5 \times 47} & , 110 \le s < 157 \\ \dfrac{4}{5} + \dfrac{s-157}{5 \times 13} & , 157 \le s < 170 \\ 1 & , s \ge 170 \end{cases}$$

The empirical and simulated probability distributions are shown in Figure B-22.

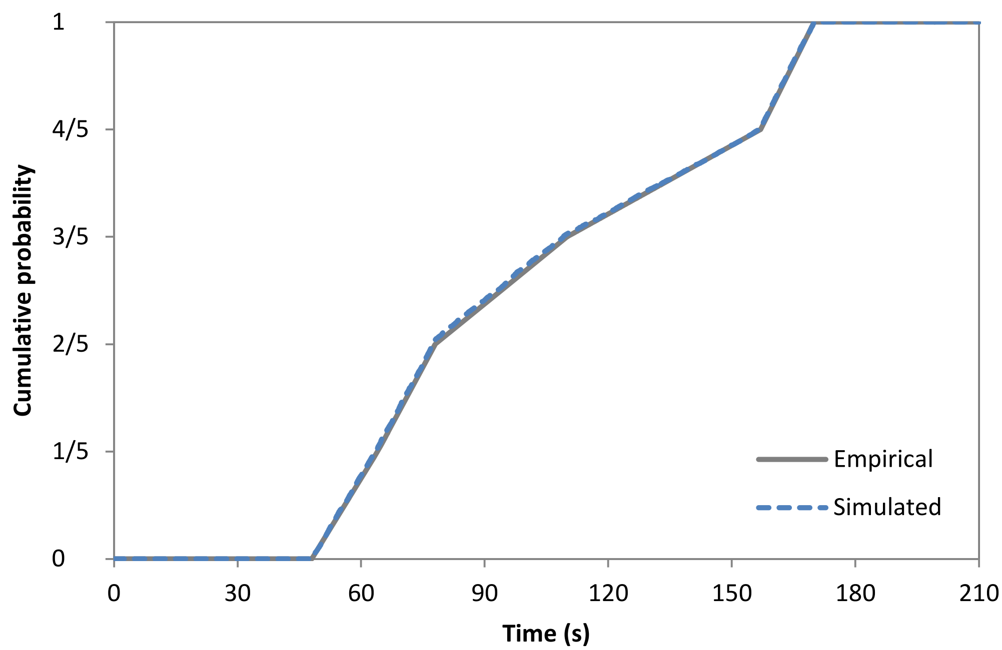


Figure B-22: Empirical and simulated probability distribution of service time of process type 5 after ICT implementation at Clinic A

Process Type 6 (S2.2 Notify referring physician)

The data set observed for the service time for process type 6 at Clinic A is

$$S \in \{60, 37, 15, 26, 60, 65, 61, 39, 60\}$$

The empirical distribution function specified from this data set is

$$F(s) = \begin{cases} 0 & , s < 15 \\ \dfrac{s-15}{8 \times 11} & , 15 \leq s < 26 \\ \dfrac{1}{8} + \dfrac{s-26}{8 \times 11} & , 26 \leq s < 37 \\ \dfrac{2}{8} + \dfrac{s-37}{8 \times 2} & , 37 \leq s < 39 \\ \dfrac{3}{8} + \dfrac{s-39}{8 \times 21} & , 39 \leq s < 60 \\ \dfrac{4}{8} + \dfrac{3(s-60)}{8 \times 1} & , 60 \leq s < 61 \\ \dfrac{7}{8} + \dfrac{s-61}{8 \times 4} & , 61 \leq s < 65 \\ 1 & , s \geq 65 \end{cases}$$

The empirical and simulated probability distributions are shown in Figure B-23.

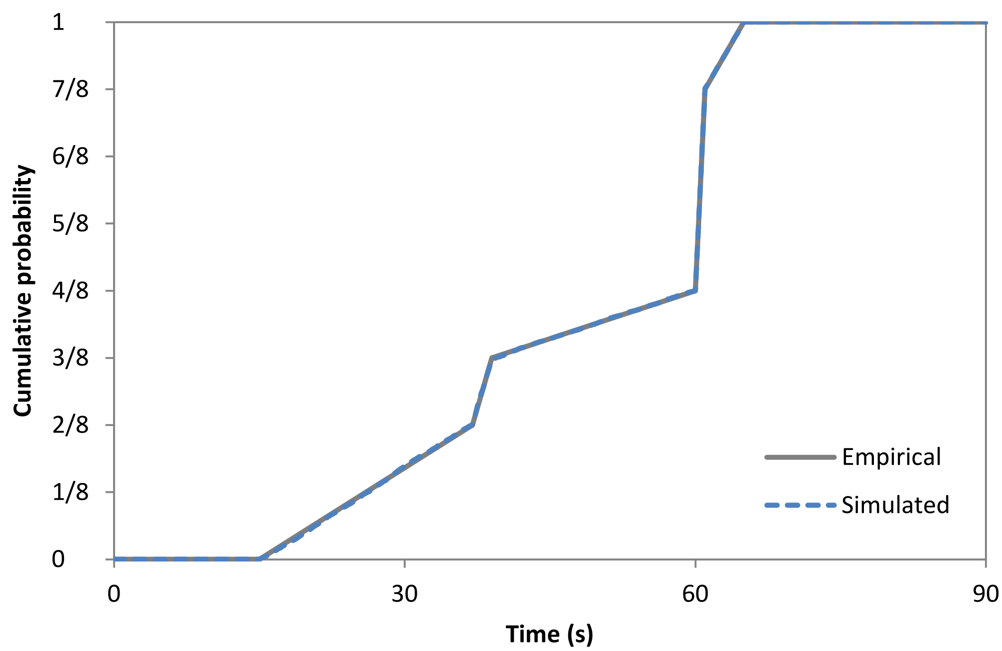


Figure B-23: Empirical and simulated probability distribution of service time of process type 6 at Clinic A

Process Type 7 (S2.3 Create chart)

The data set observed for the service time of task 1 for process type 7 prior to ICT implementation at Clinic A is

$$S \in \{45, 75, 50, 67\}$$

The empirical distribution function specified from this data set is

$$F(s) = \begin{cases} 0 & , s < 45 \\ \dfrac{s-45}{3 \times 5} & , 45 \leq s < 50 \\ \dfrac{1}{3} + \dfrac{s-50}{3 \times 17} & , 50 \leq s < 67 \\ \dfrac{2}{3} + \dfrac{s-67}{3 \times 8} & , 67 \leq s < 75 \\ 1 & , s \geq 75 \end{cases}$$

Summary statistics for the service time of task 2 for process type 7 prior to ICT implementation at Clinic A is given in Table B-10.

Table B-10: Summary statistics for service time of task 2 for process type 7 prior to ICT implementation at Clinic A

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
18	184	187	68	69	337

The service time distribution of task 2 for process type 7 prior to ICT implementation at Clinic A is described by

$$Weibull\ (\alpha = 3.027, \beta = 206.429)$$

The empirical and simulated probability distributions for task 1 are shown in Figure B-24a. A density-histogram plot of the empirical and simulated data and the fitted Weibull distribution for task 2 is shown in Figure B-24b.

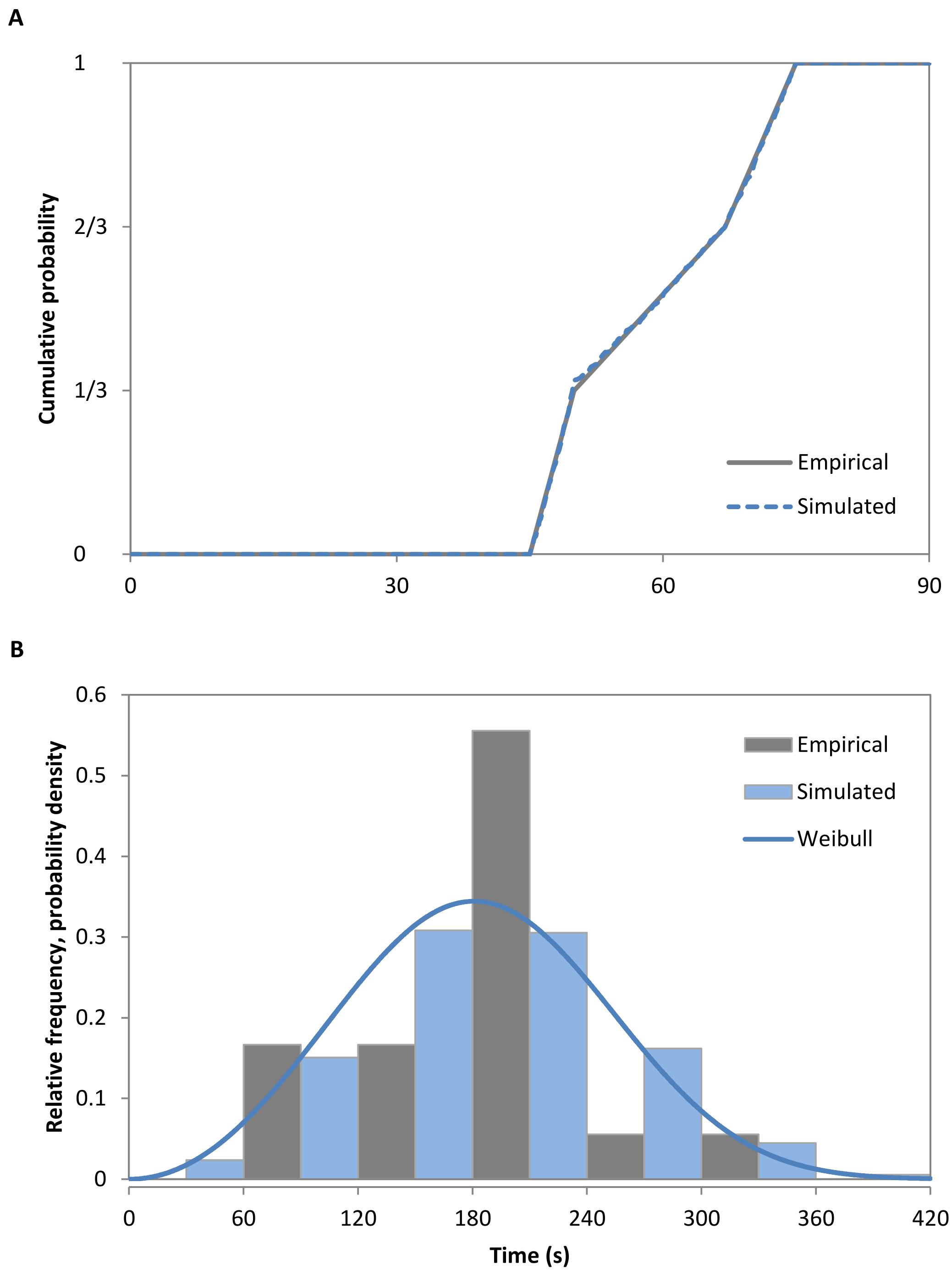


Figure B-24: (A) Empirical and simulated probability distribution of service time of task 1 and (B) Density-histogram plot of empirical and simulated data and fitted Weibull distribution for service time of task 2 of process type 7 prior to ICT implementation at Clinic A

The data set observed for the service time for process type 7 after ICT implementation at Clinic A is

$$S \in \{51, 80, 94, 76, 59, 74\}$$

The empirical distribution function specified from this data set is

$$F(s) = \begin{cases} 0 & , s < 51 \\ \dfrac{s-51}{5 \times 8} & , 51 \leq s < 59 \\ \dfrac{1}{5} + \dfrac{s-59}{5 \times 15} & , 59 \leq s < 74 \\ \dfrac{2}{5} + \dfrac{s-74}{5 \times 2} & , 74 \leq s < 76 \\ \dfrac{3}{5} + \dfrac{s-76}{5 \times 4} & , 76 \leq s < 80 \\ \dfrac{4}{5} + \dfrac{s-80}{5 \times 14} & , 80 \leq s < 94 \\ 1 & , s \geq 94 \end{cases}$$

The empirical and simulated probability distributions are shown in Figure B-25.

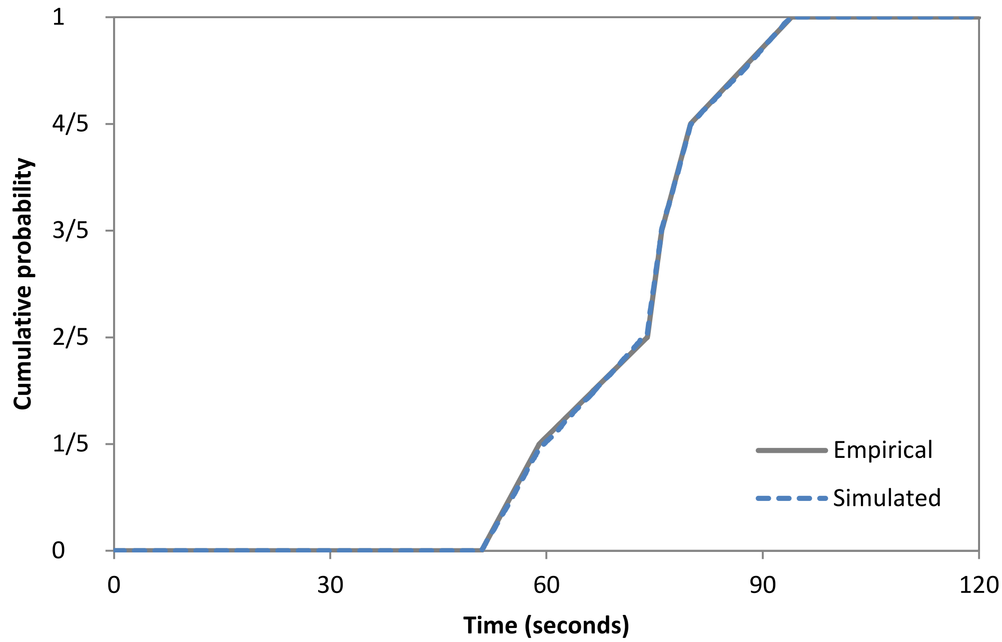


Figure B-25: Empirical and simulated probability distribution of service time of process type 7 after ICT implementation at Clinic A

Process Type 8 (S2.4 Appointment reminder)

No data was observed for the service time of process type 8 because the clinics had already implemented the ICT prior to the study. The PCCs provided the estimates shown in Table B-11 to describe service time.

Table B-11: Estimated statistics for service time of process type 8 prior to ICT implementation

Minimum (s)	Mode (s)	90^{th} percentile (s)
30	300	420

ExpertFit software is used to estimate parameters for a Weibull distribution. The service time distribution for process type 8 prior to ICT implementation is described by

$$Weibull\ (\alpha = 3.263, \beta = 302.040, \gamma = 30)$$

A density-histogram plot of the simulated data and the fitted Weibull distribution is shown in Figure B-26.

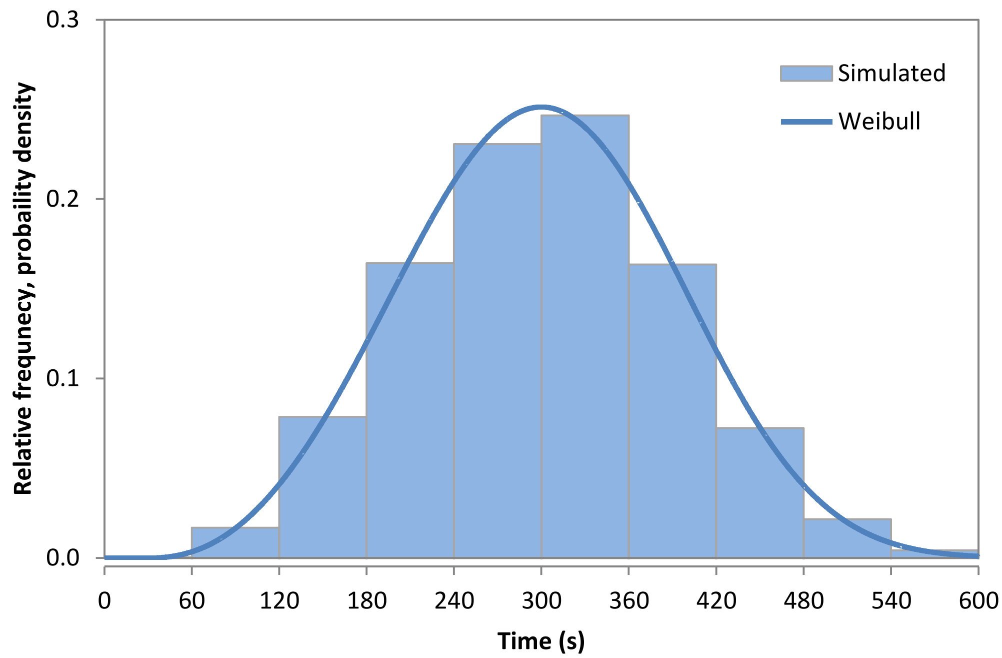


Figure B-26: Density-histogram plot of simulated data and fitted Weibull distribution for service time of process type 8 prior to ICT implementation

Process type 8 is eliminated after the implementation of ICT, so the service time for process type 8 after ICT implementation is zero.

Process Type 9 (S3.1.1 Obtain patient data)

The data set observed for the service time of task 1 for process type 9 for a new patient prior to ICT implementation at Clinic A is

$$S \in \{23, 18, 20, 24\}$$

The empirical distribution function specified from this data set is

$$F(s) = \begin{cases} 0 & , s < 18 \\ \dfrac{s-18}{3 \times 2} & , 18 \leq s < 20 \\ \dfrac{1}{3} + \dfrac{s-20}{3 \times 3} & , 20 \leq s < 23 \\ \dfrac{2}{3} + \dfrac{s-23}{3 \times 1} & , 23 \leq s < 24 \\ 1 & , s \geq 24 \end{cases}$$

Summary statistics for the service time of task 2 for process type 9 prior to ICT implementation at Clinic A is given in Table B-12.

Table B-12: Summary statistics for service time of task 2 for process type 9 prior to ICT implementation at Clinic A

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
12	101	96	31	66	165

The service time distribution of task 2 for process type 9 for a new patient prior to ICT implementation at Clinic A is described by

$$log\text{-}logistic\ (\alpha = 6.688, \beta = 94.357)$$

The data set observed for the service time of task 3 for process type 9 prior to ICT implementation at Clinic A is

$$S \in \{20, 20, 7, 13\}$$

The empirical distribution function specified from this data set is

$$F(s) = \begin{cases} 0 & , s < 7 \\ \dfrac{s-7}{3 \times 6} & , 7 \leq s < 13 \\ \dfrac{1}{3} + \dfrac{2(s-13)}{3 \times 7} & , 13 \leq s < 20 \\ 1 & , s \geq 20 \end{cases}$$

The empirical and simulated probability distributions for task 1 are shown in Figure B-27a. A density-histogram plot of the empirical and simulated data and the fitted Weibull distribution for task 2 is shown in Figure B-27b. The empirical and simulated probability distributions for task 3 are shown in Figure B-27c.

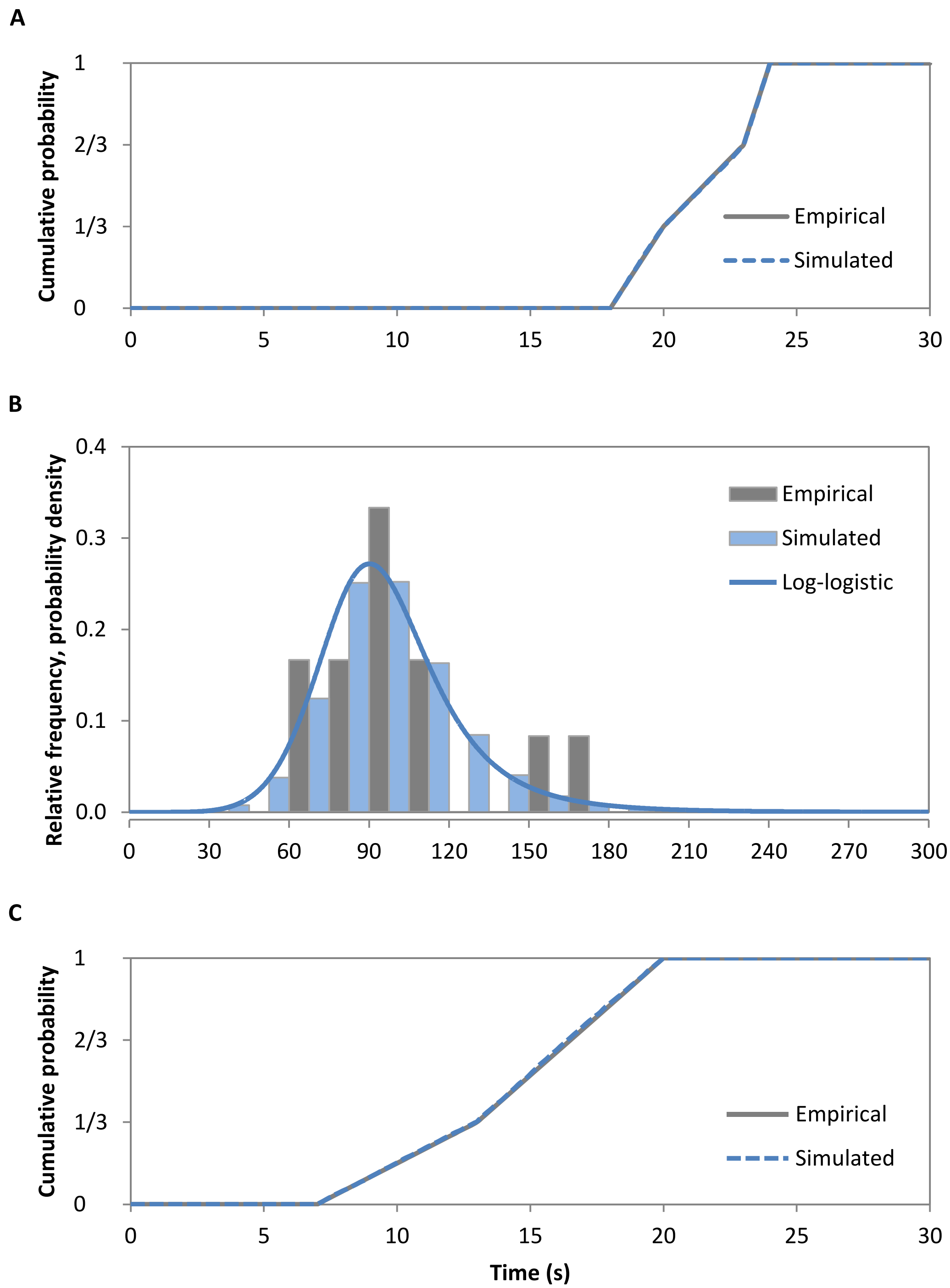


Figure B-27: (A) Empirical and simulated probability distribution of service time of task 1, (B) Density-histogram plot of empirical and simulated data and fitted log-logistic distribution for service time of task 2, and (C) Empirical and simulated probability distribution of service time of task 3 of process type 9 prior to ICT implementation at Clinic A

Summary statistics for the service time of process type 9 for a new patient after ICT implementation at Clinic A is given in Table B-13.

Table B-13: Summary statistics for service time of process type 9 after ICT implementation at Clinic A

Task	Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
9.1	18	39	34	12	25	65
9.2	15	56	50	25	26	128
9.3	18	42	42	19	5	74

The service time distribution for process type 9 after ICT implementation at Clinic A is described by

$$\begin{gathered} gamma\ (\alpha = 0.897, \beta = 15.820, \gamma = 24.974) \\ + \textit{log-logistic}\ (\alpha = 4.706, \beta = 15.820) \\ + Weibull\ (\alpha = 2.465, \beta = 47.247) \end{gathered}$$

Density-histograms plots of the empirical and simulated data and the fitted gamma distribution is shown in Figure B-28a, the fitted log-logistic distribution is shown in Figure B-28b, and the fitted Weibull distribution is shown in Figure B-28c.

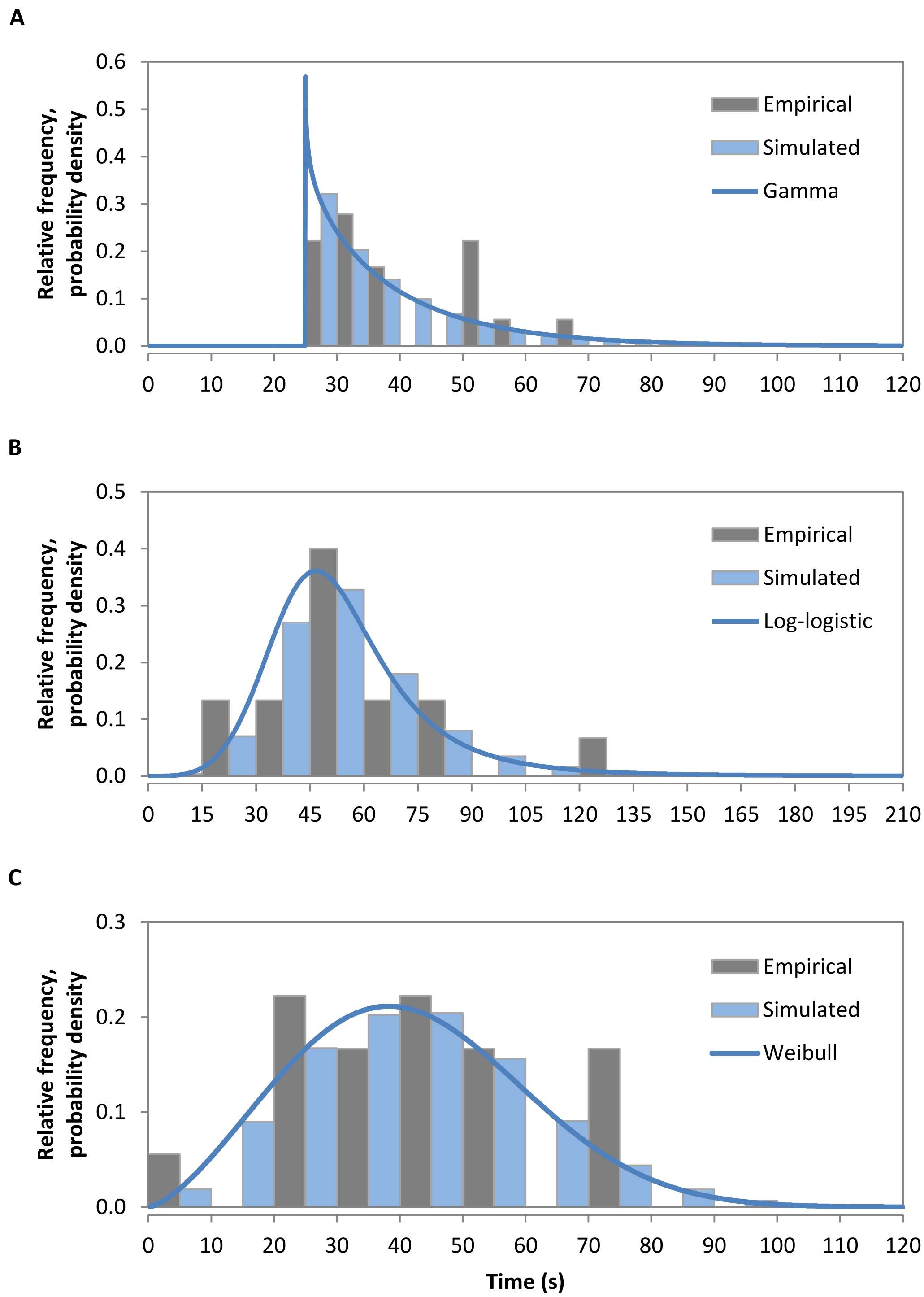


Figure B-28: Density-histogram plots of empirical and simulated data and (A) fitted gamma distribution for service time of task 1, (B) fitted log-logistic distribution for service time of task 2, and (C) fitted Weibull distribution for service time of task 3 of process type 9 after ICT implementation at Clinic A

Summary statistics for the service time for process type 9 for a returning patient at Clinic A is given in Table B-14.

Table B-14: Summary statistics for service time for process type 9 at Clinic A

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
12	18	15	10	7	36

The service time distribution for process type 9 at Clinic A is described by

$$S \sim gamma\,(\alpha = 0.744, \beta = 14.953, \gamma = 6.963)$$

A density-histogram plot of the empirical and simulated data and the fitted gamma distribution is shown in Figure B-29.

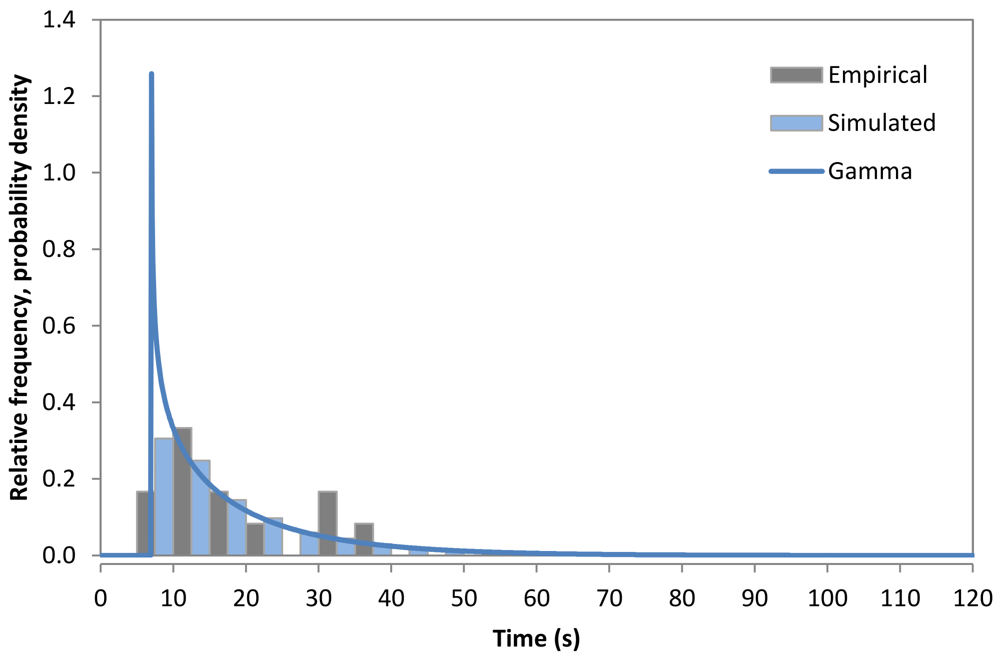


Figure B-29: Density-histogram plot of empirical and simulated data and fitted gamma distribution for service time for process type 9 at Clinic A

It is assumed that a scheduled appointment has an equal probability of serving a new patient and a follow up.

Process Type 10 (S3.2.2 Notify clinician)

Summary statistics for the service time for process type 10 at Clinic A is given in Table B-15.

Table B-15: Summary statistics for service time for process type 10 at Clinic A

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
10	21	19	16	5	57

The service time distribution for process type 10 at Clinic A is described by

$$S \sim gamma\ (\alpha = 2.011, \beta = 10.593)$$

A density-histogram plot of the empirical and simulated data and the fitted gamma distribution is shown in Figure B-30.

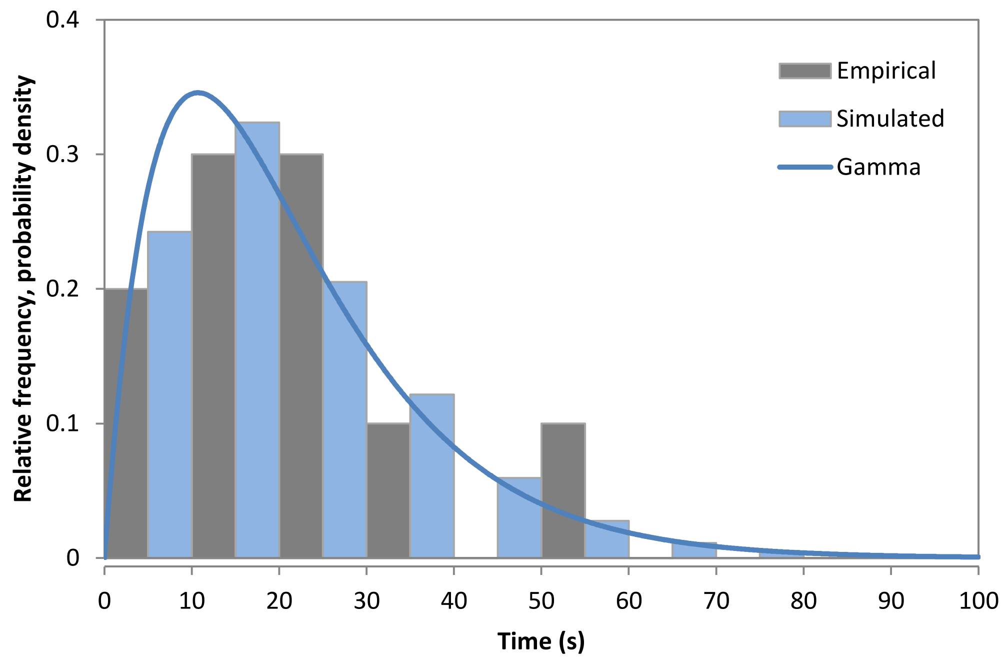


Figure B-30: Density-histogram plot of empirical and simulated data and fitted gamma distribution for service time for process type 10 at Clinic A

Process Type 11 (S3.3.1 Report to referring physician)

The PCC is not involved with process type 11 at Clinic A so the service time for process type 11 at Clinic A is zero.

Process Type 12 (S3.3.2 Close chart)

No data was observed for the service time of process type 12 at Clinic A. It is assumed that the service time distribution for process type 12 at Clinic A follows the same distribution as Clinic B. The service time for process type 12 at Clinic B will be described below.

Process Type 13 (Other interruptions)

Summary statistics for the service time for process type 13 at Clinic A is given in Table B-16.

Table B-16: Summary statistics for service time for process type 13 at Clinic A

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
115	91	60	87	7	523

The service time distribution for process type 10 at Clinic A is described by

$$S \sim lognormal\ (\alpha = 0.873, \beta = 62.818)$$

A density-histogram plot of the empirical and simulated data and the fitted lognormal distribution is shown in Figure B-31.

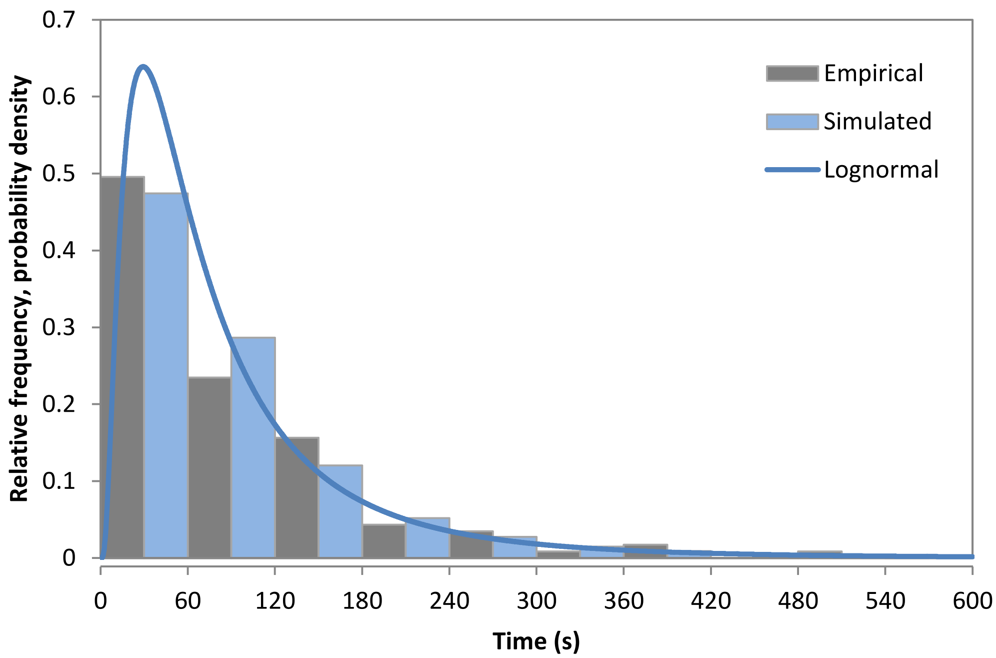


Figure B-31: Density-histogram plot of empirical and simulated data and fitted lognormal distribution for service time for process type 13 at Clinic A

Clinic B

Process Type 1 (S1.1 Create record and S1.2 Develop care plan)

The data set observed for the service time of process type 1 at Clinic B is

$$S \in \{111, 137\}$$

The empirical distribution function specified from this data set is

$$F(s) = \begin{cases} 0 & , s < 111 \\ \dfrac{s - 111}{1 \times 26} & , 111 \leq s < 137 \\ 1 & , s \geq 137 \end{cases}$$

The empirical and simulated probability distributions are shown in Figure B-32.

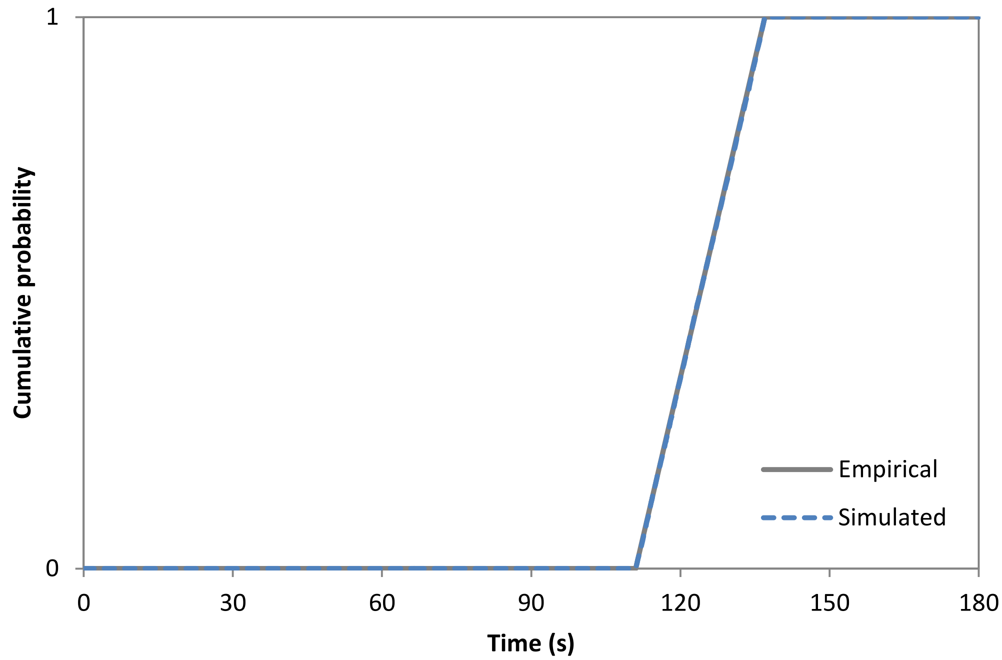


Figure B-32: Empirical and simulated probability distribution of service time of process type 1 at Clinic B

Process Type 2 (S1.3 Schedule appointment – First attempt)

The empirical distribution of outcomes observed over 104 attempts to contact patients at Clinic B is shown in Figure B-33.

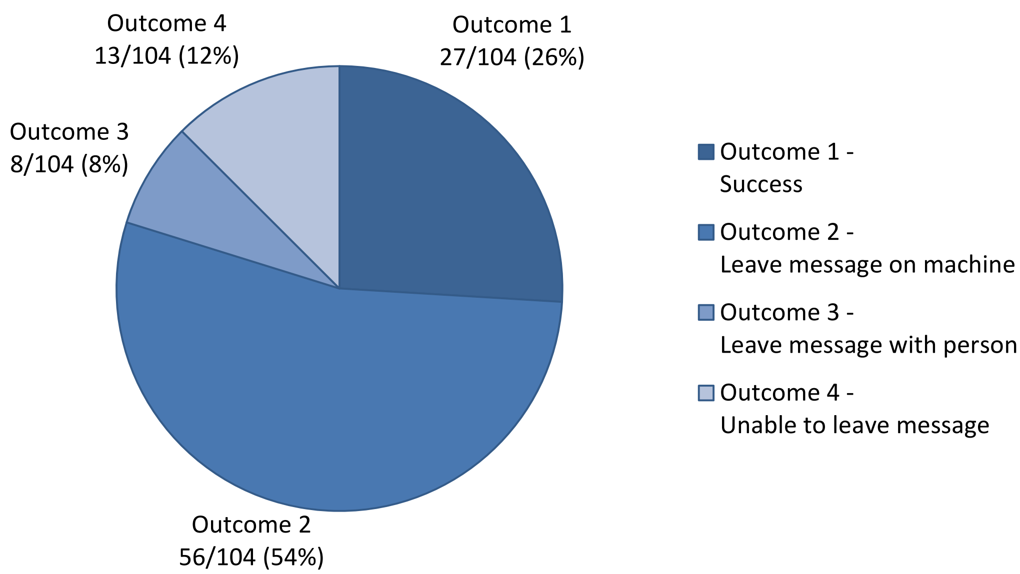


Figure B-33: Distribution of outcomes for process type 2 at Clinic B

Outcome 1

Summary statistics for the service time of outcome 1 for process type 2 at Clinic B is given in Table B-17.

Table B-17: Summary statistics for service time of outcome 1 for process type 2 at Clinic B

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
27	185	170	38	129	262

The service time distribution of outcome 1 for process type 2 at Clinic B is described by

$$lognormal\ (\alpha = 0.198, \beta = 181.235)$$

A density-histogram plot of the empirical and simulated data and the fitted lognormal distribution is shown in Figure B-34.

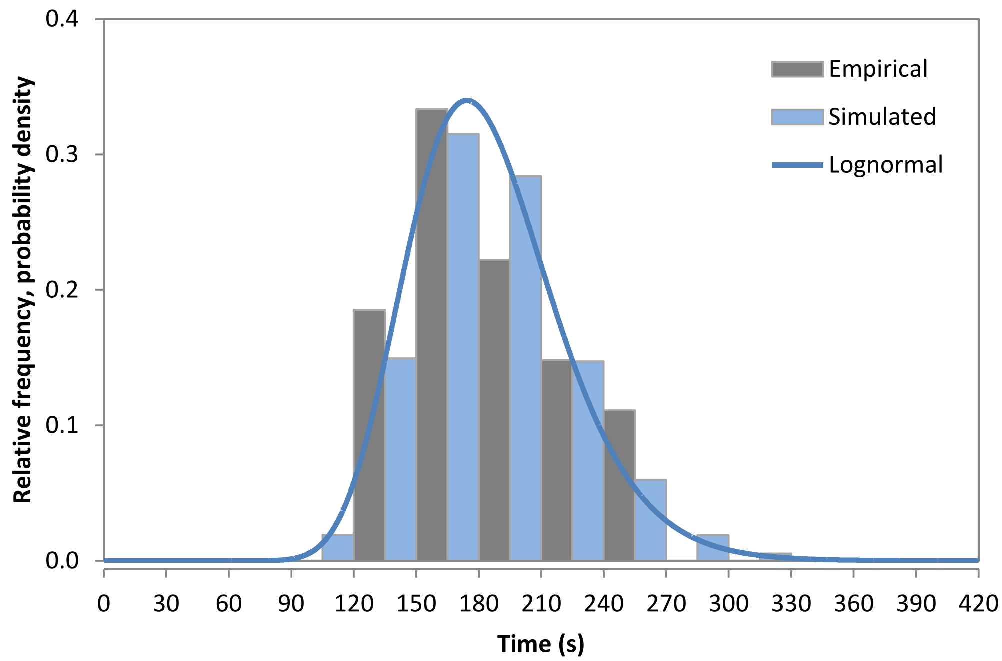


Figure B-34: Density-histogram plot of empirical and simulated data and fitted lognormal distribution for service time of outcome 1 for process type 2 at Clinic B

Outcome 2

Summary statistics for the service time of outcome 2 for process type 2 at Clinic B is given in Table B-18.

Table B-18: Summary statistics for service time of outcome 2 for process type 2 at Clinic B

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
56	69	69	15	36	128

The service time distribution of outcome 2 for process type 2 at Clinic B is described by

$$log\text{-}logistic\ (\alpha = 8.835, \beta = 67.669)$$

A density-histogram plot of the empirical and simulated data and the fitted log-logistic distribution is shown in Figure B-35.

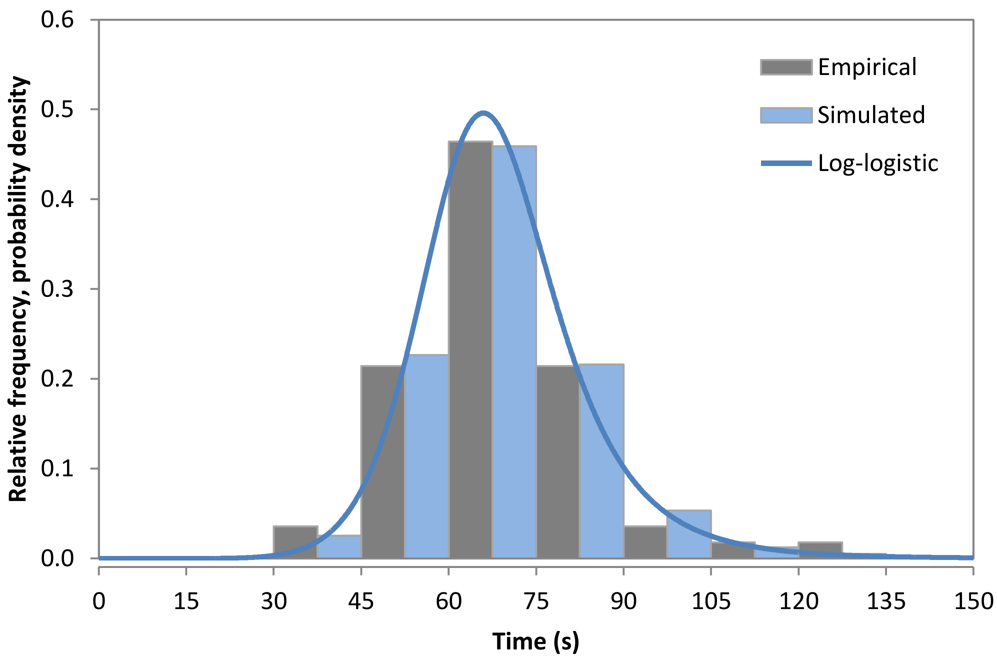


Figure B-35: Density-histogram plot of empirical and simulated data and fitted log-logistic distribution for service time of outcome 2 for process type 2 at Clinic B

Outcome 3

The data set observed for the service time of outcome 3 for process type 2 at Clinic B is

$$S \in \{129, 76, 47, 66, 58, 60, 46, 63\}$$

The empirical distribution function specified from this data set is

$$F(s) = \begin{cases} 0 & , s < 46 \\ \dfrac{s-46}{7 \times 1} & , 46 \leq s < 47 \\ \dfrac{1}{7} + \dfrac{s-47}{7 \times 11} & , 47 \leq s < 58 \\ \dfrac{2}{7} + \dfrac{s-58}{7 \times 2} & , 58 \leq s < 60 \\ \dfrac{3}{7} + \dfrac{s-60}{7 \times 3} & , 60 \leq s < 63 \\ \dfrac{4}{7} + \dfrac{s-63}{7 \times 3} & , 63 \leq s < 66 \\ \dfrac{5}{7} + \dfrac{s-66}{7 \times 10} & , 66 \leq s < 76 \\ \dfrac{6}{7} + \dfrac{s-76}{7 \times 53} & , 76 \leq s < 129 \\ 1 & , s \geq 129 \end{cases}$$

The empirical and simulated probability distributions are shown in Figure B-36.

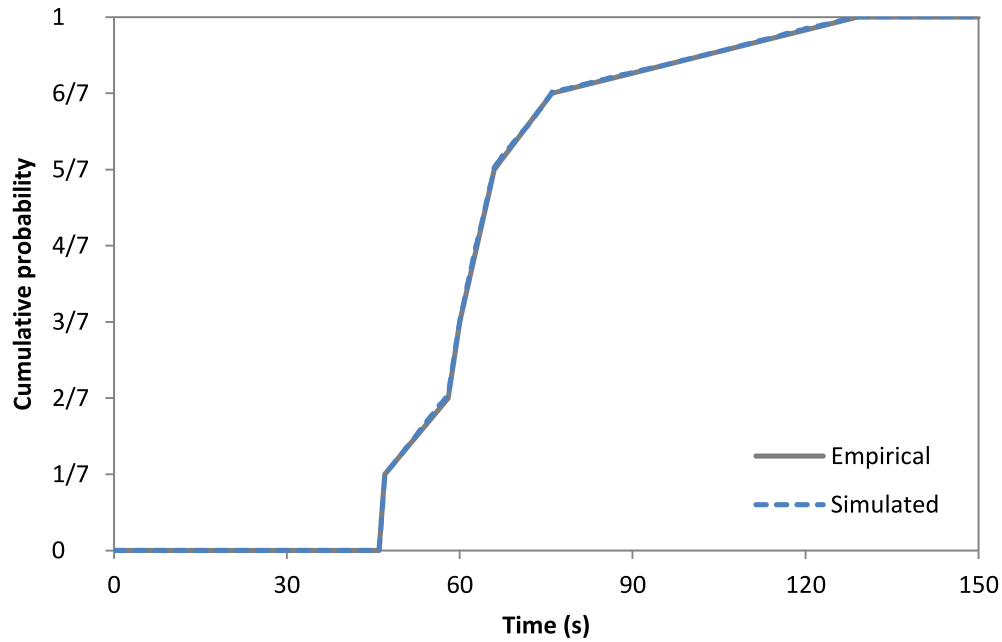


Figure B-36: Empirical and simulated probability distribution of service time of outcome 3 for process type 2 at Clinic B

Outcome 4

Summary statistics for the service time of outcome 4 for process type 2 at Clinic B is given in Table B-19.

Table B-19: Summary statistics for service time of outcome 4 for process type 2 at Clinic B

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
13	72	69	33	23	126

The service time distribution of outcome 4 for process type 2 at Clinic B is described by

$$Weibull\ (\alpha = 2.417, \beta = 80.850)$$

A density-histogram plot of the empirical and simulated data and the fitted Weibull distribution is shown in Figure B-37.

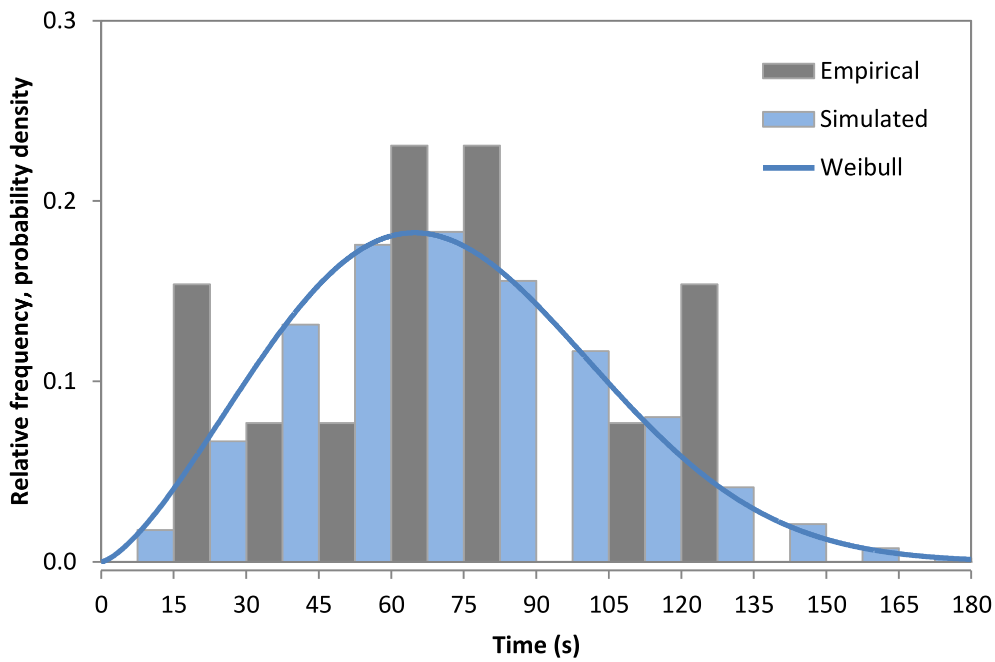


Figure B-37: Density-histogram plot of empirical and simulated data to fitted Weibull distribution for service time of outcome 4 for process type 2 at Clinic B

Process Type 3 (S1.3 Schedule appointment – Patient call back)

Summary statistics for the service time for process type 3 at Clinic B is given in Table B-20.

Table B-20: Summary statistics for service time for process type 3 at Clinic B

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
13	163	126	107	77	480

The service time distribution for process type 10 at Clinic A is described by

$$S \sim log\text{-}logistic\ (\alpha = 4.502, \beta = 133.630)$$

A density-histogram plot of the empirical and simulated data and the fitted log-logistic distribution is shown in Figure B-38.

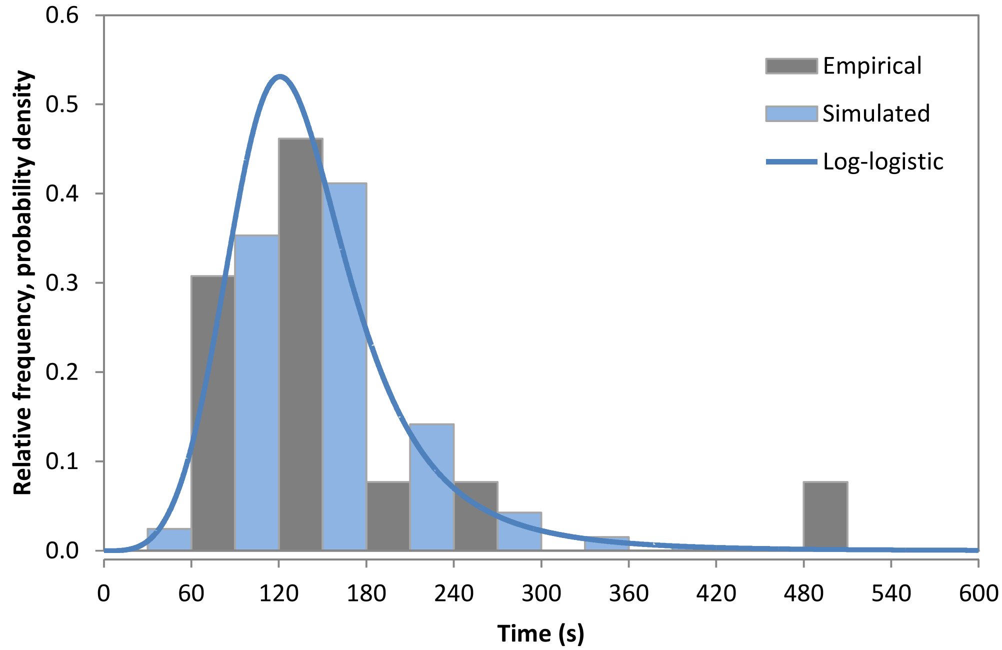


Figure B-38: Density-histogram plot of empirical and simulated data and fitted log-logistic distribution for service time for process type 3 at Clinic B

Process Type 4 (S1.3 Schedule appointment – Subsequent attempt)

The service time for process type 4 follows the same distributions as process type 2.

Process Type 5 (S2.1 Patient mailout)

Clinic B does not send out patient mailouts so the service time for process type 5 at Clinic B is zero.

Process Type 6 (S2.2 Notify referring physician)

Summary statistics for the service time for process type 6 at Clinic B is given in Table B-21.

Table B-21: Summary statistics for service time for process type 6 at Clinic B

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
16	34	23	28	13	125

The service time distribution for process type 6 at Clinic B is described by

$$S \sim Weibull\ (\alpha = 0.792, \beta = 18.186, \gamma = 12.963)$$

A density-histogram plot of the empirical and simulated data and the fitted Weibull distribution is shown in Figure B-39.

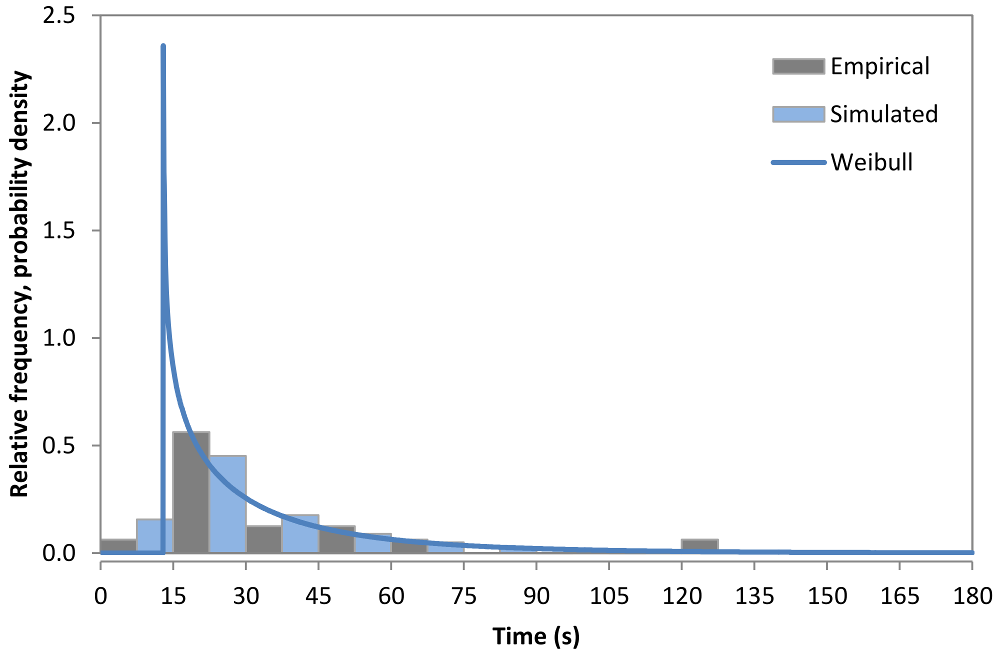


Figure B-39: Density-histogram plot of empirical and simulated data and fitted Weibull distribution for service time for process type 6 at Clinic B

Process Type 7 (S2.3 Create chart)

Summary statistics for the service time of process type 7 at Clinic B is given in Table B-22.

Table B-22: Summary statistics for service time of process type 7 at Clinic B

Task	Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
1.1	14	17	15	9	5	32
1.2	21	124	88	109	45	545

The service time distribution for process type 1 at Clinic A is described by

$$S \sim gamma\ (\alpha = 5.706, \beta = 2.892)$$
$$+\ log\text{-}logistic\ (\alpha = 3.492, \beta = 94.980)$$

Density-histograms plots of the empirical and simulated data and the fitted gamma distribution is shown in Figure B-40a and the fitted log-logistic distribution is shown in Figure B-40b.

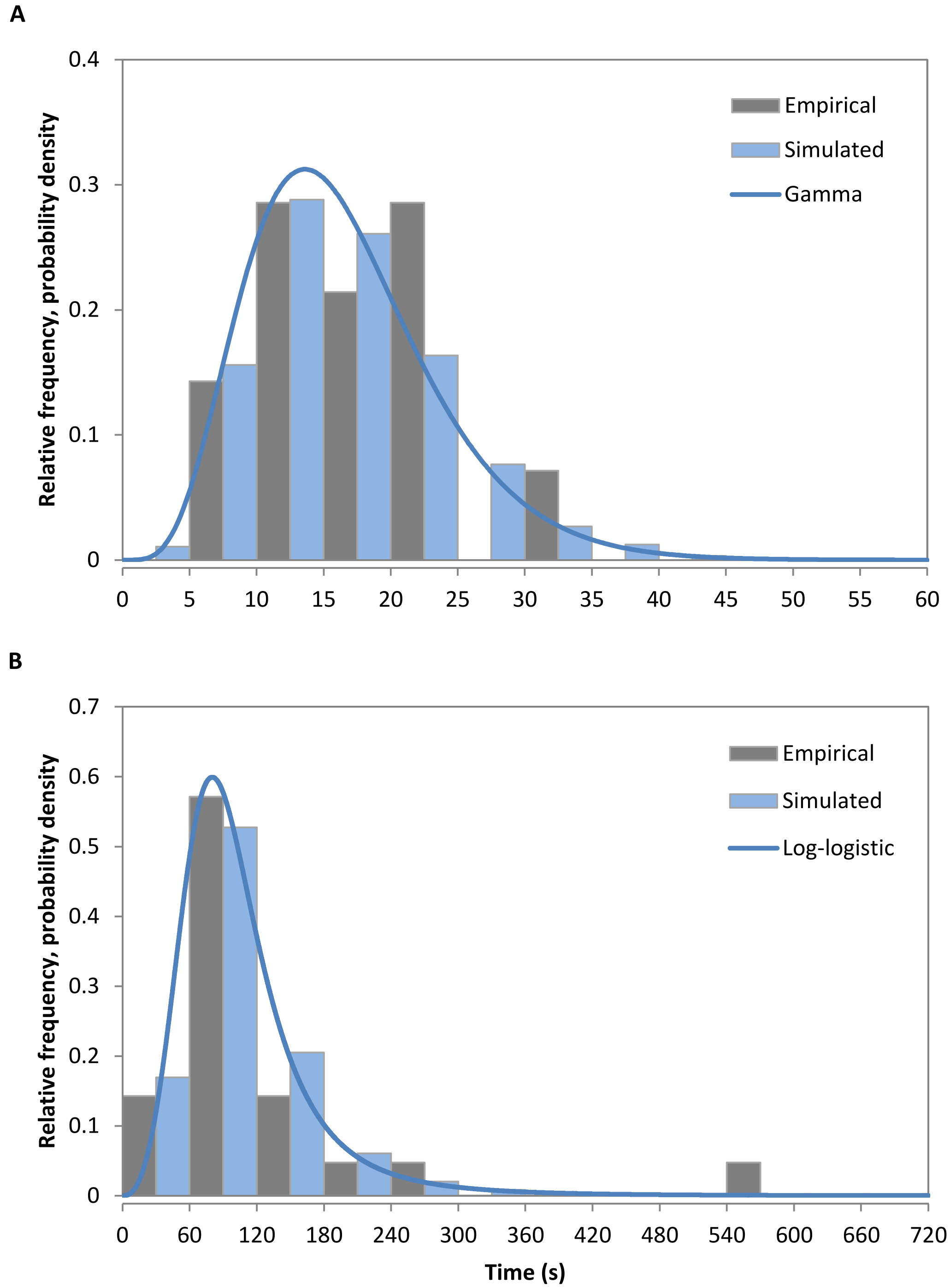


Figure B-40: Density-histogram plot of empirical and simulated data and fitted (A) gamma and (B) log-logistic distributions for service time of process type 7 at Clinic B

Process Type 8 (S2.4 Appointment reminder)

No data was observed for the service time of process type 8 because the clinics had already implemented the ICT prior to the study. The service time for process type 8 at Clinic B is estimated and follows the same distribution as Clinic A.

Process Type 9 (S3.1.1 Obtain patient data)

Summary statistics for the service time for process type 9 at Clinic B is given in Table B-23.

Table B-23: Summary statistics for service time for process type 9 at Clinic B

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
16	39	32	21	16	98

The service time distribution for process type 9 at Clinic B is described by

$$S \sim Weibull\ (\alpha = 1.072, \beta = 23.486, \gamma = 15.882)$$

A density-histogram plot of the empirical and simulated data and the fitted Weibull distribution is shown in Figure B-41.

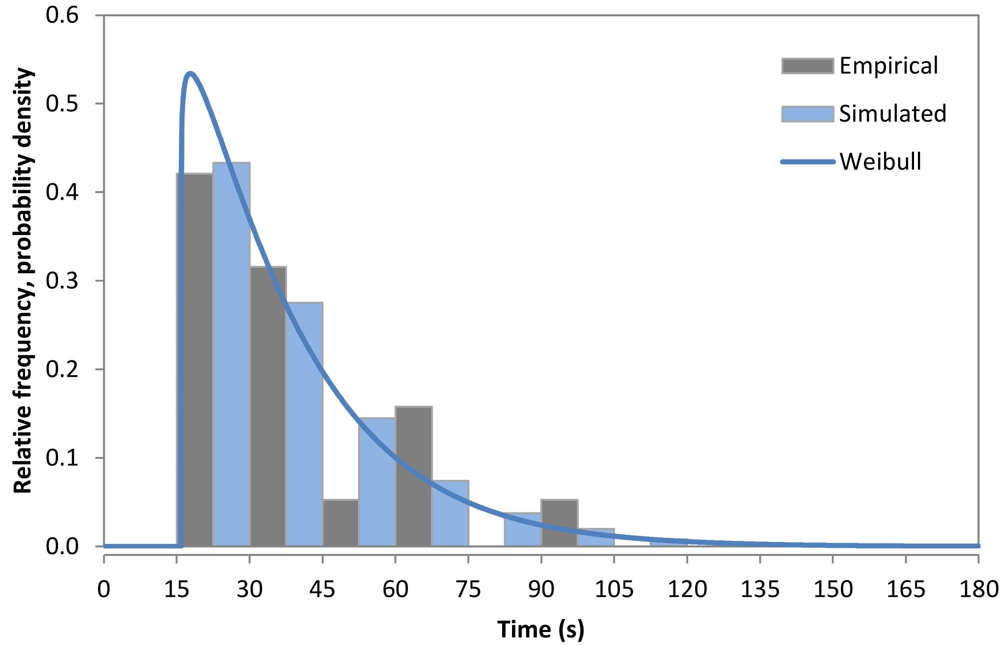


Figure B-41: Density-histogram plot of empirical and simulated data and fitted Weibull distribution for service time for process type 9 at Clinic B

Process Type 10 (S3.2.2 Notify clinician)

Summary statistics for the service time for process type 10 at Clinic B is given in Table B-24.

Table B-24: Summary statistics for service time for process type 10 at Clinic B

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
13	38	33	29	13	130

The service time distribution for process type 10 at Clinic B is described by

$$S \sim log\text{-}logistic\ (\alpha = 3.486, \beta = 31.353)$$

A density-histogram plot of the empirical and simulated data and the fitted log-logistic distribution is shown in Figure B-42.

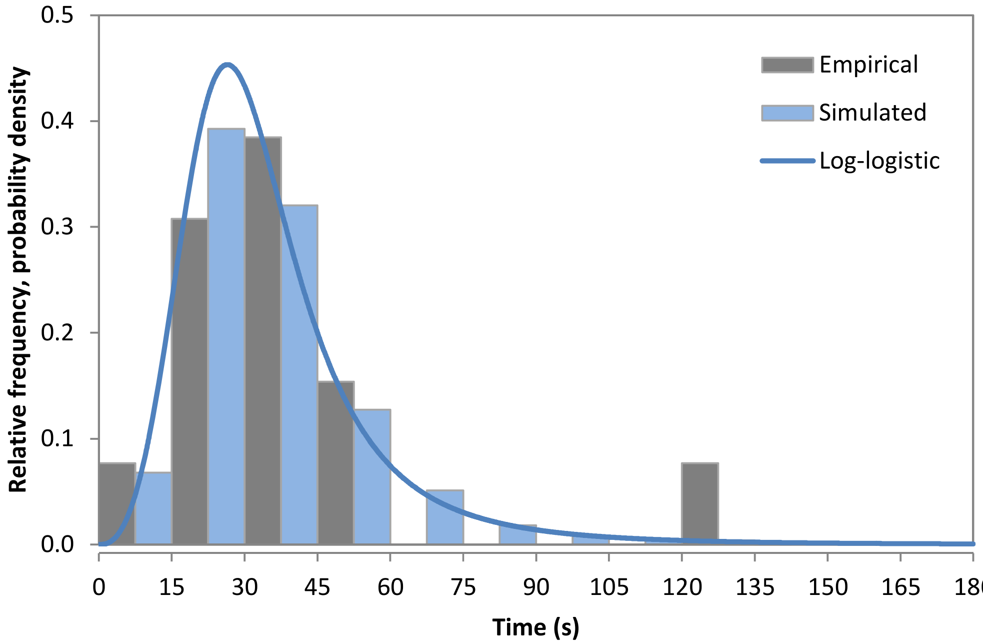


Figure B-42: Density-histogram plot of empirical and simulated data and fitted log-logistic distribution for service time for process type 10 at Clinic B

Process Type 11 (S3.3.1 Report to referring physician)

Summary statistics for the service time for process type 11 at Clinic B is given in Table B-25.

Table B-25: Summary statistics for service time for process type 11 at Clinic B

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
13	166	137	110	49	433

The service time distribution for process type 10 at Clinic B is described by

$$S \sim lognormal\ (\alpha = 0.616, \beta = 137.753)$$

A density-histogram plot of the empirical and simulated data and the fitted lognormal distribution is shown in Figure B-43.

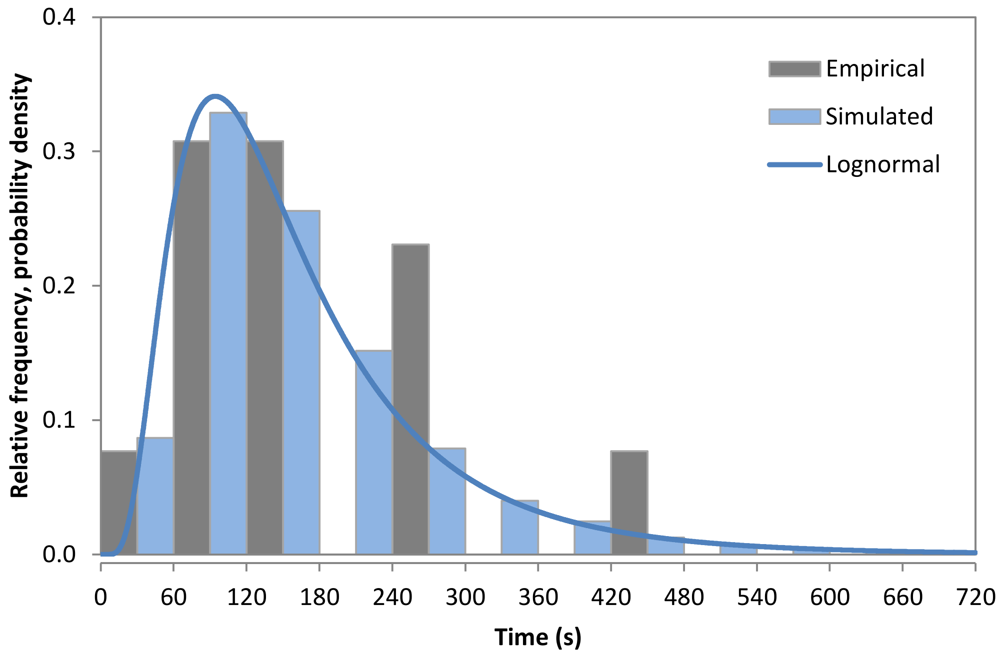


Figure B-43: Density-histogram plot of empirical and simulated data and fitted lognormal distribution for service time for process type 11 at Clinic B

Process Type 12 (S3.3.2 Close chart)

Summary statistics for the service time for process type 12 at Clinic B is given in Table B-26.

Table B-26: Summary statistics for service time for process type 12 at Clinic B

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
46	98	85	60	19	255

The service time distribution for process type 12 at Clinic B is described by

$$S \sim Weibull\ (\alpha = 1.339, \beta = 86.669, \gamma = 18.435)$$

A density-histogram plot of the empirical and simulated data and the fitted Weibull distribution is shown in Figure B-44.

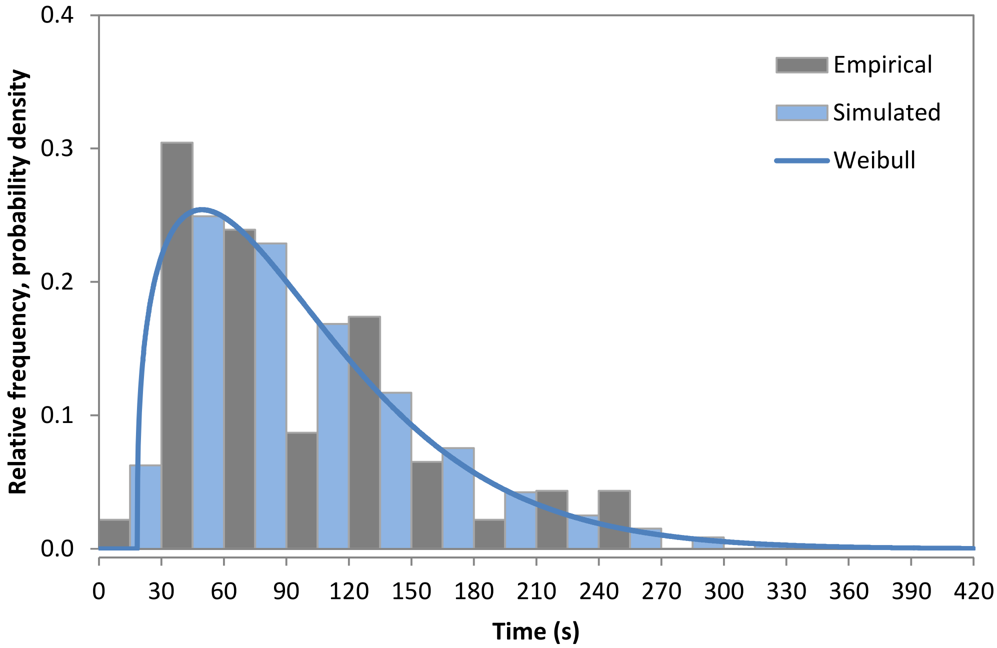


Figure B-44: Density-histogram plot of empirical and simulated data and fitted Weibull distribution for service time for process type 12 at Clinic B

Process Type 13 (Other interruptions)

Summary statistics for the service time for process type 13 at Clinic B is given in Table B-27.

Table B-27: Summary statistics for service time for process type 13 at Clinic B

Sample Size	Mean (s)	Median (s)	Standard Deviation (s)	Minimum (s)	Maximum (s)
48	71	60	48	7	190

The service time distribution for process type 10 at Clinic B is described by

$$S \sim gamma\ (\alpha = 2.093, \beta = 33.884)$$

A density-histogram plot of the empirical and simulated data and the fitted gamma distribution is shown in Figure B-45.

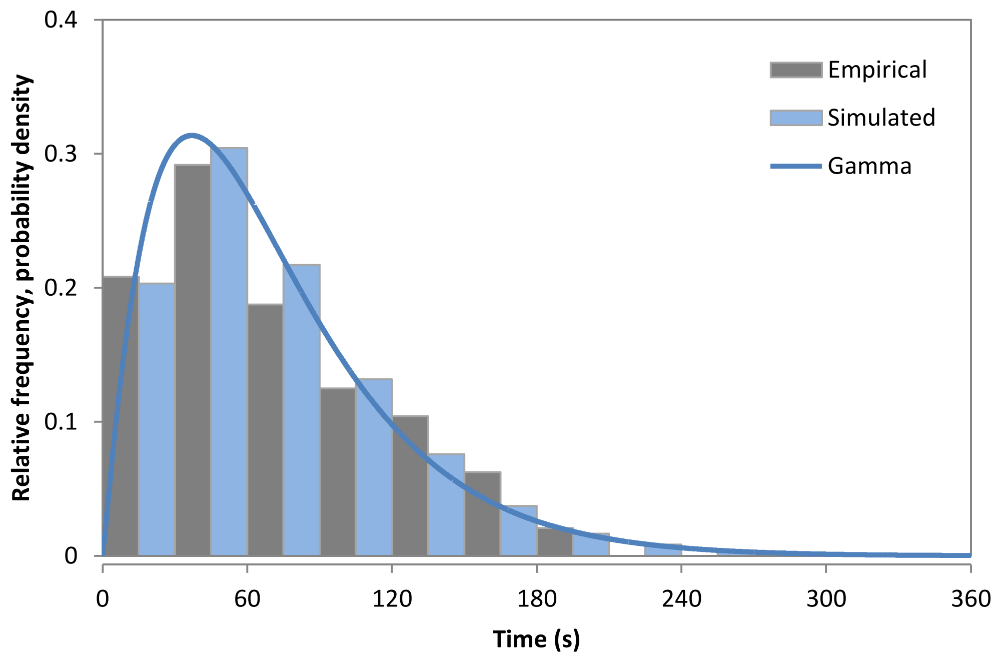


Figure B-45: Density-histogram plot of empirical and simulated data and fitted gamma distribution for service time for process type 13 at Clinic B

B.3 MATLAB Code for Patient Care in the PCN

```
function simPCC(c,n,t)
% Simulate PCC model
% simPCC(c,n,t) performs n simulation runs,
% c = 'A' for Clinic A
% c = 'B' for Clinic B
% t = 0 prior to ICT
% t = 1 after ICT
% Outputs selected summary statistics.

clinic = c;
nruns = n;
utilization = zeros(nruns,1);
ICT = t;

%-----------------------------------------------------------------
if (clinic == 'A')
    str = sprintf('Simulating Clinic A'); disp(str);
elseif (clinic == 'B')
    str = sprintf('Simulating Clinic B'); disp(str);
else
    str = sprintf('Invalid clinic'); disp(str);
end
%-----------------------------------------------------------------



%-----------------------------------------------------------------
%-----------------------------------------------------------------
% Service Times
%-----------------------------------------------------------------
%-----------------------------------------------------------------
% Process Type 1
% S1.1 & S1.2 Create record and develop care plan
% Default Priority = 900, Default Preemption = 0
%-----------------------------------------------------------------
set_param('PCCv5/Time-Based Entity Generator',...
    'GenerateEntityAtSimulationStart','off');
%-----------------------------------------------------------------
% Clinic A - Process Type 1 service times
% P1 EMR record and triage + P1a manual record
% LL (scale = 164.55412, shape = 3.91684)
% --> LL (g = 5.10324, b = 0.25531) +
% gamma (g = 9.94286, a = 1.12993, b = 16.81675)
if (clinic == 'A')
    set_param('PCCv5/Event-Based Random Number', ...
        'distribution','Log-logistic');
    set_param('PCCv5/Event-Based Random Number', ...
        'thresholdLogl','5.10324');
    set_param('PCCv5/Event-Based Random Number', ...
        'scaleLogl','0.25531');

    set_param('PCCv5/Event-Based Random Number21', ...
        'distribution','Gamma');
```

```
    set_param('PCCv5/Event-Based Random Number21', ...
        'thresholdGam','9.94286');
    set_param('PCCv5/Event-Based Random Number21', ...
        'shapeGam','1.12993');
    set_param('PCCv5/Event-Based Random Number21', ...
        'scaleGam','16.81675');

% Clinic B - Process Type 1 service times
% P1 EMR record + P1a manual record == empirical + zero
elseif (clinic == 'B')
    set_param('PCCv5/Event-Based Random Number', ...
        'distribution','Arbitrary continuous');
    set_param('PCCv5/Event-Based Random Number', ...
        'valueVecCont','[111 137]');
    set_param('PCCv5/Event-Based Random Number', ...
        'cdfVecCont','[0 1]');

    set_param('PCCv5/Event-Based Random Number21', ...
        'distribution','Arbitrary discrete');
    set_param('PCCv5/Event-Based Random Number21', ...
        'valueVecDisc','[0]');
    set_param('PCCv5/Event-Based Random Number21', ...
        'probVecDisc','[1]');
end
%-----------------------------------------------------------------
%-----------------------------------------------------------------
% Process Type 2
% S1.3 Schedule Appointment (first attempt)
% Default Priority = 600, Default Preemption = 0
%-----------------------------------------------------------------
set_param('PCCv5/Event-Based Entity Generator',...
    'GenerateEntityAtSimulationStart','on');
%-----------------------------------------------------------------
% Clinic A
% Probability of outcome 1 (appt scheduled) = 0.356,
% probability of outcome 2 (lmom) = 0.400,
% probability of outcome 3 (lmwp) = 0.155,
% probability of outcome 4 (utlm) = 0.089.
if (clinic == 'A')
    set_param('PCCv5/Event-Based Random Number1', ...
        'distribution','Arbitrary discrete');
    set_param('PCCv5/Event-Based Random Number1', ...
        'valueVecDisc','[1 2 3 4]');
    set_param('PCCv5/Event-Based Random Number1', ...
        'probVecDisc','[16/45 18/45 7/45 4/45]');

% Clinic B
% Probability of outcome 1 (appt scheduled) = 0.260,
% probability of outcome 2 (lmom) = 0.539,
% probability of outcome 3 (lmwp) = 0.076,
% probability of outcome 4 (utlm) = 0.125.
elseif (clinic == 'B')
    set_param('PCCv5/Event-Based Random Number1', ...
        'distribution','Arbitrary discrete');
    set_param('PCCv5/Event-Based Random Number1', ...
```

```
        'valueVecDisc','[1 2 3 4]');
    set_param('PCCv5/Event-Based Random Number1', ...
        'probVecDisc','[27/104 56/104 8/104 13/104]');
end
%-----------------------------------------------------------------
% Clinic A - Process Type 2 service times
if (clinic == 'A')
    % For outcome 1 (appt scheduled)
    % LL (scale = 202.47831, shape = 5.43949)
    % --> LL (g = 5.31063, b = 0.18384)
    set_param('PCCv5/Event-Based Random Number2', ...
        'distribution','Log-logistic');
    set_param('PCCv5/Event-Based Random Number2', ...
        'thresholdLogl','5.31063');
    set_param('PCCv5/Event-Based Random Number2', ...
        'scaleLogl','0.18384');
    % For outcome 2 (lmom)
    % LL (scale = 60.07902, shape = 11.57989)
    % --> LL (g = 4.09566, b = 0.08636)
    set_param('PCCv5/Event-Based Random Number3', ...
        'distribution','Log-logistic');
    set_param('PCCv5/Event-Based Random Number3', ...
        'thresholdLogl','4.09566');
    set_param('PCCv5/Event-Based Random Number3', ...
        'scaleLogl','0.08636');
    % For outcome 3 (lmwp)
    % Arbitrary continuous
    set_param('PCCv5/Event-Based Random Number16', ...
        'distribution','Arbitrary continuous');
    set_param('PCCv5/Event-Based Random Number16', ...
        'valueVecCont','[39 64 66 70 84 97 108]');
    set_param('PCCv5/Event-Based Random Number16', ...
        'cdfVecCont','[0 1/6 2/6 3/6 4/6 5/6 1]');
    % For outcome 4 (utlm)
    % Arbitrary continuous
    set_param('PCCv5/Event-Based Random Number22', ...
        'distribution','Arbitrary continuous');
    set_param('PCCv5/Event-Based Random Number22', ...
        'valueVecCont','[70 74 83 94]');
    set_param('PCCv5/Event-Based Random Number22', ...
        'cdfVecCont','[0 1/3 2/3 1]');

% Clinic B - Process Type 2 service times
elseif (clinic == 'B')
    % For outcome 1 (appt scheduled)
    % Lognormal (scale = 181.23471, shape = 0.19822)
    % --> Lognormal (m = 5.19979, s = 0.19822)
    set_param('PCCv5/Event-Based Random Number2', ...
        'distribution','Lognormal');
    set_param('PCCv5/Event-Based Random Number2', ...
        'thresholdLogn','0');
    set_param('PCCv5/Event-Based Random Number2', ...
        'scaleLogn','5.19979');
    set_param('PCCv5/Event-Based Random Number2', ...
        'shapeLogn','0.19822');
```

```
    % For outcome 2 (lmom)
    % LL (scale = 67.66942, shape = 8.83504)
    % --> LL (g = 4.21463, b = 0.11319)
    set_param('PCCv5/Event-Based Random Number3', ...
        'distribution','Log-logistic');
    set_param('PCCv5/Event-Based Random Number3', ...
        'thresholdLogl','4.21463');
    set_param('PCCv5/Event-Based Random Number3', ...
        'scaleLogl','0.11319');
    % For outcome 3 (lmwp)
    % Arbitrary continuous
    set_param('PCCv5/Event-Based Random Number16', ...
        'distribution','Arbitrary continuous');
    set_param('PCCv5/Event-Based Random Number16', ...
        'valueVecCont','[46 47 58 60 63 66 76 129]');
    set_param('PCCv5/Event-Based Random Number16', ...
        'cdfVecCont','[0 1/7 2/7 3/7 4/7 5/7 6/7 1]');
    % For outcome 4 (utlm)
    % Weibull (a = 2.41698, b = 80.84969, g = 0)
    set_param('PCCv5/Event-Based Random Number22', ...
        'distribution','Weibull');
    set_param('PCCv5/Event-Based Random Number22', ...
        'thresholdWbl','0');
    set_param('PCCv5/Event-Based Random Number22', ...
        'scaleWbl','80.84969');
    set_param('PCCv5/Event-Based Random Number22', ...
        'shapeWbl','2.41698');
end
%----------------------------------------------------------------
%----------------------------------------------------------------
% ProcessType 3
% S1.3 Schedule Appointment (patient returning call)
% Default Priority = 1100, Default Preemption = 0
%----------------------------------------------------------------
set_param('PCCv5/Time-Based Entity Generator1',...
    'GenerateEntityAtSimulationStart','off');
%----------------------------------------------------------------
% Probability of success (1 - appt scheduled) = 0.95,
% probability of failure (2 - decline) = 0.05.
set_param('PCCv5/Event-Based Random Number8','distribution',...
    'Arbitrary discrete');
set_param('PCCv5/Event-Based Random Number8','valueVecDisc', ...
    '[1 2]');
set_param('PCCv5/Event-Based Random Number8','probVecDisc', ...
    '[0.95 0.05]');
%----------------------------------------------------------------
% Clinic A - Process Type 3 service times
if (clinic == 'A')
    % Arbitrary continuous
    set_param('PCCv5/Event-Based Random Number4', ...
        'distribution','Arbitrary continuous');
    set_param('PCCv5/Event-Based Random Number4', ...
        'valueVecCont','[57 117 145 161 167 205 333 346 677]');
    set_param('PCCv5/Event-Based Random Number4', ...
        'cdfVecCont','[0 1/8 2/8 3/8 4/8 5/8 6/8 7/8 1]');
```

```
% Clinic B - Process Type 3 service times
elseif (clinic == 'B')
    % LL (scale = 133.62991, shape = 4.50152)
    % --> LL (g = 4.89507, b = 0.22215)
    set_param('PCCv5/Event-Based Random Number4', ...
        'distribution','Log-logistic');
    set_param('PCCv5/Event-Based Random Number4', ...
        'thresholdLogl','4.89507');
    set_param('PCCv5/Event-Based Random Number4', ...
        'scaleLogl','0.22215');
end
%----------------------------------------------------------------
%----------------------------------------------------------------
% Process Type 4
% S1.3 Schedule Appointment (second attempt)
% Default Priority = 500, Default Preemption = 0
%----------------------------------------------------------------
set_param('PCCv5/Time-Based Entity Generator2',...
    'GenerateEntityAtSimulationStart','off');
%----------------------------------------------------------------
% Clinic A
% Probability of outcome 1 (appt scheduled) = 0.36,
% probability of outcome 2 (lmom) = 0.40,
% probability of outcome 3 (lmwp) = 0.15,
% probability of outcome 4 (utlm) = 0.09.
if (clinic == 'A')
    set_param('PCCv5/Event-Based Random Number5', ...
        'distribution','Arbitrary discrete');
    set_param('PCCv5/Event-Based Random Number5', ...
        'valueVecDisc','[1 2 3 4]');
    set_param('PCCv5/Event-Based Random Number5', ...
        'probVecDisc','[16/45 18/45 7/45 4/45]');

% Clinic B
% Probability of outcome 1 (appt scheduled) = 0.26,
% probability of outcome 2 (lmom) = 0.54,
% probability of outcome 3 (lmwp) = 0.08,
% probability of outcome 4 (utlm) = 0.13.
elseif (clinic == 'B')
    set_param('PCCv5/Event-Based Random Number5', ...
        'distribution','Arbitrary discrete');
    set_param('PCCv5/Event-Based Random Number5', ...
        'valueVecDisc','[1 2 3 4]');
    set_param('PCCv5/Event-Based Random Number5', ...
        'probVecDisc','[27/104 56/104 8/104 13/104]');
end
%----------------------------------------------------------------
% Clinic A - Process Type 4 service times
% (same as Process Type 2)
if (clinic == 'A')
    % For outcome 1 (appt scheduled)
    % LL (scale = 202.47831, shape = 5.43949)
    % --> LL (g = 5.31063, b = 0.18384)
    set_param('PCCv5/Event-Based Random Number7', ...
```

```
        'distribution','Log-logistic');
    set_param('PCCv5/Event-Based Random Number7', ...
        'thresholdLogl','5.31063');
    set_param('PCCv5/Event-Based Random Number7', ...
        'scaleLogl','0.18384');
    % For outcome 2 (lmom)
    % LL (scale = 60.07902, shape = 11.57989)
    % --> LL (g = 4.09566, b = 0.08636)
    set_param('PCCv5/Event-Based Random Number27', ...
        'distribution','Log-logistic');
    set_param('PCCv5/Event-Based Random Number27', ...
        'thresholdLogl','4.09566');
    set_param('PCCv5/Event-Based Random Number27', ...
        'scaleLogl','0.08636');
    % For outcome 3 (lmwp)
    % Arbitrary continuous
    set_param('PCCv5/Event-Based Random Number6', ...
        'distribution','Arbitrary continuous');
    set_param('PCCv5/Event-Based Random Number6', ...
        'valueVecCont','[39 64 66 70 84 97 108]');
    set_param('PCCv5/Event-Based Random Number6', ...
        'cdfVecCont','[0 1/6 2/6 3/6 4/6 5/6 1]');
    % For outcome 4 (utlm)
    % Arbitrary continuous
    set_param('PCCv5/Event-Based Random Number26', ...
        'distribution','Arbitrary continuous');
    set_param('PCCv5/Event-Based Random Number26', ...
        'valueVecCont','[70 74 83 94]');
    set_param('PCCv5/Event-Based Random Number26', ...
        'cdfVecCont','[0 1/3 2/3 1]');

% Clinic B - Process Type 4 service times
% (same as Process Type 2)
elseif (clinic == 'B')
    % For outcome 1 (appt scheduled)
    % Lognormal (scale = 181.23471, shape = 0.19822)
    % --> Lognormal (m = 5.19979, s = 0.19822)
    set_param('PCCv5/Event-Based Random Number7', ...
        'distribution','Lognormal');
    set_param('PCCv5/Event-Based Random Number7', ...
        'thresholdLogn','0');
    set_param('PCCv5/Event-Based Random Number7', ...
        'scaleLogn','5.19979');
    set_param('PCCv5/Event-Based Random Number7', ...
        'shapeLogn','0.19822');
    % For outcome 2 (lmom)
    % LL (scale = 67.66942, shape = 8.83504)
    % --> LL (g = 4.21463, b = 0.11319)
    set_param('PCCv5/Event-Based Random Number27', ...
        'distribution','Log-logistic');
    set_param('PCCv5/Event-Based Random Number27', ...
        'thresholdLogl','4.21463');
    set_param('PCCv5/Event-Based Random Number27', ...
        'scaleLogl','0.11319');
    % For outcome 3 (lmwp)
```

```
    % Arbitrary continuous
    set_param('PCCv5/Event-Based Random Number6', ...
        'distribution','Arbitrary continuous');
    set_param('PCCv5/Event-Based Random Number6', ...
        'valueVecCont','[46 47 58 60 63 66 76 129]');
    set_param('PCCv5/Event-Based Random Number6', ...
        'cdfVecCont','[0 1/7 2/7 3/7 4/7 5/7 6/7 1]');
    % For outcome 4 (utlm)
    % Weibull (a = 2.41698, b = 80.84969, g = 0)
    set_param('PCCv5/Event-Based Random Number26', ...
        'distribution','Weibull');
    set_param('PCCv5/Event-Based Random Number26', ...
        'thresholdWbl','0');
    set_param('PCCv5/Event-Based Random Number26', ...
        'scaleWbl','80.84969');
    set_param('PCCv5/Event-Based Random Number26', ...
        'shapeWbl','2.41698');
end
%----------------------------------------------------------------
%----------------------------------------------------------------
% Process Type 5
% S2.1 Patient Mailout
% Default Priority = 800, Default Preemption = 0
%----------------------------------------------------------------
set_param('PCCv5/Event-Based Entity Generator1',...
    'GenerateEntityAtSimulationStart','on');
%----------------------------------------------------------------
% Clinic A - Process Type 5 service times
if (clinic == 'A')
    if (ICT == 0)
        % mail
        % Arbitrary continuous
        set_param('PCCv5/Event-Based Random Number9', ...
            'distribution','Arbitrary continuous');
        set_param('PCCv5/Event-Based Random Number9', ...
            'valueVecCont','[30 50 63]');
        set_param('PCCv5/Event-Based Random Number9', ...
            'cdfVecCont','[0 1/2 1]');

    elseif (ICT == 1)
        % email
        % Arbitrary continuous
        set_param('PCCv5/Event-Based Random Number9', ...
            'distribution','Arbitrary continuous');
        set_param('PCCv5/Event-Based Random Number9', ...
            'valueVecCont','[48 64 78 110 157 170]');
        set_param('PCCv5/Event-Based Random Number9', ...
            'cdfVecCont','[0 1/5 2/5 3/5 4/5 1]');
    end

% Clinic B - Process Type 5 service times
elseif (clinic == 'B')
    set_param('PCCv5/Event-Based Random Number9', ...
        'distribution','Arbitrary discrete');
    set_param('PCCv5/Event-Based Random Number9', ...
```

```
        'valueVecDisc','[0]');
    set_param('PCCv5/Event-Based Random Number9', ...
        'probVecDisc','[1]');
end
%-----------------------------------------------------------------
%-----------------------------------------------------------------
% Process Type 6
% S2.2 Notify Referring Physician
% Default Priority = 700, Default Preemption = 0
%-----------------------------------------------------------------
% Clinic A - Process Type 6 service times
if (clinic == 'A')
    % Arbitrary continuous
    set_param('PCCv5/Event-Based Random Number10', ...
        'distribution','Arbitrary continuous');
    set_param('PCCv5/Event-Based Random Number10', ...
        'valueVecCont','[15 26 37 39 60 61 65]');
    set_param('PCCv5/Event-Based Random Number10', ...
        'cdfVecCont','[0 1/8 2/8 3/8 4/8 7/8  1]');

% Clinic B - Process Type 6 service times
elseif (clinic == 'B')
    % Weibull (a = 0.79156, b = 18.18630, g = 12.96296)
    set_param('PCCv5/Event-Based Random Number10', ...
        'distribution','Weibull');
    set_param('PCCv5/Event-Based Random Number10', ...
        'thresholdWbl','12.96296');
    set_param('PCCv5/Event-Based Random Number10', ...
        'scaleWbl','18.18630');
    set_param('PCCv5/Event-Based Random Number10', ...
        'shapeWbl','0.79156');
end
%-----------------------------------------------------------------
%-----------------------------------------------------------------
% Process Type 7
% S2.3 Prepare Chart
% Default Priority = 400, Default Preemption = 0
%-----------------------------------------------------------------
% Clinic A - Process Type 7 service times
if (clinic == 'A')
    if (ICT == 0)
        % Create green chart
        % Arbitrary continuous
        set_param('PCCv5/Event-Based Random Number11', ...
            'distribution','Arbitrary continuous');
        set_param('PCCv5/Event-Based Random Number11', ...
            'valueVecCont','[45 50 67 75]');
        set_param('PCCv5/Event-Based Random Number11', ...
            'cdfVecCont','[0 1/3 2/3 1]');
        % Create beige chart
        % Weibull (a = 3.02716, b = 206.42937, g = 0)
        set_param('PCCv5/Event-Based Random Number23', ...
            'distribution','Weibull');
        set_param('PCCv5/Event-Based Random Number23', ...
            'thresholdWbl','0');
```

```
        set_param('PCCv5/Event-Based Random Number23', ...
            'scaleWbl','206.42937');
        set_param('PCCv5/Event-Based Random Number23', ...
            'shapeWbl','3.02716');

    elseif (ICT == 1)
        % Create chart note
        % Arbitrary continuous
        set_param('PCCv5/Event-Based Random Number11', ...
            'distribution','Arbitrary continuous');
        set_param('PCCv5/Event-Based Random Number11', ...
            'valueVecCont','[51 59 74 76 80 94]');
        set_param('PCCv5/Event-Based Random Number11', ...
            'cdfVecCont','[0 1/5 2/5 3/5 4/5 1]');
        % N/A
        set_param('PCCv5/Event-Based Random Number23', ...
            'distribution','Arbitrary discrete');
        set_param('PCCv5/Event-Based Random Number23', ...
            'valueVecDisc','[0]');
        set_param('PCCv5/Event-Based Random Number23', ...
            'probVecDisc','[1]');
    end

% Clinic B - Process Type 7 service times
elseif (clinic == 'B')
    % Prepare labels
    % gamma (g = 0, a = 5.70620, b = 2.89159)
    set_param('PCCv5/Event-Based Random Number11', ...
        'distribution','Gamma');
    set_param('PCCv5/Event-Based Random Number11', ...
        'thresholdGam','0');
    set_param('PCCv5/Event-Based Random Number11', ...
        'shapeGam','5.70620');
    set_param('PCCv5/Event-Based Random Number11', ...
        'scaleGam','2.89159');
    % Prepare charts
    % LL (scale = 94.98035, shape = 3.49239)
    % --> LL (g = 4.55367, b = 0.28634)
    set_param('PCCv5/Event-Based Random Number23', ...
        'distribution','Log-logistic');
    set_param('PCCv5/Event-Based Random Number23', ...
        'thresholdLogl','4.55367');
    set_param('PCCv5/Event-Based Random Number23', ...
        'scaleLogl','0.28634');
end
%----------------------------------------------------------------
%----------------------------------------------------------------
% Process Type 8
% S2.4 Appointment Reminders
% Default Priority = 300, Default Preemption = 0
%----------------------------------------------------------------
set_param('PCCv5/Time-Based Entity Generator3',...
    'GenerateEntityAtSimulationStart','off');
%----------------------------------------------------------------
% Process Type 8 service times
```

```
if (ICT == 0)
    % Weibull (a = 3.26320, b = 302.04003, g = 30)
    % NO DATA
    set_param('PCCv5/Event-Based Random Number12', ...
        'distribution','Weibull');
    set_param('PCCv5/Event-Based Random Number12', ...
        'thresholdWbl','30');
    set_param('PCCv5/Event-Based Random Number12', ...
        'scaleWbl','302.04003');
    set_param('PCCv5/Event-Based Random Number12', ...
        'shapeWbl','3.26320');
elseif (ICT == 1)
    % N/A
    set_param('PCCv5/Event-Based Random Number12', ...
        'distribution','Arbitrary discrete');
    set_param('PCCv5/Event-Based Random Number12', ...
        'valueVecDisc','[0]');
    set_param('PCCv5/Event-Based Random Number12', ...
        'probVecDisc','[1]');
end
%-----------------------------------------------------------------
%-----------------------------------------------------------------
% Process Type 9
% S3.1.1 Obtain patient data
% Default Priority = 1200, Default Preemption = 0
%-----------------------------------------------------------------
set_param('PCCv5/Time-Based Entity Generator4',...
    'GenerateEntityAtSimulationStart','off');
%-----------------------------------------------------------------
% Clinic A - Process Type 9 service times
if (clinic == 'A')
    % Probability of (1-intake) = 0.5,
    % probability of (2-follow up) = 0.5.
    set_param('PCCv5/Event-Based Random Number13', ...
        'distribution','Arbitrary discrete');
    set_param('PCCv5/Event-Based Random Number13', ...
        'valueVecDisc','[1 2]');
    set_param('PCCv5/Event-Based Random Number13', ...
        'probVecDisc','[0.5 0.5]');
    % For (1-intake)
    if (ICT == 0)
        % Prepare clipboard
        % Arbitrary continuous
        set_param('PCCv5/Event-Based Random Number24', ...
            'distribution','Arbitrary continuous');
        set_param('PCCv5/Event-Based Random Number24', ...
            'valueVecCont','[18 20 23 24]');
        set_param('PCCv5/Event-Based Random Number24', ...
            'cdfVecCont','[0 1/3 2/3 1]');
        % Prepare forms
        % LL (scale = 94.35656, shape = 6.68817)
        % --> LL (g = 4.54708, b = 0.14952)
        set_param('PCCv5/Event-Based Random Number25', ...
            'distribution','Log-logistic');
        set_param('PCCv5/Event-Based Random Number25', ...
```

```
            'thresholdLogl','4.54708');
        set_param('PCCv5/Event-Based Random Number25', ...
            'scaleLogl','0.14952');
        % Instruct patient
        % Arbitrary continuous
        set_param('PCCv5/Event-Based Random Number17', ...
            'distribution','Arbitrary continuous');
        set_param('PCCv5/Event-Based Random Number17', ...
            'valueVecCont','[7 13 20]');
        set_param('PCCv5/Event-Based Random Number17', ...
            'cdfVecCont','[0 1/3 1]');
    elseif (ICT == 1)
        % Prepare iPad
        % gamma (g = 24.97368, a = 0.89714, b = 15.82023)
        set_param('PCCv5/Event-Based Random Number24', ...
            'distribution','Gamma');
        set_param('PCCv5/Event-Based Random Number24', ...
            'thresholdGam','24.97368');
        set_param('PCCv5/Event-Based Random Number24', ...
            'shapeGam','0.89714');
        set_param('PCCv5/Event-Based Random Number24', ...
            'scaleGam','15.82023');
        % Instruct patient
        % LL (scale = 51.179, shape = 4.70632)
        % --> LL (g = 3.93533, b = 0.21248)
        set_param('PCCv5/Event-Based Random Number25', ...
            'distribution','Log-logistic');
        set_param('PCCv5/Event-Based Random Number25', ...
            'thresholdLogl','3.93533');
        set_param('PCCv5/Event-Based Random Number25', ...
            'scaleLogl','0.21248');
        % Upload to HQ
        % Weibull (a = 2.4648, b = 47.24713, g = 0)
        set_param('PCCv5/Event-Based Random Number17', ...
            'distribution','Weibull');
        set_param('PCCv5/Event-Based Random Number17', ...
            'thresholdWbl','0');
        set_param('PCCv5/Event-Based Random Number17', ...
            'scaleWbl','47.24713');
        set_param('PCCv5/Event-Based Random Number17', ...
            'shapeWbl','2.4648');
    end
    % For (2-follow up)
    % gamma (g = 6.96296, a = 0.74368, b = 14.95317)
    set_param('PCCv5/Event-Based Random Number18', ...
        'distribution','Gamma');
    set_param('PCCv5/Event-Based Random Number18', ...
        'thresholdGam','6.96296');
    set_param('PCCv5/Event-Based Random Number18', ...
        'shapeGam','0.74368');
    set_param('PCCv5/Event-Based Random Number18', ...
        'scaleGam','14.95317');

% Clinic B - Process Type 9 service times
elseif (clinic == 'B')
```

```
    % Probability of (1-intake) = 0.5,
    % probability of (2-follow up) = 0.5.
    set_param('PCCv5/Event-Based Random Number13', ...
        'distribution','Arbitrary discrete');
    set_param('PCCv5/Event-Based Random Number13', ...
        'valueVecDisc','[1 2]');
    set_param('PCCv5/Event-Based Random Number13', ...
        'probVecDisc','[0.5 0.5]');
    % For (1-intake)
    % Obtain patient data
    % Weibull (a = 1.0718, b = 23.48610, g = 15.88158)
    set_param('PCCv5/Event-Based Random Number24', ...
        'distribution','Weibull');
    set_param('PCCv5/Event-Based Random Number24', ...
        'thresholdWbl','15.88158');
    set_param('PCCv5/Event-Based Random Number24', ...
        'scaleWbl','23.48610');
    set_param('PCCv5/Event-Based Random Number24', ...
        'shapeWbl','1.0718');
    % N/A
    set_param('PCCv5/Event-Based Random Number25', ...
        'distribution','Arbitrary discrete');
    set_param('PCCv5/Event-Based Random Number25', ...
        'valueVecDisc','[0]');
    set_param('PCCv5/Event-Based Random Number25', ...
        'probVecDisc','[1]');
    % N/A
    set_param('PCCv5/Event-Based Random Number17', ...
        'distribution','Arbitrary discrete');
    set_param('PCCv5/Event-Based Random Number17', ...
        'valueVecDisc','[0]');
    set_param('PCCv5/Event-Based Random Number17', ...
        'probVecDisc','[1]');
    % For (2-follow up)
    % Obtain patient data
    % Weibull (a = 1.0718, b = 23.48610, g = 15.88158)
    set_param('PCCv5/Event-Based Random Number18', ...
        'distribution','Weibull');
    set_param('PCCv5/Event-Based Random Number18', ...
        'thresholdWbl','15.88158');
    set_param('PCCv5/Event-Based Random Number18', ...
        'scaleWbl','23.48610');
    set_param('PCCv5/Event-Based Random Number18', ...
        'shapeWbl','1.0718');
end
%----------------------------------------------------------------
%----------------------------------------------------------------
% Process Type 10
% S3.1.2 Notify clinician
% Default Priority = 1300, Default Preemption = 0
%----------------------------------------------------------------
set_param('PCCv5/Event-Based Entity Generator2',...
    'GenerateEntityAtSimulationStart','on');
%----------------------------------------------------------------
% Clinic A - Process Type 10 service times
```

```
if (clinic == 'A')
    % Telephone:
    % gamma (g = 0, a = 2.01069, b = 10.59337)
    set_param('PCCv5/Event-Based Random Number19', ...
        'distribution','Gamma');
    set_param('PCCv5/Event-Based Random Number19', ...
        'thresholdGam','0');
    set_param('PCCv5/Event-Based Random Number19', ...
        'shapeGam','2.01069');
    set_param('PCCv5/Event-Based Random Number19', ...
        'scaleGam','10.59337');

% Clinic B - Process Type 10 service times
elseif (clinic == 'B')
    % LL (scale = 31.35252, shape = 3.48632)
    % --> LL (g = 3.44529, b = 0.28684)
    set_param('PCCv5/Event-Based Random Number19', ...
        'distribution','Log-logistic');
    set_param('PCCv5/Event-Based Random Number19', ...
        'thresholdLogl','3.44529');
    set_param('PCCv5/Event-Based Random Number19', ...
        'scaleLogl','0.28684');
end
%-----------------------------------------------------------------
%-----------------------------------------------------------------
% Process Type 11
% S3.3.1 Report to Referring Clinician
% Default Priority = 200, Default Preemption = 0
%-----------------------------------------------------------------
set_param('PCCv5/Time-Based Entity Generator5',...
    'GenerateEntityAtSimulationStart','off');
%-----------------------------------------------------------------
% Clinic A - Process Type 11 service times
if (clinic == 'A')
    % N/A for MCC
    set_param('PCCv5/Event-Based Random Number14', ...
        'distribution','Arbitrary discrete');
    set_param('PCCv5/Event-Based Random Number14', ...
        'valueVecDisc','[0]');
    set_param('PCCv5/Event-Based Random Number14', ...
        'probVecDisc','[1]');

% Clinic B - Process Type 11 service times
elseif (clinic == 'B')
    % Lognormal (scale = 137.75333, shape = 0.61594)
    % --> Lognormal (m = 4.92546, s = 0.61594)
    set_param('PCCv5/Event-Based Random Number14', ...
        'distribution','Lognormal');
    set_param('PCCv5/Event-Based Random Number14', ...
        'thresholdLogn','0');
    set_param('PCCv5/Event-Based Random Number14', ...
        'scaleLogn','4.92546');
    set_param('PCCv5/Event-Based Random Number14', ...
        'shapeLogn','0.61594');
end
```

```
%----------------------------------------------------------------
%----------------------------------------------------------------
% Process Type 12
% S3.3.2 Close Chart
% Default Priority = 100, Default Preemption = 0
%----------------------------------------------------------------
set_param('PCCv5/Event-Based Entity Generator3',...
    'GenerateEntityAtSimulationStart','on')
%----------------------------------------------------------------
% Clinic A - Process Type 12 service times
if (clinic == 'A')
    % Weibull (a = 1.339051, b = 86.66880, g = 18.43458)
    set_param('PCCv5/Event-Based Random Number20', ...
        'distribution', 'Weibull');
    set_param('PCCv5/Event-Based Random Number20', ...
        'thresholdWbl','18.43458');
    set_param('PCCv5/Event-Based Random Number20', ...
        'scaleWbl','86.66880');
    set_param('PCCv5/Event-Based Random Number20', ...
        'shapeWbl','1.339051');

% Clinic B - Process Type 12 service times
elseif (clinic == 'B')
    % Weibull (a = 1.339051, b = 86.66880, g = 18.43458)
    set_param('PCCv5/Event-Based Random Number20', ...
        'distribution', 'Weibull');
    set_param('PCCv5/Event-Based Random Number20', ...
        'thresholdWbl','18.43458');
    set_param('PCCv5/Event-Based Random Number20', ...
        'scaleWbl','86.66880');
    set_param('PCCv5/Event-Based Random Number20', ...
        'shapeWbl','1.339051');
end
%----------------------------------------------------------------
%----------------------------------------------------------------
% Process Type 13
% Other interruptions
% Default Priority = 1000, Default Preemption = 0
%----------------------------------------------------------------
set_param('PCCv5/Time-Based Entity Generator6',...
    'GenerateEntityAtSimulationStart','off');
%----------------------------------------------------------------
% Clinic A - Process Type 13 service times
if (clinic == 'A')
    % Lognormal (scale = 62.81757, shape = 0.87286)
    % --> Lognormal (m = 4.14023, s = 0.87286)
    set_param('PCCv5/Event-Based Random Number15', ...
        'distribution','Lognormal');
    set_param('PCCv5/Event-Based Random Number15', ...
        'thresholdLogn','0');
    set_param('PCCv5/Event-Based Random Number15', ...
        'scaleLogn','4.14023');
    set_param('PCCv5/Event-Based Random Number15', ...
        'shapeLogn','0.87286');
```

```
% Clinic B - Process Type 13
elseif (clinic == 'B')
    % gamma (g = 0, a = 2.09291, b = 33.88427)
    set_param('PCCv5/Event-Based Random Number15', ...
        'distribution','Gamma');
    set_param('PCCv5/Event-Based Random Number15', ...
        'thresholdGam','0');
    set_param('PCCv5/Event-Based Random Number15', ...
        'shapeGam','2.09291');
    set_param('PCCv5/Event-Based Random Number15', ...
        'scaleGam','33.88427');
end
%-----------------------------------------------------------------
%-----------------------------------------------------------------
% Queue Discipline
%-----------------------------------------------------------------
set_param('PCCv5/Priority Queue','Capacity','Inf');
set_param('PCCv5/Priority Queue','SortingAttributeName', ...
    'Priority');
set_param('PCCv5/Priority Queue','SortingDirection', ...
    'Descending');
%-----------------------------------------------------------------
%-----------------------------------------------------------------
% Preemption Table for 13 process types,
% Y-types (3, 9, 10 and 13) preempt X-types (1, 5, 6, 7, 11, 12)
y = [ 3 9 10 13 ];
x = [ 1 5 6 7 11 12 ];
T = zeros(14,14);
for j = 1:length(y)
    for i = 1:length(x)
        T(y(j)+1, x(i)+1) = 1;
    end
end
set_param( ...
    'PCCv5/Discrete Event Subsystem/__fcn_ss__/Direct Lookup
Table (n-D)', ...
    'Table',mat2str(T));
%-----------------------------------------------------------------
%-----------------------------------------------------------------
% Empirical distribution of appointment times (in sim clock time)
% for Process Type 9 arrival times
if (clinic == 'A')
    apptTime = [ 1800 2700 3600 4500 5400 7200 8100 9000 ...
        10800 12600 13500 18000 18900 19800 21600 22500 23400 ...
        24300 25200 26100 27000 28800 ];
    apptTimeDist = [ 7 1 42 1 21 34 1 18 12 2 1 46 6 13 24 4 ...
        15 5 9 1 7 1 ]/271;
elseif (clinic == 'B')
    apptTime = [ 1800 3600 4500 5400 7200 9000 10800 18000 ...
        19800 21600 22500 23400 24300 25200 26100 ];
    apptTimeDist = [ 18 23 1 11 7 11 5 6 44 10 1 2 1 6 1 ]/147;
end
% Calculate cumulative distribution
apptTimeCumDist = zeros(length(apptTimeDist),1);
apptTimeCumDist(1) = apptTimeDist(1);
```

```
for i = 2:length(apptTimeDist)
    apptTimeCumDist(i) = apptTimeCumDist(i-1) + apptTimeDist(i);
end
%-----------------------------------------------------------------
%-----------------------------------------------------------------

for i = 1:nruns
    %-------------------------------------------------------------
    % Entity Generation (Arrival Times)
    %-------------------------------------------------------------
    %-------------------------------------------------------------
    % Process Type 1
    % S1.1 & S1.2 Create record and develop care plan
    % Default Priority = 900, Default Preemption = 0
    %-------------------------------------------------------------
    % Clinic A - Process Type 1 arrival times
    if (clinic == 'A')
        % Generate random number of new referrals for the week
        % newRefWeek ~ negative binomial (s = 25, p = 0.50322)
        newRefWeek = sum(floor(log(rand(25,1))/log(1-0.50322)));
        % Generate random number of new referrals that arrive at
        % morning and afternoon delivery as a binomial
        % distribution with newRefWeek trials and p = 0.1
        % (10 equiprobable deliveries per week).
        newRefAM = sum(rand(newRefWeek,1) <= 0.1);
        newRefPM = sum(rand(newRefWeek,1) <= 0.1);
        % Generate random morning and afternoon delivery time
        % uniformly distributed within 30 minutes of
        % 10 am and 2 pm (in simulation clock time).
        delTimeAM = randi([5400,9000],1,1);
        delTimePM = randi([19800,23400],1,1);
        % Generate intergeneration times for new referrals.
        % If there are no new referrals that day,
        % set to infinity.
        if (newRefAM + newRefPM == 0)
            newRefInterGenTimes = inf;
        else
            newRefInterGenTimes = zeros(newRefAM + newRefPM,1);
            newRefInterGenTimes(1) = delTimeAM;
            newRefInterGenTimes(newRefAM + 1) = ...
                delTimePM - delTimeAM;
        end
    % Clinic B - Process Type 1 arrival times
    elseif (clinic == 'B')
        % Generate random number of new referrals for the week
        % newRefWeek ~ negative binomial (s = 25, p = 0.55704)
        newRefWeek = sum(floor(log(rand(25,1))/log(1-0.55704)));
        % Generate random number of new referrals for the day as
        % a binomial distribution with newRefWeek trials and
        % p = 0.2 (5 equiprobable deliveries per week).
        newRefDay = sum(rand(newRefWeek,1) <= 0.2);
        % Generate random delivery time (triage complete)
        % uniformly distributed within 10 minutes of 1:30 pm
        % (in simulation clock time).
        delTime = randi([19500,20100],1,1);
```

```
        % Generate intergeneration times for new referrals.
        % If there are no new referrals that day,
        % set to infinity.
        if (newRefDay == 0)
            newRefInterGenTimes = inf;
        else
            newRefInterGenTimes = zeros(newRefDay,1);
            newRefInterGenTimes(1) = delTime;
        end
    end
        set_param('PCCv5/Event-Based Sequence', ...
            'VectorOutputValues',mat2str(newRefInterGenTimes));
    %-------------------------------------------------------------
    %-------------------------------------------------------------
    % ProcessType 2
    % S1.3 Schedule Appointment (first attempt)
    % Default Priority = 600, Default Preemption = 0
    %-------------------------------------------------------------
    % Process Type 2 arrival triggered by success of Process
    % Type 1
    %-------------------------------------------------------------
    %-------------------------------------------------------------
    % ProcessType 3
    % S1.3 Schedule Appointment (patient returning call)
    % Default Priority = 1100, Default Preemption = 0
    %-------------------------------------------------------------
    % Process Type 3 arrival times
    % Generate random number of new referrals returning calls
    if (clinic == 'A')
        % 1 in 3 failures (29/45) call back,
        % distributed over 5 days.
        newRefWeek = sum(floor(log(rand(25,1))/log(1-0.50322)));
        newRefRtn = sum(rand(newRefWeek,1) <= ...
            ((1/3)*(29/45)*(1/5)));
    elseif (clinic == 'B')
        % 1 in 3 failures (77/104) call back,
        % distributed over 5 days.
        newRefWeek = sum(floor(log(rand(25,1))/log(1-0.55704)));
        newRefRtn = sum(rand(newRefWeek,1) <= ...
            ((1/3)*(77/104)*(1/5)));
    end
    % Generate mean arrival times for new referrals returning
    % phone calls.
    % If there are none that day, set to infinity.
    if (newRefRtn == 0 )
        newRefRtnMean = Inf;
    else
        newRefRtnMean = 28800 / newRefRtn;
    end
    set_param('PCCv5/Time-Based Entity Generator1', ...
        'distribution','Exponential');
    set_param('PCCv5/Time-Based Entity Generator1','mean',...
        num2str(newRefRtnMean));
    %-------------------------------------------------------------
    %-------------------------------------------------------------
```

```
% Process Type 4
% S1.3 Schedule Appointment (second attempt)
% Default Priority = 500, Default Preemption = 0
%------------------------------------------------------------
% Process Type 4 arrival times
% Generate random number of second attempts
if (clinic == 'A')
    % 2 in 3 failures (29/45) require second attempt
    % distributed over 5 days.
    newRefWeek = sum(floor(log(rand(25,1))/log(1-0.50322)));
    secAtt = sum(rand(newRefWeek,1) <= ...
        ((2/3)*(29/45)*(1/5)));
elseif (clinic == 'B')
    % 2 in 3 failures (77/104) require second attempt,
    % distributed over 5 days.
    newRefWeek = sum(floor(log(rand(25,1))/log(1-0.55704)));
    secAtt = sum(rand(newRefWeek,1) <= ...
        ((2/3)*(77/104)*(1/5)));
end
% Generate intergeneration times for second attempts.
% If there are none that day, set to infinity.
if (secAtt == 0)
    secAttInterGenTimes = Inf;
else
    secAttInterGenTimes = zeros(secAtt,1);
    secAttInterGenTimes(1) = 1;
end
set_param('PCCv5/Event-Based Sequence1', ...
    'VectorOutputValues',mat2str(secAttInterGenTimes));
%------------------------------------------------------------
%------------------------------------------------------------
% Process Type 5
% S2.1 Patient Mailout
% Default Priority = 800, Default Preemption = 0
%------------------------------------------------------------
% Process Type 6
% S2.2 Notify Referring Physician
% Default Priority = 700, Default Preemption = 0
%------------------------------------------------------------
% Process Type 7
% S2.3 Prepare Chart
% Default Priority = 400, Default Preemption = 0
%------------------------------------------------------------
%------------------------------------------------------------
% Process Type 5, 6 & 7 arrival triggered by success of
% Process Type 2, 3 or 4
%------------------------------------------------------------
%------------------------------------------------------------
% Process Type 8
% S2.4 Appointment Reminders
% Default Priority = 300, Default Preemption = 0
%------------------------------------------------------------
% Process Type 8 arrival times
% Before automated reminder system
if (ICT == 0)
```

```
        % Generate random number of appointments for the month
        if (clinic == 'A')
            % apptMonth ~ negative binomial (s = 18, p = 0.07190)
            apptMonth = sum(floor(log(rand(18,1))/ ...
                log(1-0.07190)));
        elseif (clinic == 'B')
            % apptMonth ~ negative binomial (s = 25, p = 0.17132)
            apptMonth = sum(floor(log(rand(25,1))/ ...
                log(1-0.17132)));
        end
        % Generate a random number of appointment reminders
        % for the day apptRem as apptMonth distributed over
        % 20 days
        apptRem = sum(rand(apptMonth,1) <= 0.05);
        % Generate intergeneration times for appt reminders
        % If there are none that day, set to infinity.
        if (apptRem == 0)
            apptRemInterGenTimes = Inf;
        else
            apptRemInterGenTimes = zeros(apptRem,1);
            apptRemInterGenTimes(1) = 1;
        end
    % After automated reminder system
    elseif (ICT == 1)
        apptRemInterGenTimes = Inf;
    end
    set_param('PCCv5/Event-Based Sequence2', ...
        'VectorOutputValues',mat2str(apptRemInterGenTimes));
    %-------------------------------------------------------------
    %-------------------------------------------------------------
    % Process Type 9
    % S3.1.1 Obtain patient data
    % Default Priority = 1200, Default Preemption = 0
    %-------------------------------------------------------------
    % Process Type 9 arrival times
    % Generate random number of appointments for the month
    if (clinic == 'A')
        % apptMonth ~ negative binomial (s = 18, p = 0.07190)
        apptMonth = sum(floor(log(rand(18,1))/log(1-0.07190)));
    elseif (clinic == 'B')
        % apptMonth ~ negative binomial (s = 25, p = 0.17132)
        apptMonth = sum(floor(log(rand(25,1))/log(1-0.17132)));
    end
    % Generate a random number of appointment for the day
    % apptReg as apptMonth distributed over 20 days
    apptReg = sum(rand(apptMonth,1) <= 0.05);
    % Generate intergeneration times for appt registrations
    % If there are none that day, set to infinity.
    if (apptReg == 0)
        apptRegInterGenTimes = Inf;
    else
        apptRegGenTimes = zeros(apptReg,1);
        apptRegGenTimesSorted = zeros(apptReg,1);
        apptRegInterGenTimes = zeros(apptReg,1);
        % Assign appt times based on empirical distribution
```

```
        % Arrivals normally distributed with st.dev. = 300
        % (95% show up within +/-10 min of appt time)
        % If arrival time < 0, in sim clock time, set to 0
        for j = 1:apptReg
            t = rand(1,1);
            apptRegGenTimes(j) = ...
                round(apptTime(find(apptTimeCumDist >= t,1, ...
                'first')) + 300 * randn);
            if (apptRegGenTimes(j) < 0)
                apptRegGenTimes(j) = 0;
            end
        end
        apptRegGenTimesSorted = sort(apptRegGenTimes);
        apptRegInterGenTimes(1) = apptRegGenTimesSorted(1);
        for k = 2:apptReg
            apptRegInterGenTimes(k) = ...
                apptRegGenTimesSorted(k) - ...
                apptRegGenTimesSorted(k-1);
        end
    end
    set_param('PCCv5/Event-Based Sequence3', ...
        'VectorOutputValues',mat2str(apptRegInterGenTimes));
    %-------------------------------------------------------------
    %-------------------------------------------------------------
    % Process Type 10
    % S3.1.2 Notify clinician
    % Default Priority = 1300, Default Preemption = 0
    %-------------------------------------------------------------
    % Process Type 10 arrival triggered by completion of
    % Process Type 9
    %-------------------------------------------------------------
    %-------------------------------------------------------------
    % Process Type 11
    % S3.3.1 Report to Referring Clinician
    % Default Priority = 200, Default Preemption = 0
    %-------------------------------------------------------------
    % Process Type 11 arrival times
    % Generate random number of closures for the month
    if (clinic == 'A')
        % closeMonth ~ negative binomial (s = 4, p = 0.02016)
        closeMonth = sum(floor(log(rand(4,1))/ ...
            log(1-0.02016)));
    elseif (clinic == 'B')
        % closeMonth ~ negative binomial (s = 14, p = 0.14598)
        closeMonth = sum(floor(log(rand(14,1))/ ...
            log(1-0.14598)));
    end
    % Generate a random number of chart closures for the day
    % close as closeMonth distributed over 20 days
    close = sum(rand(closeMonth,1) <= 0.05);
    % Calculate mean generation times for chart closures.
    % If none that day, set to infinity.
    if (close == 0 )
        closeMean = Inf;
    else
```

```
        closeMean = 28800 / close;
    end
    set_param('PCCv5/Time-Based Entity Generator5', ...
        'distribution','Exponential');
    set_param('PCCv5/Time-Based Entity Generator5','mean', ...
        num2str(closeMean));
    %-------------------------------------------------------------
    %-------------------------------------------------------------
    % Process Type 12
    % S3.3.2 Close Chart
    % Default Priority = 100, Default Preemption = 0
    %-------------------------------------------------------------
    % Process Type 12 arrival triggered by completion of
    % Process Type 11
    %-------------------------------------------------------------
    %-------------------------------------------------------------
    % Process Type 13
    % Other interruptions
    % Default Priority = 1000, Default Preemption = 0
    %-------------------------------------------------------------
    % Process Type 13 arrival times
    % Exponential distribution
    set_param('PCCv5/Time-Based Entity Generator6', ...
        'Distribution','Exponential');
    if (clinic == 'A')
        set_param('PCCv5/Time-Based Entity Generator6', ...
            'Mean','1143');
    elseif (clinic == 'B')
        set_param('PCCv5/Time-Based Entity Generator6', ...
            'Mean','2475');
    end
    %-------------------------------------------------------------
    %-------------------------------------------------------------
    % Run simulation
    %-------------------------------------------------------------
    se_randomizeseeds('PCCv5');
    sim('PCCv5',[]);
    utilization(i) = u;
    %-------------------------------------------------------------
end

% Display average utilization
mean_utilization = mean(utilization);
var_utilization = var(utilization);
str = sprintf('*  utilization(avg)           %-5.3f    *',...
    mean_utilization);
disp(str);
str = sprintf('*  utilization(var)           %-5.3f    *',...
    var_utilization);
disp(str);
```