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Patient-Centered Appointment Scheduling Using Agent-Based Simulation

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Abstract

Enhanced access and continuity are key components of patient-centered care. Existing studies show that several interventions such as providing same day appointments, walk-in services, after-hours care, and group appointments, have been used to redesign the healthcare systems for improved access to primary care. However, an intervention focusing on a single component of care delivery (i.e. improving access to acute care) might have a negative impact other components of the system (i.e. reduced continuity of care for chronic patients). Therefore, primary care clinics should consider implementing multiple interventions tailored for their patient population needs. We collected rapid ethnography and observations to better understand clinic workflow and key constraints. We then developed an agent-based simulation model that includes all access modalities (appointments, walk-ins, and after-hours access), incorporate resources and key constraints and determine the best appointment scheduling method that improves access and continuity of care. This paper demonstrates the value of simulation models to test a variety of alternative strategies to improve access to care through scheduling.

Introduction

Primary care clinics are under great pressure to improve access, health outcomes, quality and efficiency of care with limited availability of resources, especially in the current funding environment. The importance of providing patient-centered care with enhanced access and continuity has been emphasized in several studies.[1,2] Interventions that vary according to the domain of care (acute care, preventive care, or chronic care) have been used to enhance primary care[3]. Same-day appointments, telephone triaging, walk-in centers, and after-hour services are used to improve access to acute care.[3] Multidisciplinary care teams, disease specific clinics, group appointments, registries, information and decision support systems, patient education and workforce development are used to improve access to care for chronic disease.[3] Community and population based programs to increase awareness, support systems for compliance and reminder systems are used to improve access to preventive care.[3] However, interventions that focus on a single component of care delivery are shown to have negative or no effect on other components of the system. For example, one study identified challenges in securing ongoing appointments for chronic care patients, due to increased availability of same-day appointments for acute care.[4] Another study evaluated the introduction of walk-in primary care clinic and reported good use by patients; however, there was no reduction in use of pre-existing services.[5] In another study, after-hours service did not show improvement in access to after-hours care, due to misconceptions about how to access the new system.[6] Therefore, multiple strategies targeting different levels or components of the health care system should be used to achieve the best performance.[3]

There are several access barriers to care including financial and non-financial barriers. While financial access barriers were found to be a primary problem experienced by 18% of US adults surveyed, 21% experienced non-financial barriers that led to unmet needs or delayed care[7]. The most commonly cited non-financial barrier was accommodation (challenges making appointments and ability to see a provider during limited hours)[8]. A systematic literature review revealed challenges for patients in obtaining appointments, longer waiting times, short business hours at the primary care clinics, unavailability of a regular physician or clinic, and low socioeconomic status to be associated with inappropriate use of emergency services.[9] Effective scheduling could address accommodation barriers; however, health centers struggle to implement novel scheduling methods due to lack of decision support tools that can be used to determine the best scheduling method tailored according to the patient population needs[10]. The number of strategies in the literature, the conflicting results of the existing studies, and the limited clinic resources make it difficult for clinic managers to determine the best set of interventions for their patient population and setting. In a recent study, two-thirds of the surveyed safety-net health centers did not have a process for same-day scheduling or had a process that needed improvement.[1] The aim of this study is to model the patient population and primary care delivery system using simulation and then use the resultant model to determine optimal scheduling methods for improved access to care and continuity of care.

Background

In a project involving four community health centers (CHCs) in Indiana, we identified several challenges for patients in obtaining appointments including long waiting times, short business hours at the primary care clinics, and unavailability of a regular physician or clinic. The most commonly used scheduling method observed was a hybrid of traditional and advanced access scheduling. Patients with perceived need for routine follow-up (e.g. chronic conditions, routine visits for prenatal and well child check, and lab tests) are often scheduled in advance with a lead-time of 2 weeks to 9 months, depending on the condition, clinic, and provider. All clinics had adopted one or more strategies to provide some same-day access for acute care. Triage appointments (a number of appointment slots are kept open for acute problems) and walk-in hours are the strategies used to provide same-day access for acute demand. Overbooking was allowed by permission of the providers or, in urgent cases, patients were referred to local emergency rooms for care. Open access scheduling was used in one clinic where 80% of the appointments were kept open for same-day access. If a patient cannot be scheduled on the same day, he/she was asked to call back next day. Another clinic had a nurse practitioner (NP) whose schedule was explicitly kept open to provide same-day access to patients with acute care needs. Some clinics had walk-in hours on certain evenings and/or on Saturdays for established patients; an effective way of providing care at more convenient times for working patients.

Patient no-show was a major challenge for all clinics. Missed appointments reduce the continuity of care for no-show patients, reduce timely access to care for patients who cannot get an appointment, waste provider resources and can negatively impact health outcomes. While appointment reminders are often used to reduce no-shows, the missed-appointment rates were still higher than desired, about 25% for the clinics using traditional scheduling with triage appointments. No-shows worsen as the length of time between making the appointment and the actual visit date increased.

Implementation of open access scheduling may hold considerable potential in clinics where there is a high rate of patients who end-up going to emergency departments, even for non-urgent problems, because they cannot get a same-day appointment. The successful implementation of advanced access scheduling is reported to reduce no-shows, improve provider utilization and patient satisfaction. However, successful implementation requires careful analysis of clinic capacity and patient demand. Inappropriate proportions of capacity allocated for open access typically causes mismatch between capacity and demand, and result in implementation failure.[11] In our study, we noted that open access scheduling faces resistance from providers and staff due to uncertainties regarding its implementation and how it would actually work.

Previous studies have cited several reasons for no-shows including patient-related factors, scheduling system problems, and environmental and financial factors. Several interventions including appointment reminders, patient education, follow-up after a missed appointment, and open access scheduling have been used to reduce no-shows.[12] However, no-shows could not be eliminated completely due to several factors. We developed a logistic regression model that includes age, lead time (time between the appointment is made and the actual appointment time), prior no-show behavior, provider type, insurance type, and appointment type, as predictors of patient no-show.[12] Most of the existing literature ends with reporting the predictors of no-shows. Here, our aim is to use no-show prediction models to estimate actual demand and develop advanced scheduling methods considering individual no-show probabilities.

Many studies in the operations research literature propose appointment scheduling methods with the goal of improving clinic accessibility and efficiency. Cayirli and Veral[13] provided an extensive literature review with eighty papers in 2003. Since 2003, more than 300 papers cited the literature review paper of Cayirli and Veral[13], showing the significant growth of research on appointment scheduling. Existing studies consider appointment scheduling in different settings including primary care, specialty care and surgical departments. Most of the appointment scheduling studies focus on single stage, single resource environments (i.e. primary care or specialty care where only doctor appointments are considered). Earlier analytical studies used queuing theory and mathematical programming methods with simplifying assumptions to determine appointment schedules[13]. Most of the analytical studies could not be validated in real environments due to unrealistic assumptions. Simulation studies included complex environmental factors such as unpunctuality, no-shows, walk-ins, etc. to find the best appointment scheduling rule. However, these studies were not easily implementable in other environments due to extensive data collection requirements. In recent years, analytical studies made more realistic assumptions including no-shows, cancellations, walk-ins, different patient types, priorities, and preferences. However, these advanced scheduling methods are rarely applied in clinical practice. In response to this gap, we sought to develop a simulation based tool that can be used in clinics to determine the best scheduling policy tailored to their patient population needs.

Over the past two decades, modeling and simulation have come of age as tools to help teams and managers support different cognitive and group processes. Simulation has been widely used in modeling health care systems in several settings, including outpatient departments.[14] Most health care simulation applications in the literature aim to provide better operational decision-making and planning tools.[15, 16] Simulation studies that model outpatient clinics focus on scheduling and capacity planning. Most of the studies model patient flow within the clinic and analyze the impact of scheduling methods on in-clinic patient waiting times and provider idle times.[16] However, the waiting time for an appointment (time between the time appointment is scheduled and actual appointment time) is also very important for clinics aiming to provide timely access to care.[10, 16] In this study, we focus on scheduling practices that directly accommodate the needs of patients while still meeting the efficiency needs of the CHCs and providers. We use agent-based simulation to model the care delivery system to incorporate population characteristics, care needs (demand), and common services provided within the health care system.[17]

Methods

We use simulation modeling, an operations research method, to model the scheduling process for provider appointments in CHCs. Rapid ethnography and observations are the key approaches used to understand the scheduling process and collect data for the simulation model. Rapid ethnography is a collection of methods used to understand the activities of users given significant time pressures and limited time in the field. The core elements of rapid ethnography include limiting or constraining the research focus and scope, using key informants, capturing rich field data by using multiple observers and interactive observation techniques, and collaborative qualitative data analysis.[18] For rapid ethnography and observations, we identify key informants including: 1) call center (or telephone room) and front office personnel as they relate to patient contact and scheduling, 2) enrollment specialists as they relate to new patients, 3) triage nurses as they relate to scheduling of acute appointments, and 4) quality assurance/information technology (QA/IT) personnel as they relate to the retrieval of appointment scheduling and provider capacity data. A team of two project members conducted interviews and obtained workflow summaries, policies, procedures, and artifacts used in the clinics. Based on the interviews performed, workflow diagrams are developed and then verified by the key informants. The simulation model is used to identify the impact of different scheduling and resource allocation strategies on key performance measures such as patient waiting times, provider productivity, patient no-shows, and continuity of care. The modeling tool is designed to be flexible so that it can be used by several clinics. The flexibility is achieved using input data files and graphical user interface. The inputs to the simulation model are:

- Provider capacity (capacity allocated for walk-ins, acute, non-acute and follow-up appointments)
- Patient population characteristics (age, gender, insurance, health status)
- Patient demand for care (demand for acute, non-acute and follow-up appointments)
- Scheduling method (traditional scheduling with triage appointments and open access scheduling)
- Scheduling horizon for each appointment type (acute, non-acute, follow-up)
- Maximum panel size for each provider

A data collection tool is developed to collect provider capacity, patient population characteristics, patient demand, no-show and cancellation data. The required variables are determined together with the QA/IT personnel, who retrieved the data from the electronic medical record system and sent the data for further analysis. The patient population characteristics including age, gender, insurance, and health status are provided as percentages with respect to the total number of patients. The provider template schedules are used to fill out the provider capacity data. The average number of annual visits per patient, no-shows and cancellations are calculated according to the appointment scheduling data provided by the QA/IT person. The data analysis results are discussed with the QA/IT personnel, COO and CEO of each clinic to validate the input data for the simulation model.

Figure 1 shows the general structure of the simulation model where the simulation model is initialized with clinic specific data (i.e. provider capacity and patient population characteristics), patient demand for care is generated based on care needs of the patient population, and appointments are scheduled according to provider availability, capacity allocated for each appointment type, and appointment scheduling method.

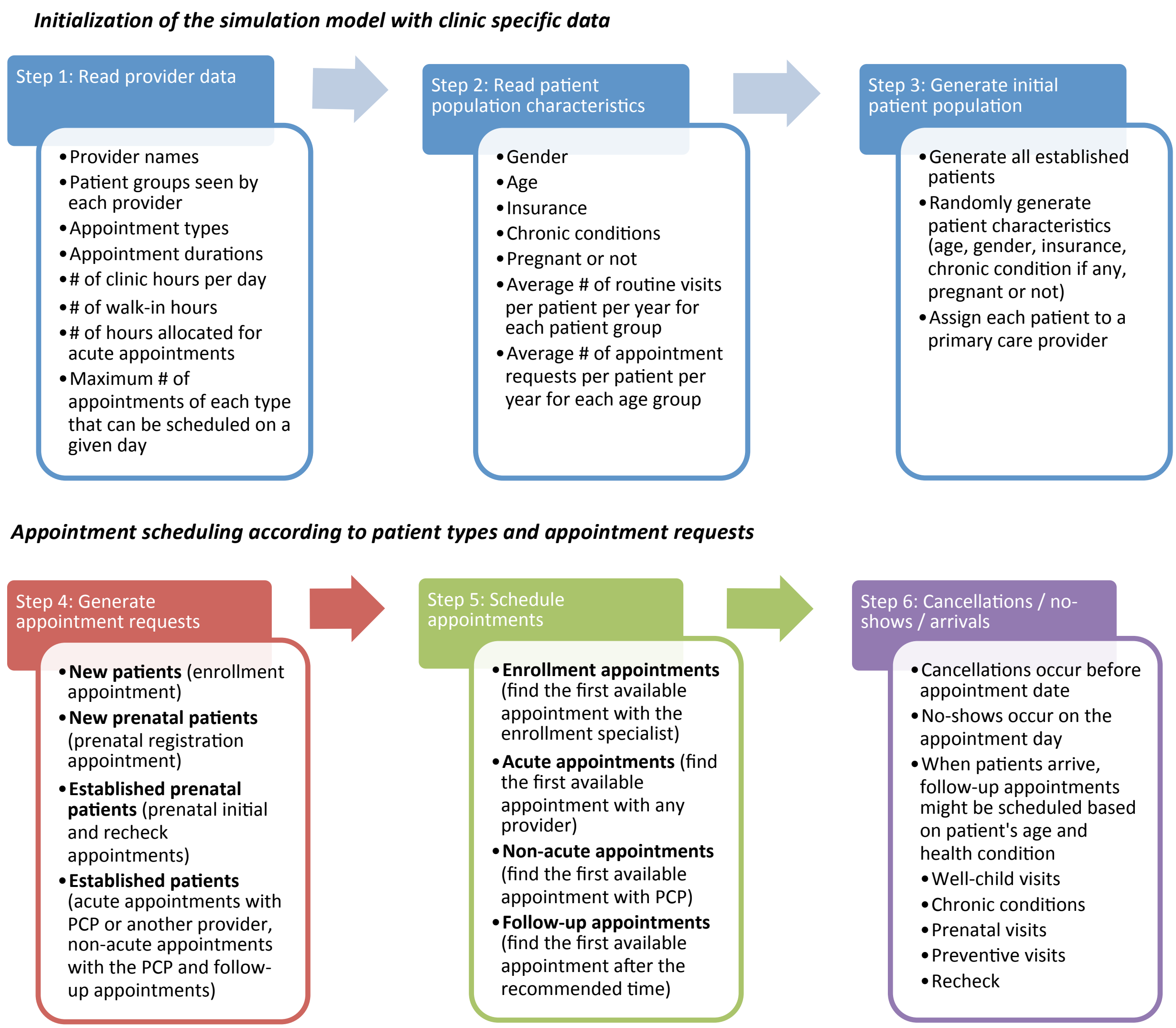

Figure 1. Simulation model

The simulation model starts with reading the provider and patient population data from an Excel file (Steps 1 and 2) and generating the initial patient population based on the number of unique patients served by the clinic (Step 3). Age, gender, insurance, and health condition (pregnancy and chronic condition) of each patient is generated based on patient demographics data. Each patient is assigned to a primary care provider based on available provider capacity and maximum panel size. The next step is generating the appointment requests for each patient (Step 4). We divided the patients into four groups based on their needs for different appointment types and resources. Once an appointment is requested, the appointment type (i.e. new, acute, routine, complex, well-child, newborn, etc.) is determined and scheduled according to patient type, resource availability, type of appointment request, and the scheduling policy used in the clinic (i.e. traditional approach with triage appointments, open-access scheduling) (Step 5). We included cancellations, arrivals and no-shows in our simulation model to calculate the access, operational, and quality measures (Step 6).

Initialization of the simulation model with clinic specific data

Step 1: The provider data required for the simulation model includes provider names, patient groups seen by each provider (i.e. pediatrics, adult, family medicine, women), number of working hours per day, number of hours allocated for acute/same-day appointments, appointment durations, and maximum number of appointments that can be scheduled. The providers allocate different durations for different types of appointments. For example, a provider might allocate 30-minute appointments for new and chronic patients, and 15-minute appointments for acute patients. The providers might have a different working schedule during the week. There might be restrictions on the number of appointments that can be scheduled on a given day (i.e. only two new patient appointments per day). An Excel file is prepared with the required information and the QA/IT person filled out that information by using the providers' template schedules. Tables 1 and 2 show sample provider data.

Table 1 – Appointment types and durations in minutes for each provider (sample data – does not include all possible appointment types)

Provider no	Providers	Patient group	New	Acute	Physical	Chronic/ complex	Well-child	Routine
1	MD1	Pediatrics	15	15	0	15	15	15
2	MD2	Adult	15	15	15	30		15
3	NP2	Adult	30	30	15	30		15
4	MD3	Women	45	30	45	45		30
5	NP2	Family medicine	30	15	30	30	30	30
6	MD4	Family medicine	30	15	15	30	15	15

Table 2 – Available provider capacity, number of hours allocated for same-day appointments, and maximum number of appointments of each type that can be scheduled on a given day (sample data – does not include all possible appointment types)

Providers	Day	Number of clinic hours	Number of walk-in hours	Number of hours allocated for acute	Number of hours allocated for non-acute	Maximum number of appointments that can be scheduled			
						New	Acute	Well child	Routine
MD1	Mon	7	4		3	2		11	
MD1	Wed	7		2	5	2		11	
MD1	Thu	7	4		3	2		11	
MD1	Fri	7		2	5	2		11	
MD2	Mon	7		2	5				
MD2	Tue	7		1	6				
MD2	Wed	7		1	6				
MD2	Thu	7		1	6				
MD2	Fri	7		2	5				

Steps 2-3: In operations research literature, simulation models, which consider modeling of care processes, patient flows and available resources, use historical data to express the demand in terms of a probability distribution function of the quantity or arrival time. In economic studies, which aim to evaluate the economic impact of diseases and health policies, demand is expressed as a function of prices, supplies, age, education, etc.[19-21] As Charfeddine and Montreuil[22] mentioned, demand for healthcare can be expressed in a better way through stochastic modeling of disease progression of each person in a patient population. Even though clinical studies model the disease progression and health status, their focus is to analyze the impact of medical interventions rather than determining the demand[23]. Healthcare demand is a function of multiple factors such as population characteristics, patient health status, treatment guidelines, adherence behavior, etc. We assume age, gender, insurance, and patient's condition

(chronic conditions, pregnancy) are predictors of number of visits. For example, the frequency and number of well-child visits change according to the age of patient. The frequency of prenatal visits change according to the stage of pregnancy. The number of routine visits change according to the health status of patients with chronic conditions. Agent-based simulation models can incorporate all these factors using agents (patient, provider, scheduler, etc.) to provide more realistic estimates of the care needs (e.g., regular provider visits, acute care visits). In the simulation model, we represent each patient as an agent. The simulation model generates the initial set of established patients at the initialization phase. The number of established patients is equal to the unique patients seen in the clinic in one year. The characteristics of each patient are generated based on initial patient demographics data. When the initial patient population is generated, each patient is assigned to a primary care provider (PCP).

Appointment scheduling according to patient types and appointment requests

Step 4: We divided patients into four groups according to two factors (new or established, and prenatal or not) due to the need for different appointment types and resources as shown in Figure 1. Once an appointment is requested, the appointment type (i.e. new, acute, routine, complex, well-child, newborn, etc.) is determined and scheduled according to resource availability, type of appointment request, and the scheduling policy used in the clinic. Figure 2 shows the overall summary of the scheduling process based on appointment types. This flowchart is prepared based on the workflow diagrams developed for the scheduling process through the key informant interviews.

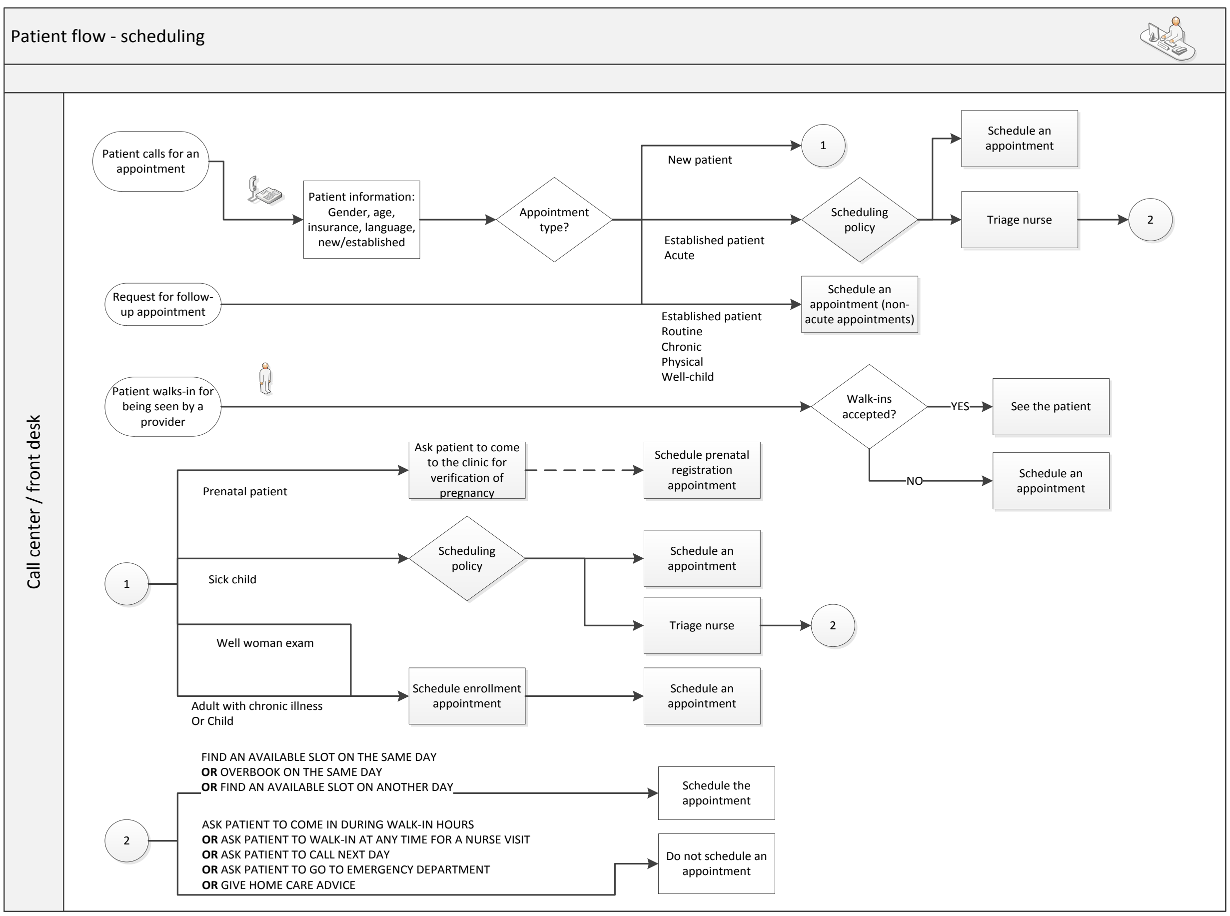

Figure 2 – Flowchart scheduling process according to appointment type and scheduling method.

Step 5: In the simulation model, we considered two types of scheduling methods (traditional scheduling with triage appointments, and open access scheduling). New patients should be scheduled for an enrollment appointment before an appointment can be scheduled with a provider. In traditional scheduling, acute appointments are scheduled on the same day or a few days in advance of triage appointment slots. Non-acute appointments and follow-up appointments are scheduled to other slots several days in advance. In open access scheduling, most of the appointment slots are open for acute and non-acute appointments and can only be scheduled on the same day (or within a few days in advance). Follow-up appointments can be scheduled several days in advance, but the slots allocated for these appointments are limited. We used different objectives for scheduling of acute, non-acute and follow-up appointments. For acute appointments, our main objective was to minimize patient waiting time. Therefore, the available slots of PCP and other providers are searched to find an appointment time as soon as possible. For non-acute appointments, we sought to maximize continuity of care and minimize patient waiting time. Therefore, we first searched the PCP schedule and then other providers' schedules to find an available slot with a reasonable waiting time. For follow-up appointments, we maximized continuity of care by scheduling the appointment with the PCP.

Step 6: We included cancellations, arrivals and no-shows in our simulation model to determine the actual number of visits. Based on our prior research and existing literature[12, 24, 25], we assumed that the no-show probability is a function of age, insurance, lead time and patient's previous no-show behavior. In the simulation model, we used the regression equation that is determined based on clinic data to calculate the no-show probabilities. We would like to note that even though age, insurance and previous attendance rates cannot be controlled, they can be used to determine the no-show rate for each individual patient. The lead time can be controlled by changing the scheduling horizon (threshold for lead time) for each type of appointment. In our simulation model, scheduling horizon was an input parameter that could be controlled by the user or that determined by the model to minimize no-show rates and maximize continuity of care.

Results

We collected data from the clinics to validate the simulation model based on current practice in the clinics. Since an agent-based simulation model is used with several assumptions related to estimation of no-shows and cancellations, the validation of the input data is important. We compared the number of appointment requests, no-shows, cancellations, and provider utilizations of the simulation model with actual data to make sure that the demand was generated correctly. The simulation model was able to generate appointment requests, no-shows, cancellations and number of visits that were close to the observed data. For example, the average number of visits per week was 573 for the 2-week data provided by one clinic and the simulation model generated an average of 557 visits per week over a 5-year simulation run. The waiting times, percentage of appointments with the PCP, and no-show rates are used as performance measures since they are related to access and continuity of care. Table 3 shows a sample comparison between two scheduling methods. The waiting times for appointments are reduced in open access scheduling. The continuity of care did not change much. The no-show rates are reduced for non-acute appointments due to lower waiting times.

Table 3 – Comparison of traditional and open access scheduling methods

Performance measure	Traditional scheduling with triage appointments Planning horizon: (30, 90, 180)	Open access scheduling Planning horizon: (2,5,180)
Waiting time for acute appointments	Average: 0.5 day Std. dev.: 0.8 day	Average: 0.8 day Std. dev.: 0.4 day
Waiting time for non-acute appointments	Average: 51 days Std. dev.: 38 days	Average: 0.8 day Std. dev.: 0.4 day
Waiting time for follow-up appointments	Average: 48 days Std. dev.: 25 days	Average: 1 day Std. dev.: 1.2 days
Continuity of care (non-acute)	66%	65%
Continuity of care (acute)	57%	60%
No-show percentage (non-acute and follow-up)	23%	10%
No-show percentage (acute)	10%	9.6%

In this study, we could not perform statistical analysis for comparing and validating the simulation model, because the real data was not available for a longer time period. However, we are planning to address this issue in the continuation of this project, which includes collection of 2-year appointment data from the clinics. We are also planning to use expert opinion for the validation of the simulation results.

Limitations

The proposed simulation model is developed based on current practice in two clinics that use traditional scheduling method. When open access scheduling is chosen, the simulation model reduces the no-show rates due to shorter waiting times. But the simulation model assumes that the patients will continue requesting appointments at the same rate. That is why more visits are scheduled and more arrivals occur when open access scheduling method is used. We believe the behavior of providers and patients will change when open access scheduling is implemented. For example, the providers may not ask the patient to schedule a follow-up appointment after the clinic visit unless it is really necessary. Due to limited number of follow-up appointment slots, the provider might ask the patient to come for a visit in 3-months. But the patient might forget to call to make the next appointment when 3-months pass. These two factors would reduce the number of appointment requests unless the clinics do not implement other interventions such as using provider and patient reminders to schedule the next appointment when the appropriate time comes. Currently, the simulation model does not incorporate these possible changes in behavior. As we develop this model further, we will work with clinics that implemented open access scheduling to be able to include the change in demand.

Next Steps

We are building upon this work with funding from Patient-Centered Outcomes Research Institute (PCORI). We will work with seven CHCs in Indiana to incorporate patients' perspectives to improve access to care for underserved populations. We will conduct rapid ethnography and workflow observation and modeling to identify the current barriers to access and use quantitative approaches to predict no-shows and determine the best scheduling policies that are determined based on patient population characteristics and available provider capacity. In that 3-year project, we will work with the clinics and further develop the proposed simulation model to include workflow and use the model and expert and patient panels to optimally determine the patient-centered interventions tailored for each clinic's patient population.

Conclusions

We used agent-based simulation to model the patient flow and appointment scheduling process in community health centers. The simulation model was designed to be flexible in terms of usability by different clinics. The inputs are entered through Excel files or graphical user interface, which makes the model useful for any clinic. This paper demonstrates the value of simulation models to test a variety of alternative strategies to improve access to care through scheduling.

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