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Exploring the Association Between Patient Waiting Time, No-Shows and Overbooking Strategy to Improve Efficiency in Health Care

Cam Tu M. Nguyen
University of Arkansas, Fayetteville

Exploring the Association between Patient Waiting Time, No-Shows and Overbooking Strategy to Improve Efficiency in Health Care

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By

Cam Tu Nguyen

Abstract

Many primary care clinics are using overbooking as a strategy to mitigate the negative impacts on operations and performance caused by patient nonattendance of appointments, also known as “no-shows”. However, overbooking tends to increase patient waiting time and worker overtime. It is also acknowledged that patient waiting time is associated with no-show behavior, yet there is a lack of observational study to quantify the relationship. The overall goal of this research is to explore the relationships between patient waiting time, no-show behavior and overbooking strategy in terms of clinic performance. Arena® simulation software is used to create a discrete-event simulation model that represents daily processes of a standard primary care clinic. The model is used to test the three variables by varying (1) the amount increase in no-show probability by tolerance group, (2) waiting time tolerance threshold, and (3) overbooking strategy. We observe from the results that the three features (waiting time, no-show behavior and overbooking strategy) are interrelated because higher no-show probability leads to higher number of no-shows, which suggests overbooking more patients, and eventually leads to longer waiting time, resulting in an increase in the patient’s no show probability. However, as limited by the size of the clinic case, we were not able to see a clear cut-off of average waiting tolerance for making overbooking decisions that are not only based on the prediction of patient no-shows, but also consider the impact on patient waiting time and its association with no-show behavior. Nevertheless, by having the waiting time as one of the constraint variables, we were able to see the trade-off of choosing a certain overbooking decision and its impact on no-shows. To fully understand the impact of the relationship between the three variables, we recommend that more observational studies should be conducted as pertaining to the desired clinic environment.

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1. Introduction

Appointment scheduling is frequently used by many healthcare providers to effectively schedule patients for visit; however, the scheduling is quite difficult when variabilities are present, one of which is patient no-shows (Zacharias & Pinedo, 2014). According to Ulmer and Troxler (2004), many clinics claimed that patient nonattendance of appointments, or "no-shows", is a significant problem. On average, 42% of scheduled appointments resulted in no-shows (Lacy et al., 2004). No-show rates are also found to differ among specialties: 21% no-show rate in psychotherapy appointments, 30% proportion of non-attendance in outpatient obstetrics and gynecology clinic, and 31% appointment failure rate in pediatric resident continuity clinics nationally (Zacharias & Pinedo, 2014). Zeng et al. (n.d.) stated, "Patient no-show is one of the most serious operational issues facing nearly all primary-care clinics due to its multi-facet damage". In addition to primary care and specialty clinics, no-shows also occur in scheduled surgery and operations. For example, an outpatient endoscopy suite experienced high no-show rate (12-24%) (Berg et al., 2013). From healthcare settings with no-show rates of 3% to healthcare settings with no-show rates of 80%, patient no-shows pose a significant threat to every clinic (LaGanga & Lawrence, 2007). Currently, there are remarkable amount of studies seeking to determine the reasons for no-shows. For example, Zeng et al. (n.d.) have combined reasons for no-shows and show some prominent factors such as appointment delay, patients' dissatisfaction, forgetfulness, time constraints (i.e. longer patient waiting time), transportation, and patients' anxiety.

There are three different approaches that many healthcare providers are implementing in hoping to decrease patient no-shows and improve clinic efficiency. One way is to implement a variety of easy and quick resolutions to decrease no-shows including but not limited to reminder calls or mailings, provide transportations when needed, provide new-patient education, accommodate schedule changes, provide incentives or disincentives (Lacy et al., 2004). These quick resolutions have been found effective; however, its result is quite modest in reducing patient no-shows. In fact, Daggy et.al (2010) have claimed that the reduction is approximately10% in absolute difference.

Another popular method in attempting to reduce patient no-shows is open-access scheduling (Bundy et al., 2005). In open-access scheduling, appointments are made for the same day (Kopach et al., 2007). This type of scheduling is proven to reduce no-show rates effectively (Bundy et al.,2005). Moreover, Kopach et al. (2007) mentioned that some of the practices who has implemented open-access scheduling have successfully reduced their no-show rates to near zero.

The last popular method, which has been adopted by many healthcare providers, is to mitigate the effects of no-shows by scheduling additional patients, also known as overbooking (Berg et al., 2013). Overbooking is a method that includes additional patients to the previous anticipated number of scheduled patients' visit, where the number of additional patients is the key decision making of the healthcare providers. Currently, many hospitals and clinics implement overbooking to reduce patient no-shows (Zacharias & Pinedo, 2014), because overbooking provides flexibility to schedule more patients (Zeng et al., n.d.). This is a benefit of overbooking; however, many healthcare researchers also agree that overbooking also has many negative effects. One of the major concerns is the increased workers' overtime from overbooking (LaGanga & Lawrence, 2007), which might lead to reduction in clinic revenue (Daggy et.al., 2010). At the Family Practice Center (FPC) of Palmetto Richland Memorial Hospital/University of South Carolina, approximately 14.2% of anticipated revenue might be lost in a typical day due to no-shows (Moore et al., 2001). In another study, Peseta et al. (2011) suggested that a pediatric clinic has suffered losses of over $1 million due to 14,000 no-shows in one year. Another negative effect is the increased patient waiting time, which might negate the situation with having increased patient no-shows (Daggy et.al., 2010). As Liu and Ziya (2014) concluded, the probability of a patient being a no-show typically increases with the patient's appointment delay, or patient waiting time. Although it is acknowledged that waiting time is associated with increase in no-show rate (Berg et al., 2013), to the best of our knowledge, there is currently a lack of observational study to quantify the relationship. A better understanding of the associations between the three features (patient waiting time, no-shows, and overbooking) will allow healthcare providers to improve the efficiency in appointment planning and to improve clinic revenue.

The overall goal of this research is to explore the relationships between patient waiting time, no-show behavior and overbooking strategy in terms of clinic performance. It is hypothesized that these three features are interrelated and that the overbooking decision should not only be based on the prediction of patient no-shows, but also consider the impact on patient waiting time and its association with no-show behavior. Thus, this research will help decision makers quantify the indirect impact of overbooking on patient no-shows so that a better decision can be made to improve clinic efficiency.

2. Methods

One of many ways to better understand the associations between the three variables of interest is to test them using simulation modeling technique. Simulation modeling is one of the most effective tools for decision-making, especially in health care (Günal & Pidd, 2010) and provides the means to explore all hypothetical scenarios in a practice setting that otherwise is expensive and time consuming to conduct (Berg et al., 2013).

In this study, Arena® simulation software is used to create a discrete-event simulation model that represents daily processes of a standard primary care clinic to achieve the objectives. The reason for using discrete-event simulation as a main methodology for this research is, as Chemweno et al. (2014) explains that because of the large variability that exists between patients care needs, predicting patient waiting time is quite difficult. They also mention that the traditional optimization model like quieting theory cannot handle this kind of complexity of patients' medical needs along with the associations between clinic recourses; however, discrete-event simulation model can be used to provide intuitions regarding clinic operations (Chemweno et al., 2014).

In Section 2.1, we present the base case simulation model, along with the assumptions, and validation of the simulation model. Then, a discussion of the base case modification is followed to satisfy the research design in exploring the relationship as specified in Figure 1.

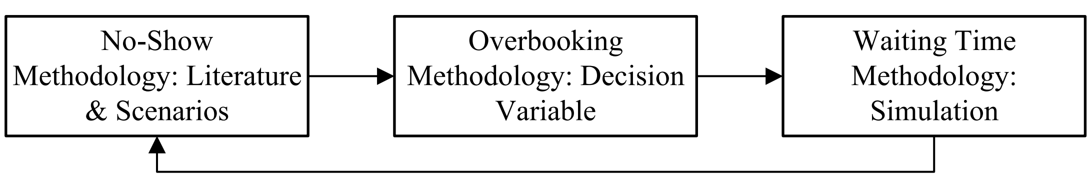


Figure 1. Relationship of Variables

First, initial no-show probability distribution is gathered through the literature. Based on no-show prediction, different overbooking decisions are tested, and the associated waiting time affected by the overbooking decisions is determined through the simulation model. Then, patient no-shows are assumed to change based on the extra waiting time of the previous visit. Different scenarios on waiting time tolerance are compared. By testing different scenarios that are based on a variety of overbooking decisions, changes in patient no-show probability, and selections of waiting tolerance, decision makers can draw various insights regarding to the trade-offs that impact the two clinic performances: number of no-shows and patient waiting time.

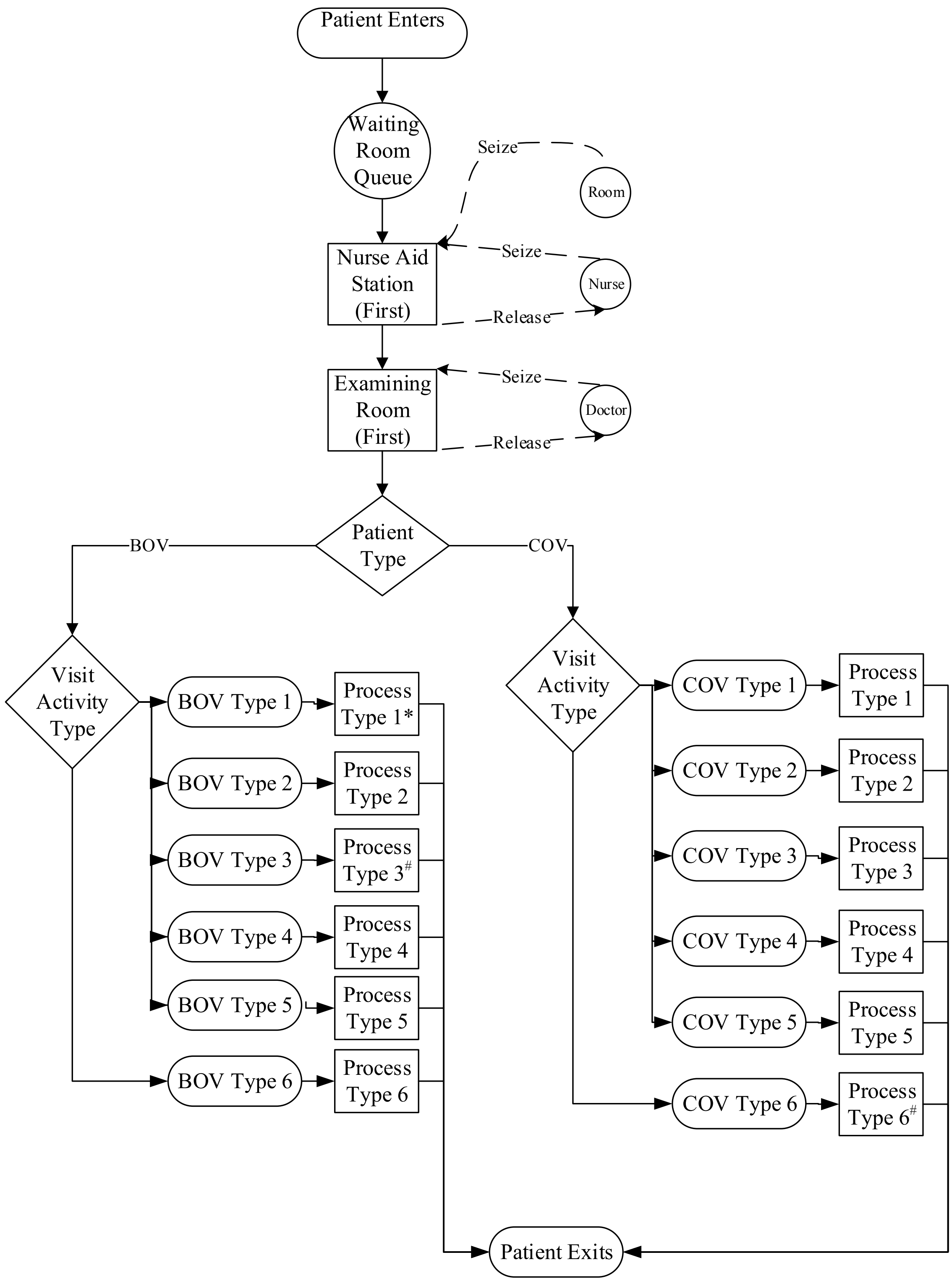
2.1 Base Case Simulation Model for an Outpatient Clinic

2.1.1 Model Development

To build an outpatient clinic simulation model for the base case, we used the family practice clinic information as described in Côté & Stein (2007). The clinic was a part of the Health Maintenance Organization (HMO). The organization's service was mostly around South-Central Texas and served approximately 60,000 patients. The description of the family clinic practice is as followed. The clinic's operation hours were from 8:30 am to 5:00 pm, having to close for lunch hours from 12:00 pm to 1:30pm, Monday through Friday. In terms of clinic resources, there were fourteen physicians, two physician aides, five registered nurses, and eight nurse aides. However, depending on daily patient load, a nurse might be designated to help one or two physicians, where each physician was allotted a maximum of three examining rooms. Although each patient was assigned to one physician, it was said that the treatment patterns of the patient visits across all physicians are analogous. At this clinic, Côté and Stein observed that there are two types of patient visits: brief office visit (BOV) or comprehensive office visit (COV). They said that the distinction between the two visits were the expected duration of visit and medical need. The expected duration of BOVs were only 15 minutes involving straightforward medical needs such as inoculations, follow-ups to previous clinic visits, or prescription renewals; whereas the expected duration of COVs were 30 minutes involving comprehensive medical needs such as physical examinations or minor emergency treatments. A conceptual model was depicted in Figure 2 to summarize the direction of patient flow for all patient types.

For each patient, the visit began when he/she arrived at the clinic. The patient would then wait in the waiting room (WR) until both the nurse and one of the three examining rooms were available. If either of the nurse or the examining room was unavailable, then the patient continued waiting there until both were available. Then, the patient advanced to a nurse aid station (NS_F – Nurse Station First Visit) where the nurse recorded the patient's vital statistics and led the patient to an examining room.

The patient then waited for the physician; meanwhile, if the care visit required x-ray or laboratory work, then the nurse must complete various request for procedure forms at the aid station. The visit progressed into the second stage, which was when the visit requires physician's attention. The duration of this stage was divided into two phases. The first phase (ER_F – Examining Room First Visit) was the same for all patient's activity type, which required the physician to come into the examining room to consult with the patient. Now, if the physician left the room, then the visit continued to the second phase. The second phase depended on the patient's activity type. The patient might need to go through a process called ER_R (Examining Room Return Visit), which required the physician to study the medical reports or prepare sample medicines for patient elsewhere while patient remained in the room. The patient might also go to a laboratory or x-ray facility (XR), see the nurse (NS_R – Nurse Station Return Visit), see the physician for extra medical consultation (ER_F), or check out (CO) at the front desk.



*Note that the details of examining room and other resources (i.e. nurse and doctor) utilizations are not completely presented in this figure because it is different among the patient's visit activity type.
#Examples of the resource utilizations and processes are detailed in Figures 3 and 4 below.

Figure 2. Overall Clinic Conceptual Model

Côté and Stein observed that there are 6 types of patient flows for BOV patients and 6 types of patient flows for COV patients, as well as the relative frequency of these flows. The information related to the direction of flows are summarized in Table 1 of Côté and Stein (2007). To show an example of the patient flows, a conceptual model of the 6th path for COV patients was created (Figure 3). For this patient type, he/she waited in the room while the physician examined the medical reports. Because the physician was still working, even not in direct contact, the patient still utilized the resource of the physician (i.e. time). The patient then visited the nurse for further instruction before going to laboratory or x-ray. Afterward, the patient was led back to the examining room for more consultation with the physician. At this point, the physician might need to grab sample medicines for the patient. Since the physician completed his/her work not in the presence of the patient, and that the examining room was no longer needed, then the examining room was released. The patient assumed to be waiting in the waiting room (WR) for further instruction from clinic personnel. The room was conceptualized to reserve for one patient at a time, so that the patient might come back to the room while waiting for the physician or nurse. If the room was no longer needed by the patient, then the room would be released for the next patient to use.

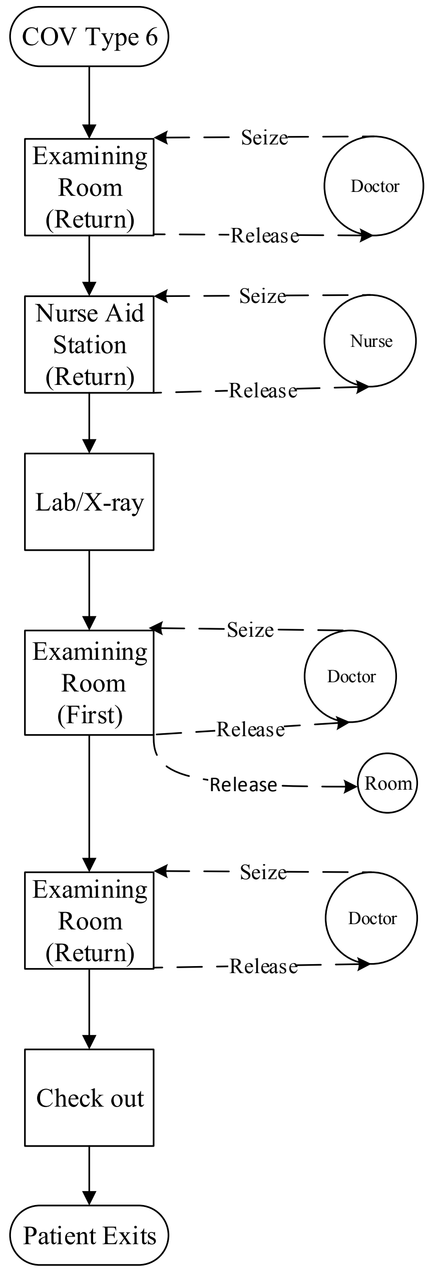


Figure 3. Conceptual Model of a Sample Flow Path for a COV Patient Visit

Another example of a different flow path for a patient visit is given in Figure 4. This patient type represented the 3rd flow path for BOV patients. For this patient type, he/she was led directly to the laboratory or x-ray immediately after seeing the physician in the examining room. The patient then returned to the reserved examining room for further consultation with the physician. Afterward, the patient visit was completed, and that the room was no longer needed, so it was released for another patient to use. The resource utilizations of this patient type were completely different from the patient type in Figure 4 with respect to the number of times the physician or nurse were needed and the time at which when the room was released.

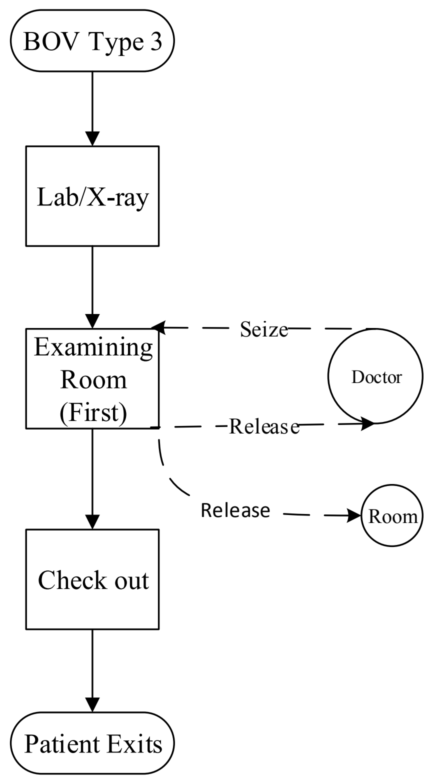


Figure 4. Conceptual Model of a Sample Flow Path for a BOV Patient Visit

The assumptions made to translate the conceptual model to the simulation model were summarized as follows.

I. Since the clinic treated relatively common health problems and conditions, the treatments do not require physicians possess a high degree of specialization (Côté & Stein, 2007). This implied that the treatments, among all 14 physicians, are analogous. Since the resources were assigned per physician (i.e., a nurse was assigned to a physician and 3 examining rooms were also assigned to a physician), we considered that the 14 physicians were working in parallel. As a result, we assumed that developing a simulation with only one physician, one nurse, and three examining rooms was sufficient. Consequently, the results of this simulation model were assumed to be representative across 14 physicians available.

II. The total number of patients served per day by the 14 physicians was 182 patients (Côté & Stein, 2007), suggesting that a maximum of 13 patients were served by one physician per day. Thus, we assumed that patients arrive according to a Poisson distribution with interarrival times following an exponential distribution with mean of 30 minutes during the 8.5 hours of a work day.

III. Regarding clinic hours of operation, the simulation model was established to operate for 8.5 hours with 1.5 hours for lunch. However, if patient was still being processed when lunch time came or when the clinic's closing time came, then all resources (i.e. physician, nurse, or examining rooms) must complete the patient's activity before leaving for lunch or closing for the day.

IV. The examining rooms were in a resource set with the following order of priorities. Examining room 1 would always be seized first if it was available. If examining room 1 was unavailable, then examining room 2 would be seized. If examining room 1 and 2 were unavailable, then examining room 3 would be seized.

V. Over a course of 5 months, data collection was performed and the descriptive statistics were summarized in Table 2 of Côté and Stein (2007). They fitted various distributions for different process times (e.g., time spent at the nurse aid station) to further use in their research (Table 3). For this study, the clinic was assumed to follow the Exponential distributions as summarized in Table 3 of Côté and Stein (2007). For instance, if the patients were currently in lab or x-ray and needed to check out later, then that estimated duration of lab or x-ray time was said to be EXPO (1/0.0433) minutes or EXPO (23.09) minutes.

VI. The termination conditions of the simulation model were that the current simulated time must be greater than 510 minutes, which was equivalent to 8.5 hours of a work day, and that there were no patients remaining in the system, which further ensured that all patients have completed their visits and left the system.

2.1.2 Model Validation

To compare and validate the simulation model with the descriptive statistics on clinic performance as in Table 2 of Côté and Stein's research (2007), we first created an attribute called "myWaitingTime" in the simulation model to record each patient's waiting time at the waiting room in the clinic, and collect the average waiting time statistic to verify. Examining the relationship between number of replications and the half-width of the confidence interval, we identified that at 35 replications, we were 95% confident to say that the mean of waiting time of 12.667 minutes as stated in Table 2 of Côté and Stein (2007) was within the 95% confidence interval of (10.258, 15.718) minutes resulted from the simulation model.

Once the number of replications was derived by using the "myWaitingTime" activity variable, we further validated our model by comparing the observed distribution of the number of occupied examining rooms from Figure 3 in Côté and Stein (2017) with the scheduled utilization of the three examining rooms from the model. For the examining room 1, the observed utilization was 82%, thus it was within the confidence interval of (53.44%, 83.44%) resulted from the simulation model. For the examining room 2, the observed utilization was 38%, thus it was within the confidence interval of (18.26%, 40.26%) from the simulation model. And finally, for the examining room 3, the observed utilization was 13%, and it was also within the confidence interval of (7.86%, 17.86%). Since all the observed distribution of number of occupied examining rooms concurred with the resulted utilization of the three examining rooms from the model, the base model was verified and validated.

2.2 Test Case Simulation Model for an Outpatient Clinic

2.2.1 Model Development

The test case simulation model was an extension of the base model in terms of continuing the patient' visits over a month period. The reason for doing so was to test the hypothesis that patient waiting time, no-show behavior, and overbook strategy were interrelated, and that the overbooking decision should not only be based on the prediction of patient no-shows, but also consider the impact on patient waiting time and its association with no-show behavior. The general structure of the extension is shown in Figure 4 below.

Every patient was assumed to visit the clinic for the first time upon creation in the simulation model. Each patient generated was also assumed to have a no-show probability following the distribution presented in Daggy et al. (2010): right-skewed with approximately half of the patients having a no-show probability of less than or equal to 10%, 80% less than or equal to 25% and an average rate of approximately 15% (Figure 3). Based on this distribution, we assumed that, on average, 50% of the patients will have a no-show probability of 5%, 30% of the patients would have a no-show probability of 17.5%, and 20% of them would have a no-show probability of 36.25%. After the patient's first visit, each patient had a waiting time statistic indicating the duration of time that he/she had waited in the waiting room (WR).

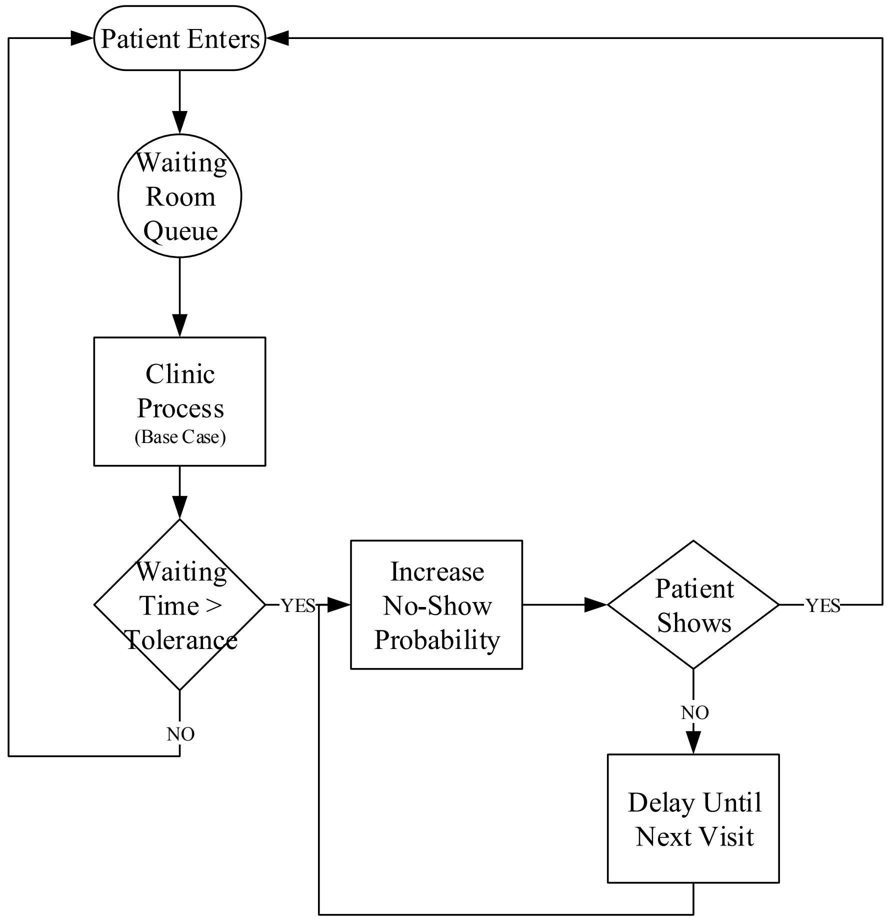


Figure 4. Conceptual Model for Overbooking and No-Shows Patients

As shown in Figure 4, when a patient came back to the clinic for a second visit, his/her no-show probability would change depending on the waiting tolerance set in the model. If his/her waiting time from the previous visit was greater than the tolerance, then the patient's no-show probability would be increased by an amount set in the model; otherwise, the no-show probability would remain the same. Based on the prediction of no-show probability, the patient might or might not show. If the patient did not show to the visit, then the visit would delay until the next visit. When a patient came back for next visit, we must account for his/her previous waiting time and added on a risk factor by increasing that patient's no-show probability, which indicated that this patient might or might not show again. Since the model would always have several patients who did not show, those patients' no-show probability could potentially exceed 100%. If that was the case, then the clinic would restraint their no-show probability to 100%. Ultimately, the number of no-shows expected to increase as patients' no-show probability approaching 100%. If the patient showed, then he/she would enter the clinic to be processed as planned. Different overbooking strategies (i.e., scheduling more patients at the same day) were also added to observe the changes on waiting time and number of no-show patients.

2.2.2 Model Validation

The test case model was separated into two phases: the first day visit and the returning visits. By doing so, this allowed us to validate the first day's statistics with the base model's statistics. If both results matched, then the test case model was validated. Using the same number of 35 replications, which was used to validate the base model, the waiting time of both the test case model and the base model resulted to be the same. Additionally, we added a no-show probability distribution following Daggy et al. (2010) to the base case model and the simulation resulted a 95% confidence interval of (1.6286, 2.4286) number of no-shows. From Daggy et al. (2010), on average, 15% of patients resulted in no-shows; with 13 patients per day for our simulation model, the average no-shows were estimated to be 1.95 (i.e., 13×0.15) patients, which was inside the 95% confidence interval from the simulation model. Thus, we concluded that the test case model was validated.

2.2.3 Test Scenarios

The test case model was used to generate a variety of scenarios to determine how the three variables affect one another at different thresholds assigned for different hypothetical scenarios.

If the no-show probability of the patient exceeded a certain threshold (Huang & Hanauer, 2014) and an appointment was not kept, then the method of booking another patient at the same time would be used (Bundy et al., 2005). After running the base model, we obtained the result of an empirical distribution of 454 patients' waiting time, which is shown in Table 1 below. Among these 454 patients, 80% had the waiting time of less than 10 minutes, and the rest had the waiting time of 10 minutes and greater. Additionally, there were about 18% of patients who waited longer than 20 minutes; approximately 16% of them waited longer than 30 minutes; about 12% waited longer than 40 minutes; and less than 10% waited longer than 50 minutes. Accordingly, we varied the threshold of waiting tolerance from 10% to 50% with a step size of 10%. A patient's no show probability would be increased if his/her previous waiting time at the clinic was above the threshold of waiting tolerance.

Table 1. Distribution of Patient Waiting Times from Base Case Simulation Model

Interval (minutes)	Frequency	Relative Frequency
[0-10)	360	79.30%
[10-20)	12	2.64%
[20-30)	6	1.32%
[30-40)	18	3.96%
[40-50)	15	3.30%
[50-60)	7	1.54%
[60-70)	8	1.76%
[70-80)	12	2.64%
[80-90)	15	3.30%
[90-infinity)	1	0.22%

Under different overbooking strategies, the effects on patient waiting time also vary. we assumed a patient's no-show behavior was dependent on previous waiting time in the clinic (Berg et al., 2013). The increase in their no-show probabilities were tested for 1%, 5%, 10% or 15% for the next return visit when previous waiting time exceeded the tolerance thresholds as shown by different scenarios in Table 2. A great number of scenario combinations were tested by varying (1) the amount increase in no-show probability, (2) waiting time tolerance threshold, and (3) overbooking strategy (Table 2).

Table 2. Different Testing Variables

Increase of No-Show Probability (%)	Waiting Tolerance (minutes)	Overbooking Decision (persons)
1	10	0
5	20	1
10	30	2
15	40	3
	50	4
		5

3. Data Analysis and Results

Since there were 4 values for the increase of no-show probability, 5 values for the waiting tolerance, and 6 values for the overbooking decision as show in Table 2, the number of test scenarios resulted to be 120 (i.e., $4 \times 5 \times 6 = 120$). The clinic performance for all 120 scenarios as summarized by average number of no-shows in a month and average patient waiting time along with corresponding confidence intervals (as represented by half-width) were recorded and shown in Table 3 below. For brevity, we refer to these two performance metrics as average number of no-shows and average patient waiting time for the rest of the report.

The organization of Table 3 was filtered by the increasing of overbooking decisions from 0 to 5 patients per day. Then, within each overbooking decision, Table 3 was again filtered by increasing of unique scenario identifiers (0 – 120), where each identifier indicated the testing value of waiting tolerance (10 – 50 minutes), increase of no-show probability (1 – 15%), and their half-widths. The table was shaded for easier comparison between scenario

Table 3. Prediction of No-Shows and Waiting Time Based on Different Scenarios

Overbooking Decision: 0 patient						
Scenario	**Waiting Tolerance (minutes)**	**Increase of No-Show Probability**	**Avg. Number of No-Shows**	**Half-width of Avg. Number of No-Shows**	**Avg. Waiting Time (minutes)**	**Half-width of Avg. Waiting Time**
1	10	0.01	12.471	0.831	23.46	0.7804
2	10	0.05	16.029	0.7338	22.005	0.7636
3	10	0.1	41.029	2.976	19.812	0.6408
4	10	0.15	69.986	3.443	18.328	0.8293
5	20	0.01	9.8	0.6372	23.405	0.8585
6	20	0.05	13.557	1.213	23.353	0.7994
7	20	0.1	28.614	2.78	20.728	0.611
8	20	0.15	53.314	3.928	19.372	0.7039
9	30	0.01	8.857	0.6526	24.763	1.021
10	30	0.05	10.643	0.7603	23.867	0.9661
11	30	0.1	21.5	2.459	22.17	0.7904
12	30	0.15	39.943	3.645	20.736	0.7545
13	40	0.01	7.886	0.6639	24.625	0.8733
14	40	0.05	9.314	0.6859	24.298	1.037
15	40	0.1	15.2	1.948	23.171	0.7768
16	40	0.15	31.971	3.248	21.007	0.6846
17	50	0.01	6.643	0.6459	25.004	0.9775
18	50	0.05	8.014	0.6038	24.094	0.9161
19	50	0.1	12.029	1.2	24.048	0.8566
20	50	0.15	25.986	2.524	22.24	0.8086
Overbooking Decision: 1 patient						
Scenario	**Waiting Tolerance (minutes)**	**Increase of No-Show Probability**	**Avg. Number of No-Shows**	**Half-width of Avg. Number of No-Shows**	**Avg. Waiting Time (minutes)**	**Half-width of Avg. Waiting Time**
21	10	0.01	13.829	0.866	28.497	1.301
22	10	0.05	18.943	1.289	26.579	1.21
23	10	0.1	53.9	3.237	22.936	1.135

24	10	0.15	83.771	3.216	21.343	1.011
25	20	0.01	11.7	0.8582	29.562	1.167
26	20	0.05	16.071	0.9736	28.417	1.031
27	20	0.1	36.457	2.103	24.633	0.8068
28	20	0.15	66.6	3.76	22.547	1.066
29	30	0.01	10.8	0.923	29.581	0.9605
30	30	0.05	13.371	1.117	28.591	0.9426
31	30	0.1	26.829	1.976	25.876	0.7878
32	30	0.15	52.5	3.347	23.596	0.8827
33	40	0.01	10.157	0.594	29.831	1.122
34	40	0.05	12.486	1.202	28.549	1.014
35	40	0.1	21.571	1.789	27.19	0.7847
36	40	0.15	42.657	3.448	24.817	0.9474
37	50	0.01	8.814	0.6679	30.505	1.261
38	50	0.05	10.643	0.8837	29.192	1.005
39	50	0.1	17.7	1.602	27.664	0.9782
40	50	0.15	35.186	3.165	24.972	1.19
Overbooking Decision: 2 patients						
Scenario	**Waiting Tolerance (minutes)**	**Increase of No-Show Probability**	**Avg. Number of No-Shows**	**Half-width of Avg. Number of No-Shows**	**Avg. Waiting Time (minutes)**	**Half-width of Avg. Waiting Time**
41	10	0.01	17.614	0.8395	34.576	1.236
42	10	0.05	24.243	1.388	31.548	0.9635
43	10	0.1	68.671	3.162	27.07	0.8854
44	10	0.15	96.214	2.887	24.758	1.168
45	20	0.01	14.929	1.04	36.154	1.396
46	20	0.05	19.843	0.8608	32.642	0.9103
47	20	0.1	48.743	3.113	28.308	1.089
48	20	0.15	81.929	3.994	25.953	1.06
49	30	0.01	12.557	0.7524	35.404	1.435
50	30	0.05	17.143	1.35	33.72	1.055
51	30	0.1	38.614	2.4	29.158	0.985
52	30	0.15	64.614	3.565	26.242	1.116
53	40	0.01	11.4	0.8869	36.33	1.138
54	40	0.05	14.229	1.189	34.929	1.225

55	40	0.1	31.829	1.681	31.088	0.8376
56	40	0.15	56.529	3.037	27.887	1.212
57	50	0.01	10.371	0.7125	36.849	1.155
58	50	0.05	13.2	0.8469	35.915	0.9646
59	50	0.1	25.143	2.327	31.16	1.294
60	50	0.15	49.271	3.283	28.015	1.179
Overbooking Decision: 3 patients						
Scenario	**Waiting Tolerance (minutes)**	**Increase of No-Show Probability**	**Avg. Number of No-Shows**	**Half-width of Avg. Number of No-Shows**	**Avg. Waiting Time (minutes)**	**Half-width of Avg. Waiting Time**
61	10	0.01	19.414	0.9176	40.724	1.246
62	10	0.05	28.543	1.448	35.445	1.062
63	10	0.1	77.314	3.135	29.898	1.558
64	10	0.15	108.9	3.928	28.587	1.768
65	20	0.01	17.214	1.054	41.655	1.462
66	20	0.05	23.071	1.157	37.857	1.322
67	20	0.1	60	3.336	31.04	1.003
68	20	0.15	91.929	3.261	30.181	1.642
69	30	0.01	14.9	0.7787	42.144	1.432
70	30	0.05	21.071	0.9628	40.35	1.357
71	30	0.1	49.314	3.047	33.687	1.157
72	30	0.15	77.086	3.56	29.568	1.26
73	40	0.01	13.386	0.7869	43.049	1.644
74	40	0.05	18.686	1.015	39.892	1.355
75	40	0.1	39.829	2.816	33.937	1.031
76	40	0.15	67.5	4.271	30.22	1.135
77	50	0.01	11.957	0.8134	44.671	1.511
78	50	0.05	15.986	0.9882	43.255	1.209
79	50	0.1	31.229	2.012	36.543	1.202
80	50	0.15	57.914	3.273	31.664	1.184
Overbooking Decision: 4 patients						
Scenario	**Waiting Tolerance (minutes)**	**Increase of No-Show Probability**	**Avg. Number of No-Shows**	**Half-width of Avg. Number of No-Shows**	**Avg. Waiting Time (minutes)**	**Half-width of Avg. Waiting Time**
81	10	0.01	22.129	1.045	47.02	1.634

82	10	0.05	33.114	1.64	44.16	1.624
83	10	0.1	88.986	3.644	34.56	1.379
84	10	0.15	120.943	3.357	32.073	1.998
85	20	0.01	19.371	1.006	49.905	2.061
86	20	0.05	26.543	1.376	45.747	1.74
87	20	0.1	74.543	2.826	36.655	1.597
88	20	0.15	104.943	3.299	33.634	1.767
89	30	0.01	18	1.115	48.946	1.63
90	30	0.05	23.771	1.131	46.471	1.79
91	30	0.1	61	2.846	36.619	1.846
92	30	0.15	91.629	3.547	32.98	1.799
93	40	0.01	15.743	0.7496	50.735	1.804
94	40	0.05	20.971	1.182	46.806	1.854
95	40	0.1	50.386	2.759	38.19	1.651
96	40	0.15	81.286	2.771	35.526	1.541
97	50	0.01	14.557	0.7419	52.564	2.107
98	50	0.05	19.571	1.143	50.264	1.993
99	50	0.1	44.314	2.786	42.258	1.184
100	50	0.15	72.829	3.1	35.783	1.63
Overbooking Decision: 5 patients						
Scenario	**Waiting Tolerance (minutes)**	**Increase of No-Show Probability**	**Avg. Number of No-Shows**	**Half-width of Avg. Number of No-Shows**	**Avg. Waiting Time (minutes)**	**Half-width of Avg. Waiting Time**
101	10	0.01	25.057	1.356	56.181	1.893
102	10	0.05	39.143	1.815	47.97	1.829
103	10	0.1	102.729	3.507	39.885	1.876
104	10	0.15	135.386	3.047	37.319	1.53
105	20	0.01	21.643	1.256	56.957	1.961
106	20	0.05	32.086	1.126	51.753	2.061
107	20	0.1	82.071	2.981	41.723	1.534
108	20	0.15	118.529	3.987	38.301	2.183
109	30	0.01	20.171	1.035	59.083	1.941
110	30	0.05	26.029	1.234	54.002	1.861
111	30	0.1	71.657	3.652	44.004	1.742
112	30	0.15	104.786	3.377	39.207	1.946

113	40	0.01	18.6	1.035	59.943	2.051
114	40	0.05	25.086	1.25	55.467	2.279
115	40	0.1	59.7	3.017	45.46	1.761
116	40	0.15	90.486	3.739	39.515	1.855
117	50	0.01	16.671	0.7977	60.245	1.449
118	50	0.05	22.5	1.075	58.927	2.016
119	50	0.1	52.314	2.541	46.585	1.935
120	50	0.15	80.171	3.673	40.324	1.661

The average number of no-shows and average waiting time for all scenarios from Table 3 were plotted in Figure 7 to visualize the change and trend. The clinic performance of number of no-shows and average waiting time exhibited some similar patterns among scenarios. Some interesting findings are as followed.

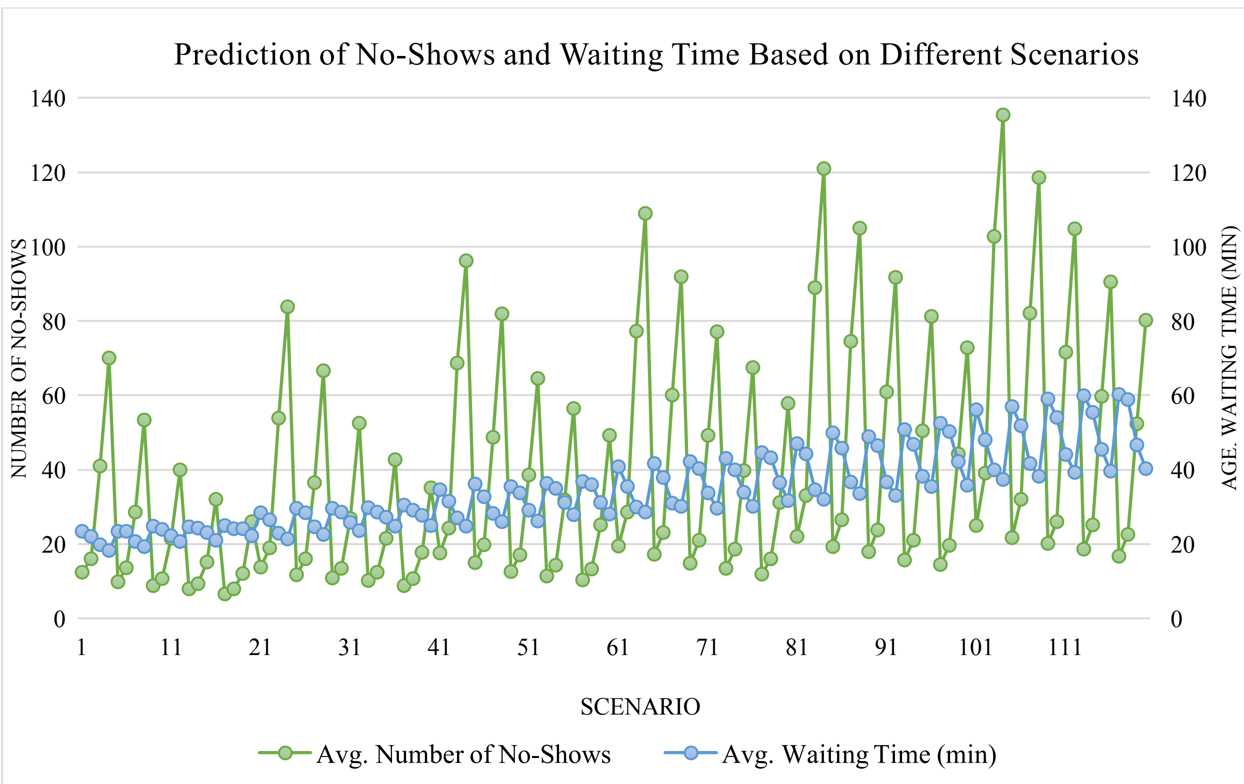


Figure 7. Distribution of Number of No-Shows and Waiting Time

Starting from scenario 1 to scenario 120, the pattern exists every 20 scenarios (i.e., one overbooking decision). Thus, 6 patterns exist for 6 overbooking decisions from 0 to 5 patients per day. Additionally, within each of the patterns, there are 5 peaks indicating the 5 waiting tolerances in combination with 4 increase of no-show probabilities.

The first pattern shows that, at the overbooking decision of 0 patient per day, at the 10 minutes' tolerance, average number of no-shows increased as no-show probability increased, and average waiting time decreased as no-show probability increased. Using 20 minute's tolerance, the same conclusion can be drawn for scenarios existing within the second pattern; however, the only difference from the 10-minute's tolerance is that the number of no-show has lessened. This is expected because, at a higher waiting tolerance, the clinic will expect more people to show up for the visit; and if so, then the waiting time will increase and the number of no-shows will decrease. It is also inevitable that if the increased of no-show probability is high, then the system results more no-shows or less patients show up, and with that, the waiting time will be less. For other patterns, the same conclusion can be used to explain the interaction of the testing variables.

As the pattern moved from left to right, corresponding to increasing of overbooking decisions from 0 to 5 patients per day, the number of no-shows increases at a small amount from overbooking decision of 0 to overbooking decision of 1 and again from overbooking decision of 1 to overbooking decision of 2. The pattern remains the same through overbooking of 5. The same findings are exhibited in the average waiting time such that the average waiting time increases at a small increment throughout all overbooking decisions. These observations are expected because as clinic overbooked more patients per day, more patients will have to wait, thus more patients decide not to come back.

To determine whether the average number of no-shows and average waiting times from the same overbooking decision group were significantly different or not, we performed statistical analyses on both variables. Using overbooking decision of 0 patient per day, the 95% confidence interval plots for the average number of no-shows (Figure 5) and for the average waiting time (Figure 6) showed clear patterns on both variables. In Figure 5, it can be seen that the average number of no-shows for scenario 1 to scenario 4 are significantly different at different level of increase in no-show probability while waiting tolerance holds (i.e. 10 minutes). The same conclusion exists for scenarios with different level of increase in no-show probability at the same waiting tolerance. The average number of no-shows for scenario 1 with 10 minutes' tolerance (95% CI: (11.64, 13.3) from Table 3) is significantly different than scenario 5 with 20 minutes's tolerance (95% CI: (9.163, 10.44), scenario 9 with 30 minutes' tolerance (95% CI: (8.205, 9.51) from Table 3), scenario 13 with 40 minutes' tolerance (95% CI: (7.222, 7.886) from Table 3), and scenario 17 ((95% CI: (5.997, 7.289) from Table 3), having the same value of increase in no-show probability (i.e., 1%). The average number of no-shows of scenario 5 is also different than that of scenario 9, 13, and 37. Furthermore, the average number of no-shows of scenario 9 is also different from that of scenario 13 and 17, and the average number of no-shows of scenario 13 is also different from that of scenario 17.

As observed, the same conclusion exists for the other overbooking decisions (i.e. 1, 2, 3, 4 or 5), the average number of no-shows of all scenarios are significantly different than one another when comparing at different waiting tolerance or at different level of increase in no-show probability.

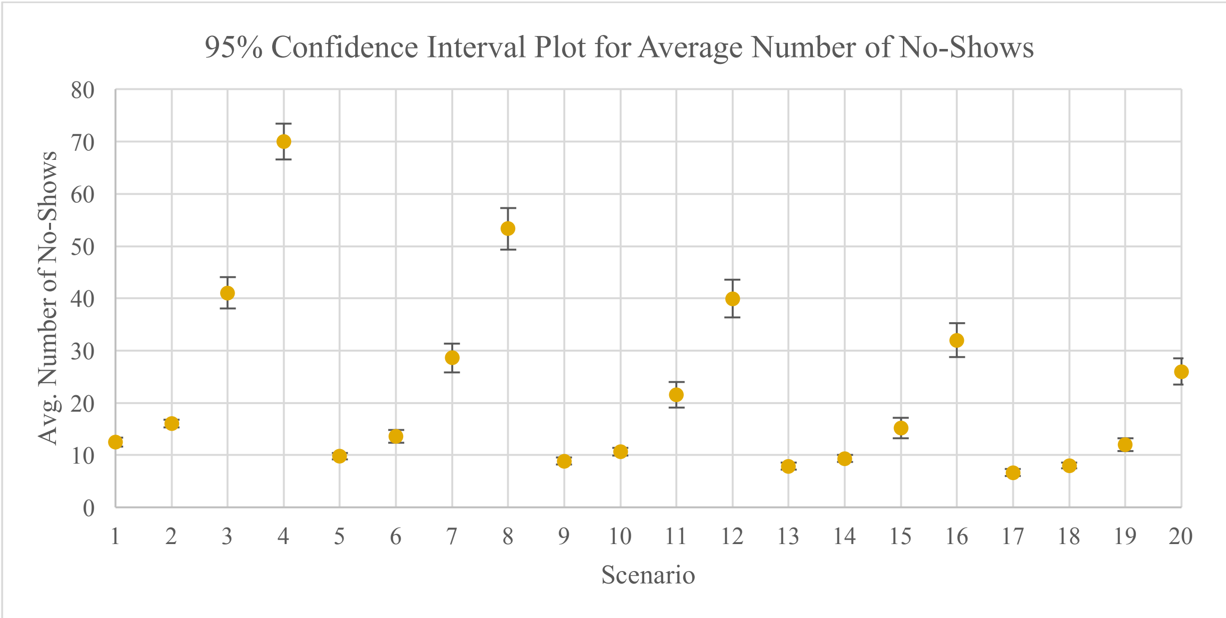


Figure 5. Confidence Interval Plot for Number of No-Shows for Overbooking of 0 Patient

In Figure 6, it is shown that the average waiting times for the same waiting tolerance are significantly different at different level of increase in no-shows. For instance, the average waiting time of scenario 1 (95% CI: (22.68, 24.24) from Table 3) is different from that of scenario 2 (95% CI: (21.24, 22.77) from Table 3), scenario 3 (95% CI: (19.17, 20.45) from Table 3), and scenario 4 (95% CI: (17.5, 19.16) from Table 3). The average waiting time for the different waiting tolerance are not significantly different when the increase in no-show probability holds at the same overbooking decision. For instance, the average waiting time of scenario 1 is not different from scenario 5 (95% CI: (17.5, 19.16) from Table 3). However, as the overbooking strategy increases, the average waiting times are significantly different from each other when waiting tolerance and increase of no-show probability hold.

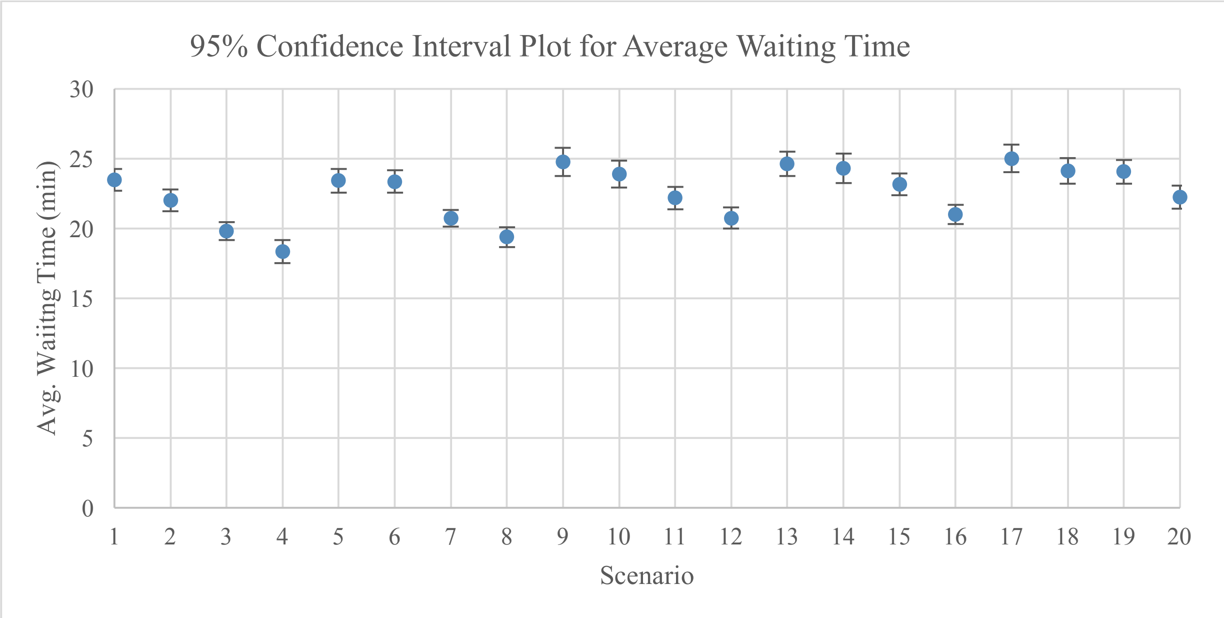


Figure 6. Confidence Interval Plot for Average Waiting Time for Overbooking of 0 Patient

As observed through the statistical analyses, we see that the average number of no-shows of all scenarios are significantly different from one another when comparing at different waiting tolerance or at different level of increase in no-show probability for any overbooking decision. We also see that the average waiting times, at different level of increase in no-show probability, are significantly different when the waiting tolerance holds, but they are not significantly different at different waiting tolerance when the increase in no-show probability holds at the same overbooking decision. Furthermore, as the overbooking strategy increases, the average waiting times are significantly different from each other when waiting tolerance and increase of no-show probability hold. The rest of confidence interval plots for statistical analyses are summarized in Appendix C (Figure 10 – 19).

Furthermore, we compare the average no-shows and average waiting time of scenarios at different overbooking decisions when the waiting tolerance and increase of no-show probability hold. We see that there are differences in the average number of no-shows. They are small when the overbooking decision changes from 0 patient to 1 patient. Then, they are larger when overbooking changes from 1 to 2. Afterward, the average of no-shows increase almost at the same increment. We see that there are differences at the average waiting times as well. The differences however do not vary much when overbooking decision changes. That is, the average waiting times increase almost at the same increment. We want to see if the metrics are affected at different overbooking strategy and at different waiting tolerance when increase of no-show probability holds. We observe that the average number of no-shows are not much different from another; however, the average waiting times are significantly different when comparing with others. This means that the statistical significance in average waiting time is caused by the overbooking decision. Finally, we also want to determine if the metrics are affected at different overbooking strategy and at different increase of no-show probability when the waiting tolerance holds. We observe that the average no-shows are significantly different when comparing with others. However, the average waiting time of overbooking 0 is different from overbooking of 1, 2, and 3. The average waiting time of overbooking 1 is not different from overbooking 2 but different from overbooking 3. Lastly, the average waiting time of overbooking 2 is not so different from overbooking of 3. This means that the statistical significance in average number of no-shows is caused by overbooking decision, and that the statistical significance in average waiting time is also caused by the overbooking decision changes but only from 1 to 2.

To further understand the association between the three variables. An extreme case of increase no-show probability of 50% was tested. Since there were 5 values for the waiting tolerance, and 6 values for the overbooking decision, the number of scenarios for additional testing resulted to be 30 (i.e. 5*6 = 30). The results are shown in Table 4 blow.

Table 4. Prediction of No-Shows and Waiting Time for 50% Increase in No-Show Probability

Increase of No-Show Probability: 50%						
Scenario	Overbooking Decision (persons)	Waiting Tolerance (minutes)	Avg. Number of No-Shows	Half-width of Number of No-Shows	Avg. Waiting Time (minutes)	Half-width of Avg. Waiting Time
121	0	10	130.429	2.312	17.057	1.022
122	0	20	120.429	3.486	17.941	1.044
123	0	30	114.671	3.553	19.194	1.494
124	0	40	106.543	4.662	18.468	1.058
125	0	50	95.514	4.952	18.369	1.222
126	1	10	144.557	2.661	20.036	1.485
127	1	20	134.271	2.634	20.579	1.36
128	1	30	124.686	3.143	19.94	1.197
129	1	40	118.471	4.139	19.034	1.205
130	1	50	109.071	5.652	19.796	1.169
131	2	10	159.3	3.182	22.358	1.976
132	2	20	149.714	2.476	21.776	1.464
133	2	30	139.4	2.959	21.537	1.283
134	2	40	131.457	4.25	21.224	1.472
135	2	50	122.086	4.529	21.853	1.56
136	3	10	170.114	2.707	23.728	2.02
137	3	20	162.2	3.059	24.804	2.123
138	3	30	157.714	3.212	26.05	1.827
139	3	40	148.529	3.828	24.223	1.492
140	3	50	140.986	5.079	23.725	1.426
141	**4**	**10**	182.814	2.724	27.511	2.61
142	4	20	176.8	2.95	28.796	2.504
143	4	30	180.314	4.057	30.163	2.679
144	4	40	171.971	4.082	29.348	2.655
145	4	50	167.329	3.941	29.326	2.013
146	5	10	194.986	3.82	28.766	2.524
147	5	20	188.657	2.731	30.051	2.845
148	5	30	180.314	4.057	30.163	2.679
149	5	40	171.971	4.082	29.348	2.655

150	5	50	167.329	3.941	29.326	2.013

The organization of Table 4 was filtered by the increasing of unique scenario identifiers (121 – 150), where each identifier indicated the testing value of overbooking decision (0 – 5 persons) and waiting tolerance (10 – 50 minutes). Each identifier also corresponded to its results of the clinic performances such as average number of no-shows, average patient waiting time and their half-widths. For a better visualization, Figure 5 shows the average number of no-shows and average patient waiting time for all scenarios including the extreme case. The red dots represent the average number of no-shows and the black dots represent the average waiting time associated with the scenarios from Table 4.

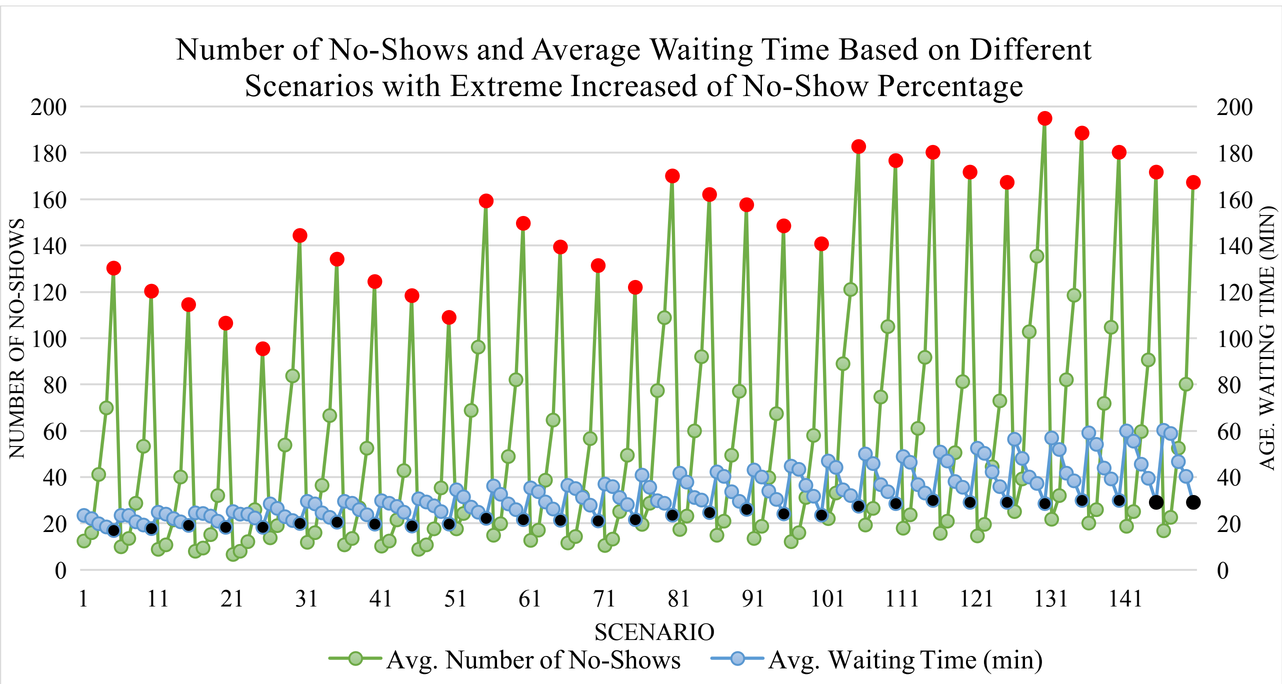


Figure 5. Distribution of Number of No-Shows and Waiting Time with Extreme Scenario

Both clinic performances change dramatically when replacing the increased no-show probability to 50%. The average number of no-shows increase greatly while the average waiting time increase gradually as well. Each peak of number of no-shows (i.e. red dots) corresponded to waiting tolerance of 10 – 50 minutes at different overbooking decisions. However, the same conclusion still applies here; as the clinic overbooked more patients per day, more patients will have to wait longer, thus more patients decide not to come back, which results in higher average number of no-shows.

We also performed statistical analyses on both variables for these extreme case scenarios. After examining the confidence interval of the average number of no-shows and the average waiting time, we saw that there were patterns on both variables. The average number of no-shows are significantly different at different waiting tolerance while overbooking decision holds, and the average number of no-shows are also significantly different at different overbooking decision while waiting tolerance holds. As for average waiting times, they are not significantly different at different waiting tolerance while overbooking decision holds or at different overbooking decision while waiting tolerance holds. However, the average waiting times at low overbooking decisions are different than those at higher overbooking decisions (Figure 20 – 21 Appendix C).

4. Conclusion, Discussion, and Future work

In terms of clinic performance, the three features (waiting time, no-show behavior and overbooking strategy) are interrelated because as clinic overbooked more patients per day, more patients will have to wait longer, thus more patients decide not to come back, which results in higher average number of no-shows. However, it is interesting to note that without using overbooking decision, at the base model, the prediction of no-shows was already 2 patients per day. Since the average waiting time did not exhibit a clear cut-off value to recommend overbooking, we now had to further investigate the trade-off value in different overbooking decisions versus average number of no-shows resulted from such decisions. For instance, looking at scenario 1 with overbooking decision of 0, the resulted no-shows were approximately 12.5 persons per day, at scenario 21 with overbooking decision of 1, the resulted no-shows were almost 14 persons per day. However, looking at scenario 41 with overbooking decision of 2, the resulted no-shows increased to almost 18 persons per day while having average waiting time increases at a steady rate. In this study, the size of the clinic case limited our capability to determine whether the overbooking decision should not solely be based on the no-shows but also on the patient waiting time. However, by having waiting tolerance and increase of no-show probability as constraints, we could say that the recommendation of overbooking strategy for this clinic was one person per day because it could might be that the extra, on average, 2.5 number of no-shows were not worth the trade-off, so that the clinic personnels could focus more on other patients.

There are some limitations to this study, one of which is the lack of observational studies that help quantifying the relationships. Because of this, there are many assumptions made when trying to translate the conceptual model to the simulation model. Another limitation is the case scenarios. At this point, all testing values are limited by the resources existed within this study. So, to further understand how resources impact the clinic performance, we recommend performing a sensitivity analysis on resources and different testing values. Another recommendation that helps draw great insights is to add different factors that affect no-shows such as appointment delay, open-access schedules, etc.

From our findings, we believe more observational studies will benefit further understanding of the relationships between the three variables: patient waiting time, no-shows and overbooking. The methodology used in this research will be broad and simple enough, in terms of modeling different hospital scenarios; the hospital's decision-makers will be able to use this research to further their understanding of the relationship between these three variables, specifically pertaining to their clinics.

5. Acknowledgements

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Appendices

Appendix A

Pseudo Code for the Base Case Simulation Model

```
CREATE Patients ~ EXPO (30) min
ASSIGN
        myArrivalTime = TNOW
        myTypeBOV = DISC(0.3751,1,0.9,20.9143,3,0.9714,4,0.9857,5,1,6)
        myTypeCOV = DISC(0.2105,1,0.7368,2,0.8422,3,0.8948,4,0.9474,5,1,6)
SEIZE Nurse
SEIZE Examining Room
ASSIGN
        myWaitingTime = TNOW – myArrivalTime
PROCESS NSF
        DELAY EXPO(1/.3201) min
        RELEASE Nurse
PROCESS ERF
        SEIZE Doctor
        DELAY EXPO(1/.0587) min
        RELEASE Doctor
DECIDE
        IF entity.type ==myTypeBOV
                GO TO Submodel BOV
        ELSE
                GO TO Submodel COV
RECORD myWaitingTime
DISPOSE Patients
```

Flow Paths for BOV Patient-Care Visit

Submodel BOV

```
DECIDE
        IF myTypeBOV == 1
                GO TO Process Type 1
        ELSE IF myTypeBOV == 2
                GO TO Process Type 2
        ELSE IF myTypeBOV == 3
                GO TO Process Type 3
        ELSE IF myTypeBOV == 4
                GO TO Process Type 4
        ELSE IF myTypeBOV == 5
                GO TO Process Type 5
```

```
    ELSE
        GO Process Type 6


Process Type 1
RELEASE Examining room
RPOCESS CHECK OUT

Process Type 2
PRCESS ERR
    SEIZE Doctor
    DELAY EXPO(1/.0846) min
    RELEASE Doctor
RELEASE Examining room
RPOCESS CHECK OUT

Process Type 3
PROCESS XR
    DELAY EXPO(1/.0433) min
PROCESS ERF
    SEIZE Doctor
    DELAY EXPO(1/.0587) min
    RELEASE Doctor
RELEASE Examining room
RPOCESS CHECK OUT

Process Type 4
PROCESS NSR
    SEIZE Nurse
    DELAY EXPO(1/.0587) min
    RELEASE Nurse
PROCESS XR
    DELAY EXPO(1/.3201) min
PROCESS ERF
    DELAY EXPO(1/.0433) min

RELEASE Examining room
RPOCESS CHECK OUT

Process Type 5
PROCESS ERR
    SEIZE Doctor
    DELAY EXPO(1/.0587) min
    RELEASE Doctor
PROCESS NSR
    SEIZE Nurse
```

```
        DELAY EXPO(1/.0846) min
        RELEASE Nurse

PROCESS XR
        DELAY EXPO(1/.3201) min
PROCESS ERF
        SEIZE Doctor
        DELAY EXPO(1/.0433) min
        RELEASE Doctor
RELEASE Examining room
RPOCESS CHECK OUT

Process Type 6
PROCESS ERR
        SEIZE Doctor
        DELAY EXPO(1/.0587) min
        RELEASE Doctor

PROCESS XR
        DELAY EXPO(1/.0846) min

PROCESS ERF
        SEIZE Doctor
        DELAY EXPO(1/.0433) min
        RELEASE Doctor
RELEASE Examining room
PROCESS ERR
        SEIZE Doctor
        DELAY EXPO(1/.0587) min
        RELEASE Doctor
RPOCESS CHECK OUT
```

Flow Paths for COV Patient-Care Visit

```
Submodel COV
DECIDE
        IF myTypeCOV == 1
                GO TO Process Type 1
        ELSE IF myTypeCOV == 2
                GO TO Process Type 2
        ELSE IF myTypeCOV == 3
                GO TO Process Type 3
        ELSE IF myTypeCOV == 4
                GO TO Process Type 4
        ELSE IF myTypeCOV == 5
```

```
                GO TO Process Type 5
        ELSE
                GO TO Process Type 6

Process Type 1
RELEASE Examining room
RPOCESS CHECK OUT
Process Type 2
RELEASE Examining room
PROCESS ERR
        SEIZE Doctor
        DELAY EXPO(1/.0587) min
        RELEASE Doctor
RPOCESS CHECK OUT

Process Type 3
RELEASE Examining room
PROCESS ERR
        SEIZE Doctor
        DELAY EXPO(1/.0587) min
        RELEASE Doctor
PROCESS XR
        DELAY EXPO(1/.0384) min
RPOCESS CHECK OUT

Process Type 4
PROCESS NSR
        SEIZE Nurse
        DELAY EXPO(1/.0587) min
        RELEASE Nurse
PROCESS XR
        DELAY EXPO(1/.3201) min
PROCESS ERF
        SEIZE Doctor
        DELAY EXPO(1/.0433) min
        RELEASE Doctor

RELEASE Examining room
PROCESS ERR
SEIZE Doctor
        DELAY EXPO(1/.0587) min
        RELEASE Doctor
PROCESS CHECK OUT

Process Type 5
PROCESS ERR
```

```
        SEIZE Doctor
        DELAY EXPO(1/.0587) min
        RELEASE Doctor
PROCESS NSR
        SEIZE Nurse
        DELAY EXPO(1/.0384) min
        RELEASE Nurse

PROCESS XR
        DELAY EXPO(1/.3201) min
PROCESS ERF
        SEIZE Doctor
        DELAY EXPO(1/.0433) min
        RELEASE Doctor
RELEASE Examining room
RPOCESS CHECK OUT


Process Type 6
PROCESS ERR
        SEIZE Doctor
        DELAY EXPO(1/.0587) min
        RELEASE Doctor
PROCESS NSR
        SEIZE Nurse
        DELAY EXPO(1/.0384) min
        RELEASE Nurse

PROCESS XR
        DELAY EXPO(1/.3201) min
PROCESS ERF
        SEIZE Doctor
        DELAY EXPO(1/.0433) min
        RELEASE Doctor
RELEASE Examining room
PROCESS ERR
        SEIZE Doctor
        DELAY EXPO(1/.0587) min
        RELEASE Doctor
RPOCESS CHECK OUT
```

Appendix B

Pseudo Code for the Test Case Simulation Model

```
PART 1: Same as Appendix A
PART 2:
ASSIGN
        myNewArrivalTime = TNOW
        vTolerance = 10
        vIncrease = 0.10
        vOrgProb1= 5
        vOrgProb2= 17.5
        vOrgProb3= 36.25
        myDist = DISC(0.5, vOrgProb1, 0.8, vOrgProb2, 1.0, vOrgProb3)
DECIDE
        IF TNOW < 1440 min
                RECORD myWaitingTime
        ELSE
                RECORD myWaitingTime
CREATE Overbooking Patients ~ overbooking strategy @ EXP (8.5) hours
HOLD All
        WAIT for SIGNAL 1
DECIDE
        IF NQ (HOLD All.Queue) > 0
                DELAY EXPO (30) min
        ELSE
                GO TO HOLD
DECIDE If WT > Tolerance
        IF (TNOW < 2280  && myNewArrivalTime  > vTolerance)  ||  (TNOW  >= 2280  &&
        myWaitingTime  > vTolerance)
                ASSIGN
                        myNoShowProb1 = myNoShowProb1*(1+vIncrease)
                        myNoShowProb2 = myNoShowProb2*(1+vIncrease)
                        myNoShowProb13= myNoShowProb3*(1+vIncrease)
                        vCount = vCount + 1
        ELSE
                GO TO PART 1

DECIDE
        IF Show
                GO TO PART 1
        ELSE
                RECORD vCount
                GO TO HOLD
```

Appendix C

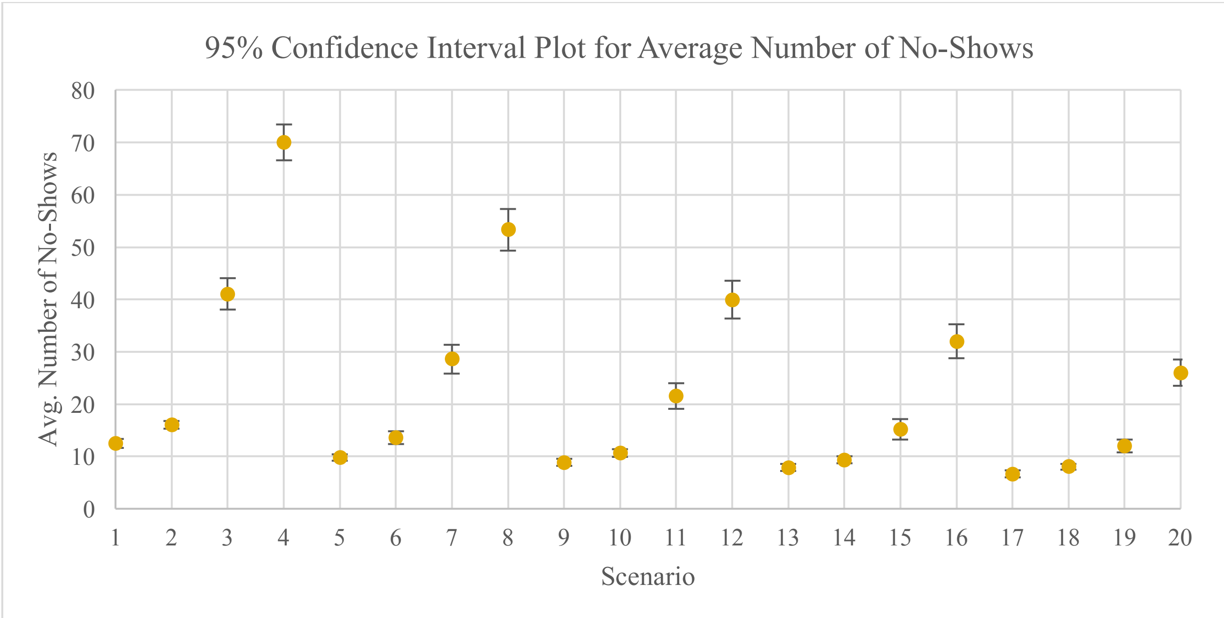

Figure 8. Confidence Interval Plot for Average Number of No-Shows for Overbooking of 0 Patient

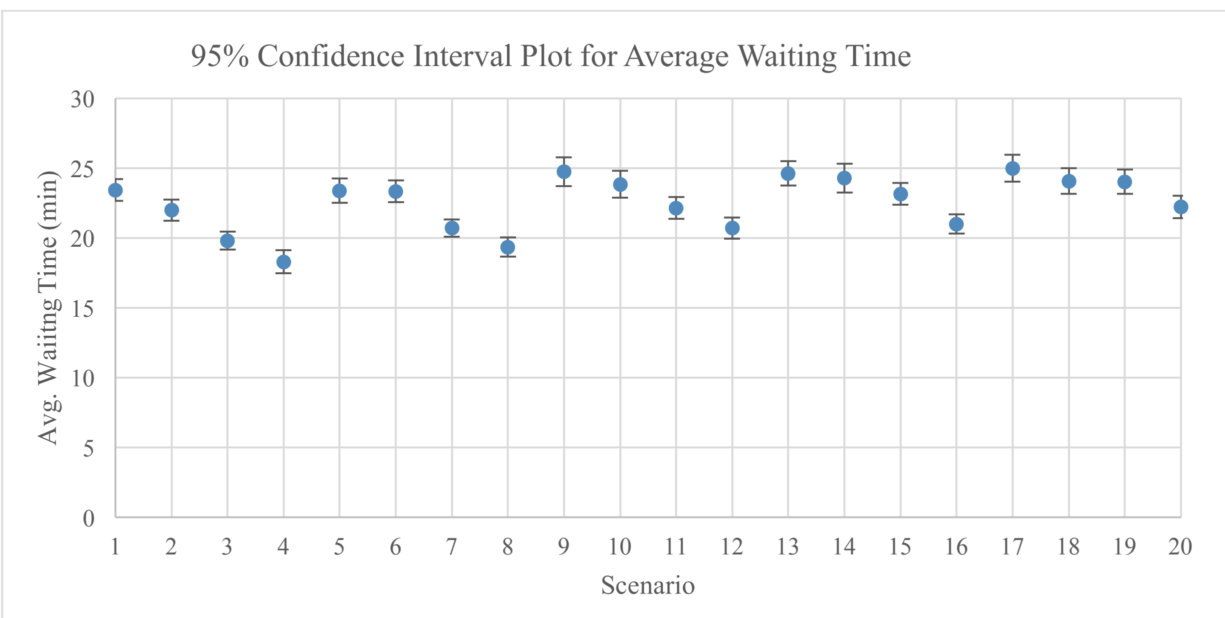

Figure 9. Confidence Interval Plot for Average Waiting Time for Overbooking of 0 Patient

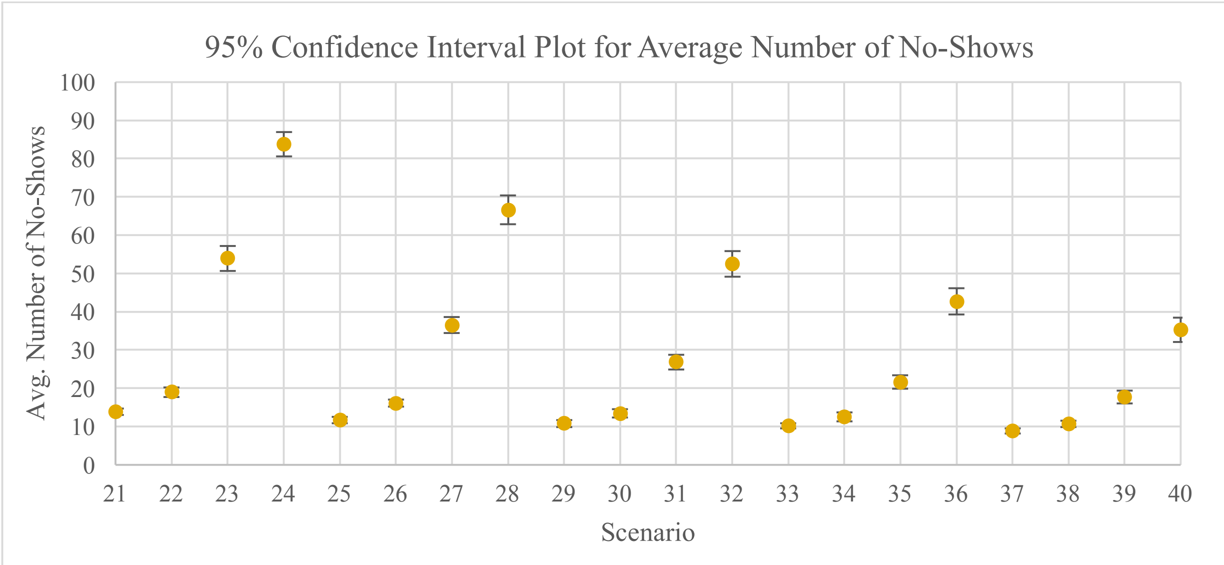

Figure 10. Confidence Interval Plot for Average Number of No-Shows for Overbooking of 1 Patient

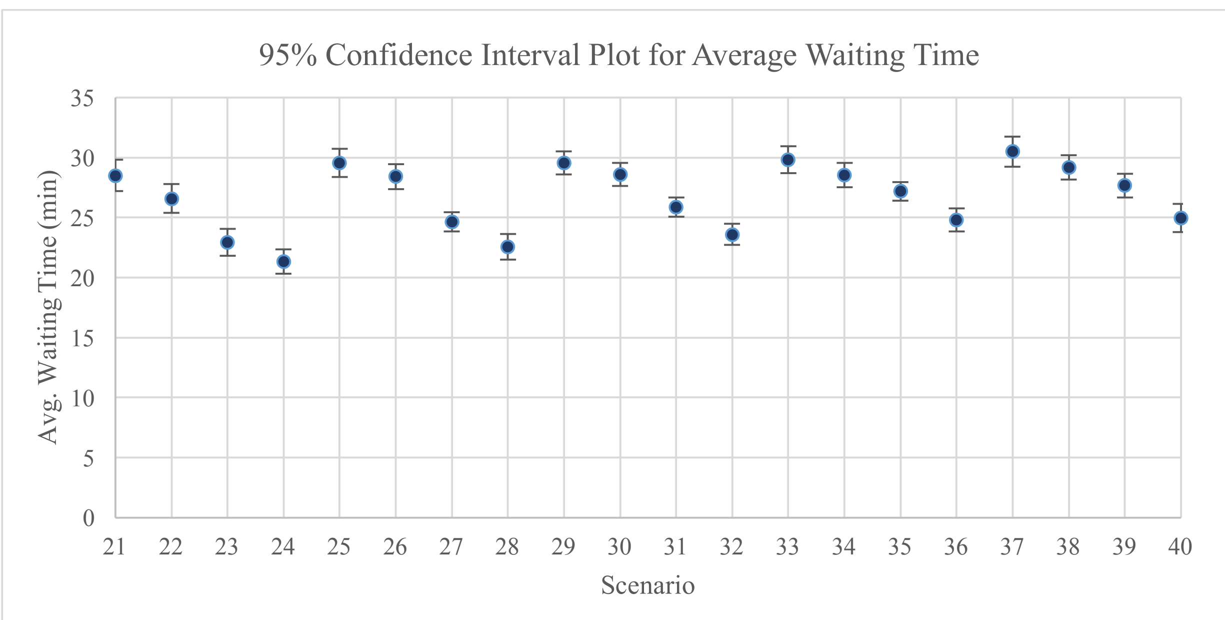

Figure 11. Confidence Interval Plot for Average Waiting Time for Overbooking of 1 Patient

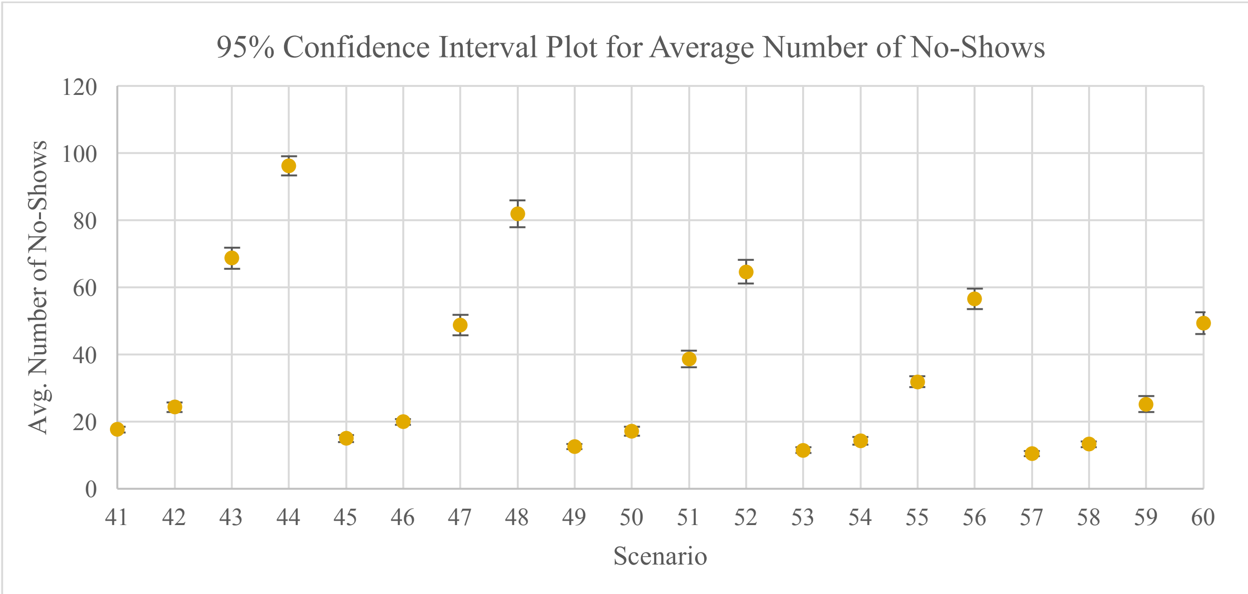

Figure 12. Confidence Interval Plot for Average Number of No-Shows for Overbooking of 2 Patients

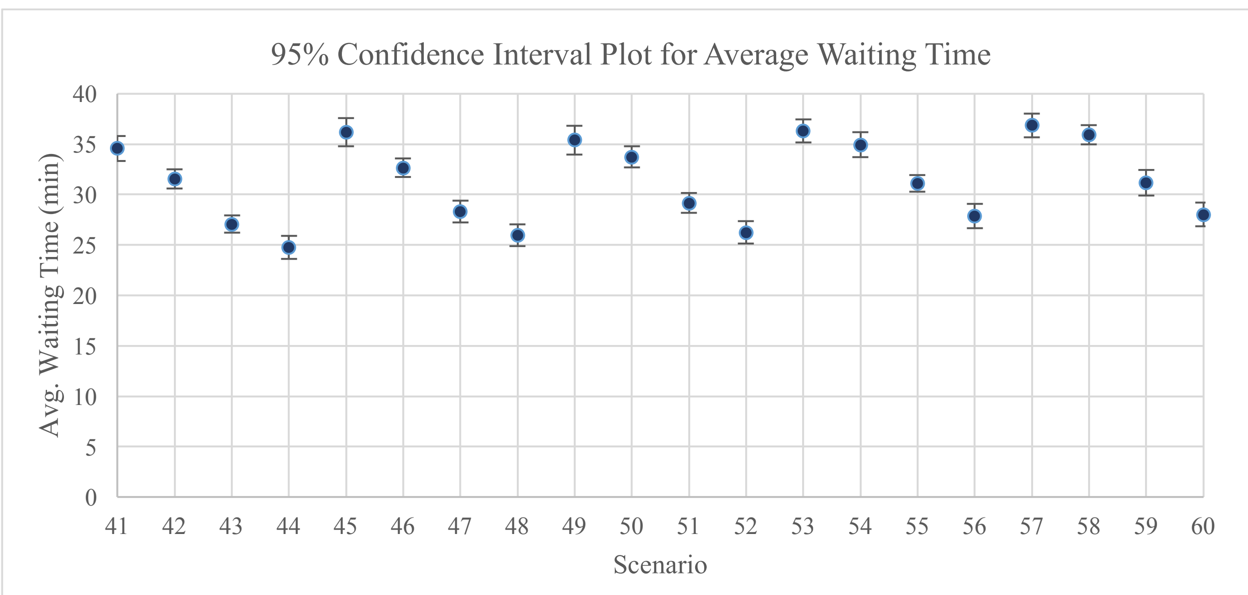

Figure 13. Confidence Interval Plot for Average Waiting Time for Overbooking of 2 Patients

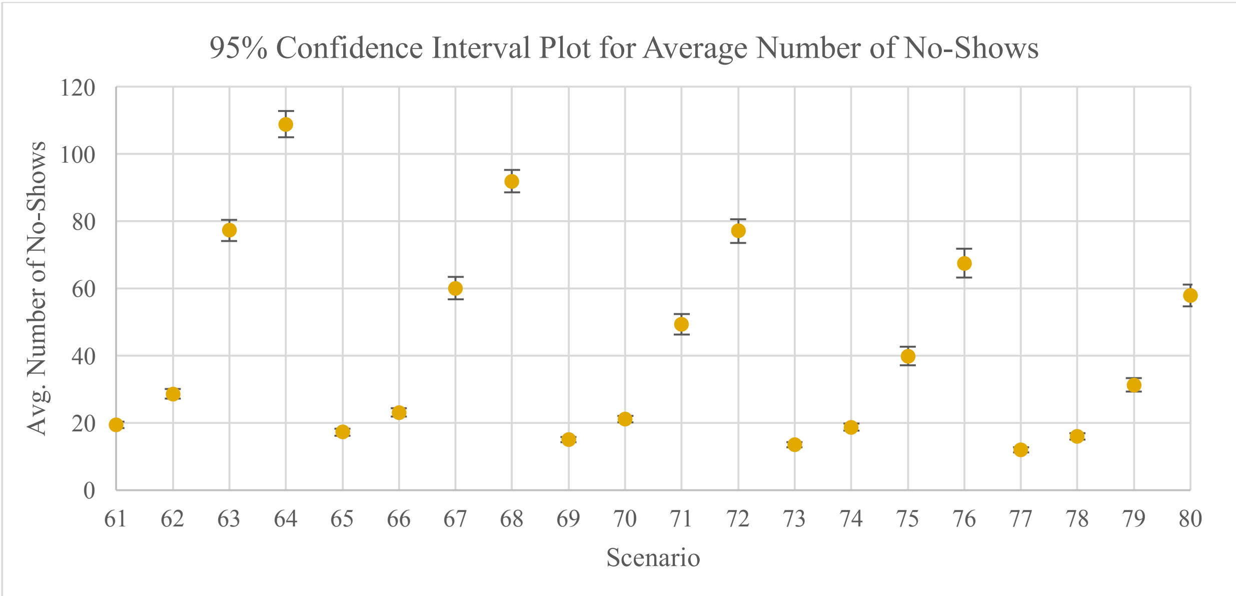

Figure 14. Confidence Interval Plot for Average Number of No-Shows for Overbooking of 3 Patients

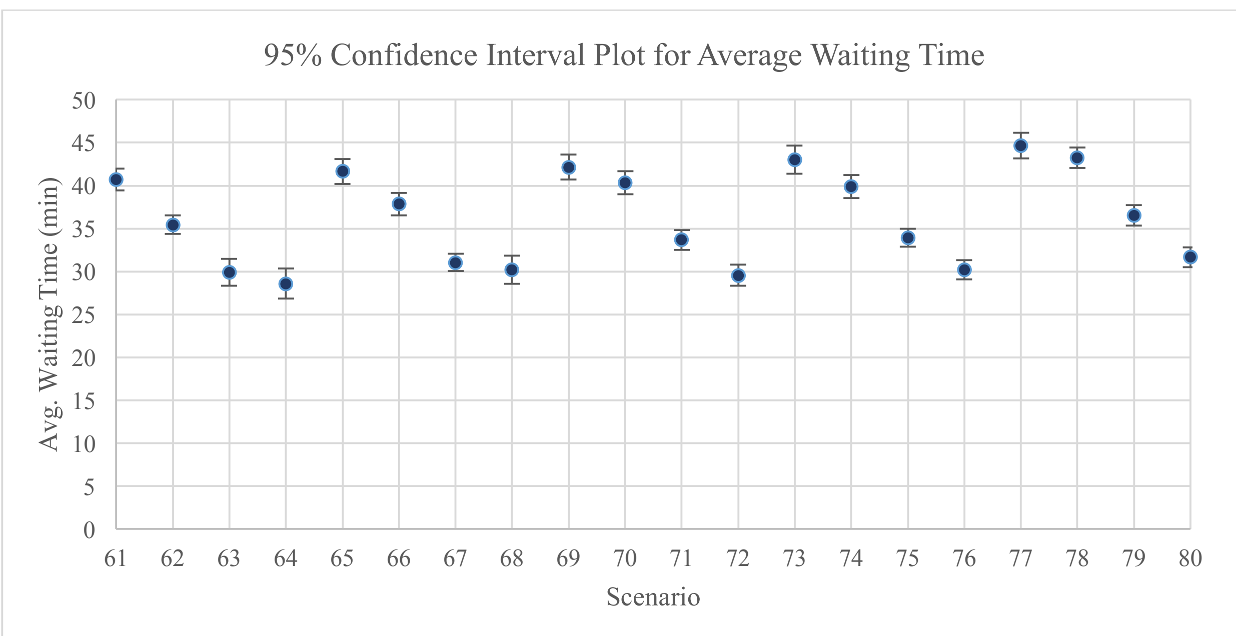

Figure 15. Confidence Interval Plot for Average Waiting Time for Overbooking of 3 Patients

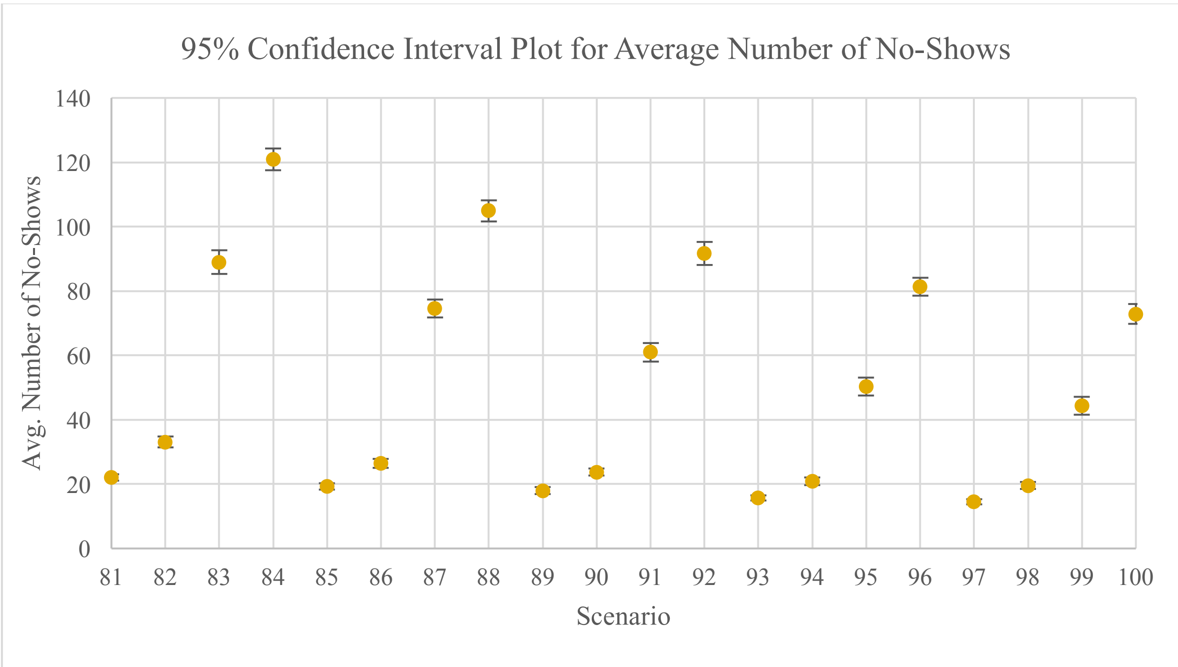

Figure 16. Confidence Interval Plot for Average Number of No-Shows for Overbooking of 4 Patients

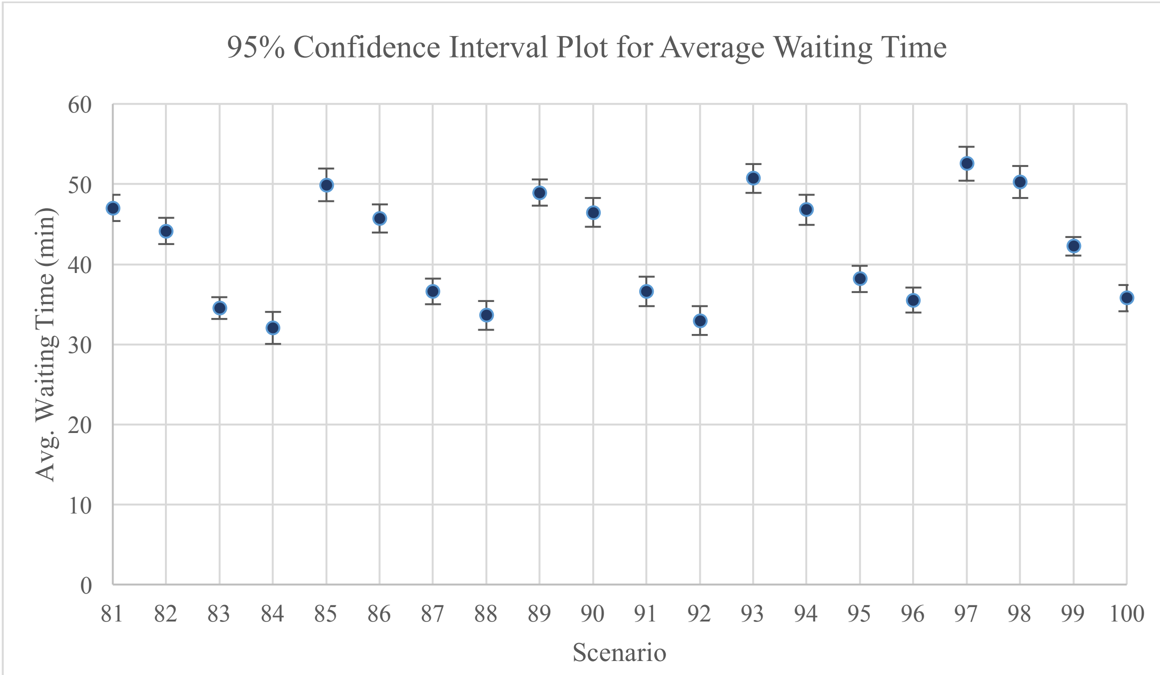

Figure 17. Confidence Interval Plot for Average Waiting Time for Overbooking of 4 Patients

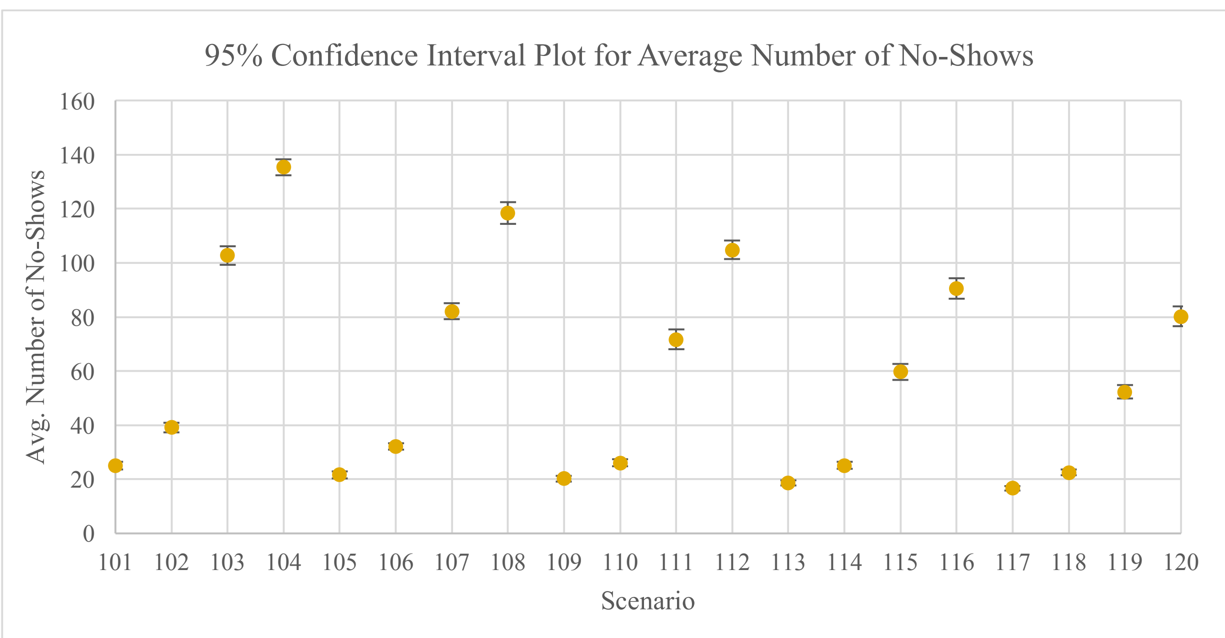

Figure 18. Confidence Interval Plot for Average Number of No-Shows for Overbooking of 5 Patients

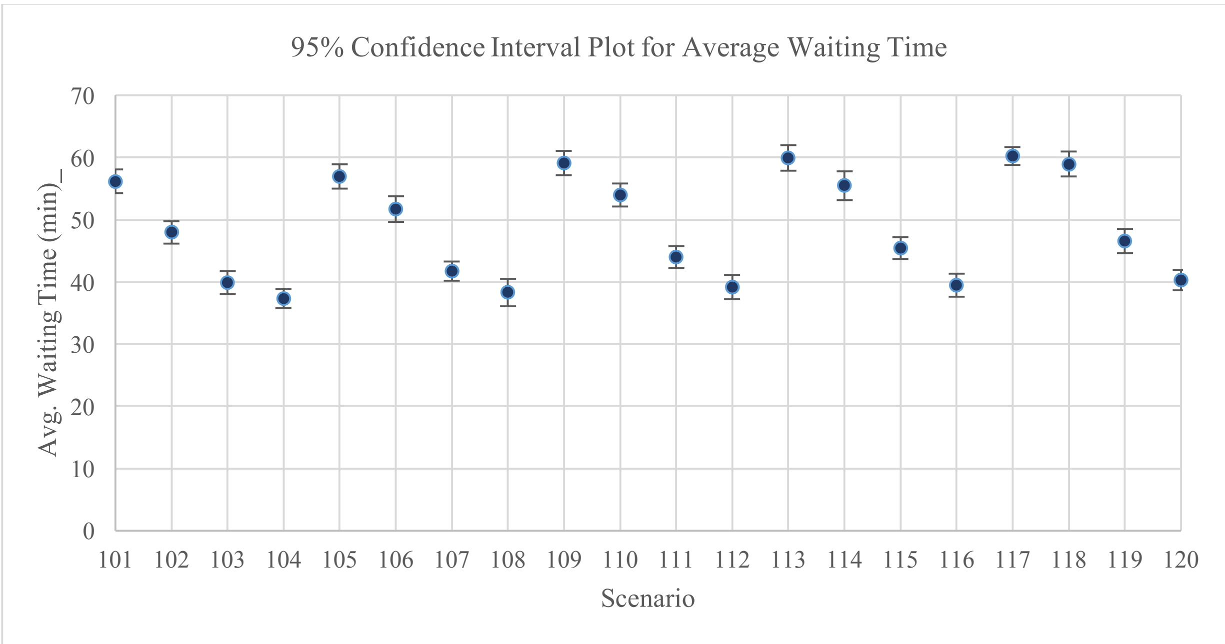

Figure 19. Confidence Interval Plot for Average Waiting Time for Overbooking of 5 Patients

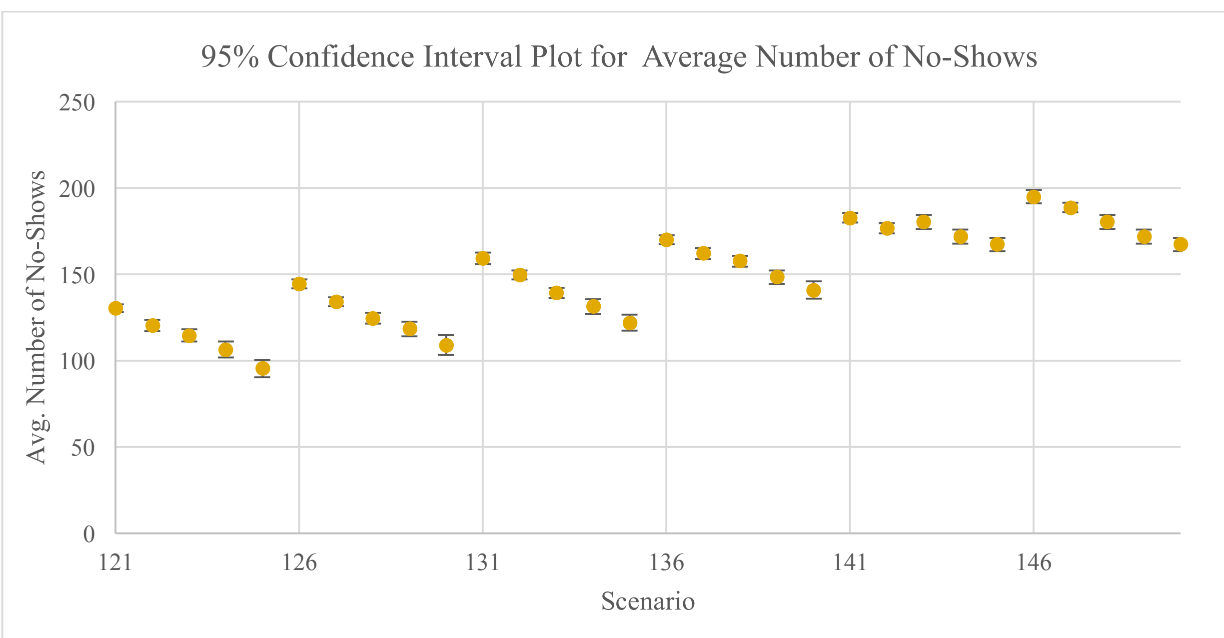

Figure 20. Confidence Interval Plot for Average Number of No-Shows for 50% Increased in No-Show Probability

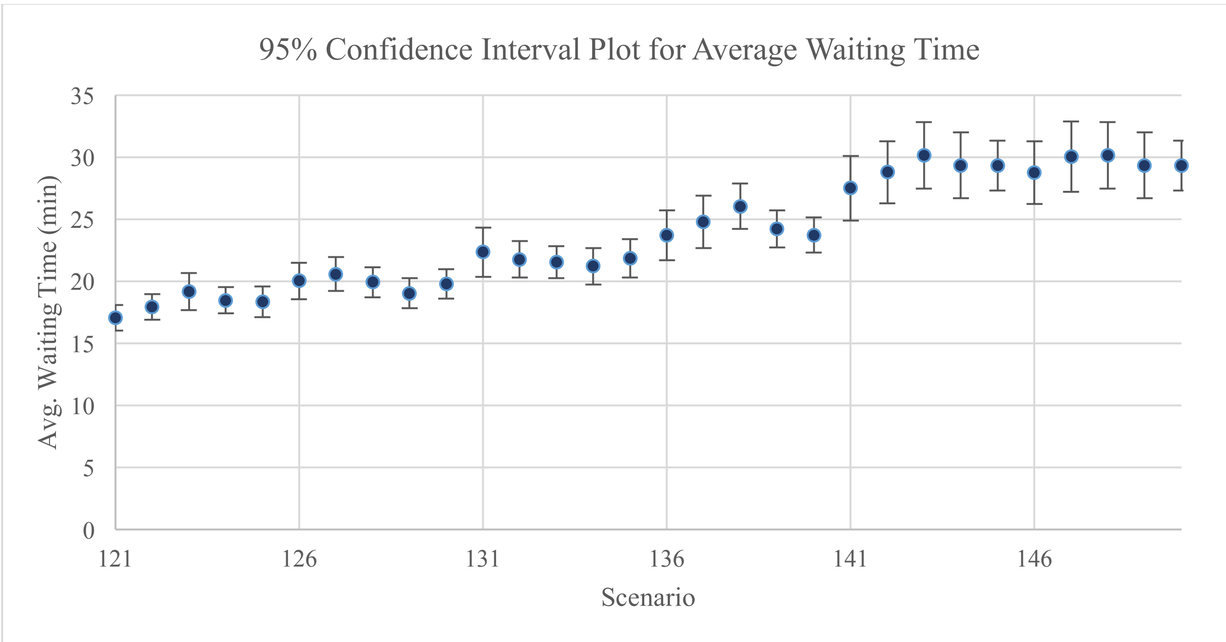

Figure 21. Confidence Interval Plot for Average Waiting Time for 50% Increased in No-Show Probability