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BAN403: Simulation of Business Processes

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Candidate numbers: 224, 250

Project 2:

Miller Pain Treatment Center

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Introduction

Dr. Keith Weems (Dr. W.) was recently appointed as the director of operations for the Miller Pain Treatment Center (AMC). Aside from his responsibilities as an attending physician in the center, he is also responsible for the care provided and the efficiency of the center. In relation to this, he is concerned that the patients might spend a considerable amount of time waiting in the center. The center's process flow includes several activities, all effecting the waiting times and thus cycle times. In addition to the quality of the care provided, waiting time is assumed to be a significant determinant of patient satisfaction. Dr. W. is aware of the importance of keeping waiting and cycle times as low as possible, and is interested in learning more about how this can be achieved. Utilizing the experience he gained in his former private clinic, he wonders if certain policy changes he conducted in the private setting would improve process flow in the more complex environment of the AMC. In particular, we identify five key questions:

- **Q1** Does **early staffing** of the front desk with one employee (PSC) from 7:30 improve the clinic's ability to stay on schedule?
- **Q2** How does **pre-processing** of patient files by residents affect the process flow by reducing resident review and teaching time during a patient's visit?
- **Q3** Can **better resident scheduling** for clinic session improve improve patient flow times?
- **Q4** How does a new **late arrival policy** affect patient flow in the AMC?
- **Q5** How can **optimizing the schedule** improve patient satisfaction?

However, all process changes are associated with certain risks, including increased costs and change in management procedures. Dr. W. hires us as consultants to deliver insights on results of the process changes to potentially convince staff and AMC management with this evidence. We use a simulation approach to achieve this.

Goals and desired outputs: This analysis is developed to benchmark, test, and analyze the process changes proposed by Dr. W. using discrete event simulation, and provide results to aid him in arguing for said changes with staff and clinic management. This is achieved by (1) building a benchmark model, (2) starting from the benchmark, building models for Q1 – Q5, and (3) evaluating output of these models against the benchmark model. We label the process change models "M1" – "M5". Since Dr. W. thinks about process improvements mostly to increase patient satisfaction, we focus our output analysis on average (1) cycle time and (2) waiting time for all patients in comparing the five questions to our benchmark model.

Assumptions: Staffing includes unlimited front desk personnel and a single clinical assistant

(CA), as these roles are typically not bottlenecks. Patients do not bail out once they have entered at the registration. They leave the system either after treatment and check-out, or if they are not assigned a room before 16:00. Although this setting allows for over-time work of all staff, it sets a realistic limit by sending patients home who have not entered an examination room before 16:00.

Furthermore, the paper remains ambiguous about the need for follow-up patients to register. It only states that they do not have to sign in, yet does not specifically rule out registration. This does not become clear through case-figure 2 either. Consequently, we assume that every patient has to register, simply because otherwise staff would not know if the patient has arrived already, which would not be realistic. We argue in the same way for check-out. Additionally, "sign in" is disregarded as a separate process step, since no data is given in the case. We see "sign in" as the arrival event that takes virtually no time.

Considering the case that the PA does not consult with the attending, we assume that the patient at hand still has to wait for the doctor to be available to sign the prescription. The signing itself, however, does not take any time, as stated in the paper. In our opinion, this is closer to the real world, instead of the patient immediately leaving without the signature. Furthermore, we assume that the service time of PA and Attending is exponentially distributed with a mean of 3 minutes, since the paper states only the mean.

Priorities in the waiting and examination rooms follow the appointment schedule, except for if a scheduled patient has not arrived yet. In this case, the next waiting patient is treated.

Input Analysis

Fortunately, the paper provides a lot of information about the process, including collected data for most activities.

Clinic schedule: In the case's benchmark process, we operate under a 100% appointment utilization rate, scheduling a new or returning patient every 15 minutes. $30/(30+40) = 43\%$ of those are new patients and $40/(30+40) = 57\%$ are return patients. Follow-up patients are added to 43% of these time slots to keep the 30:40:30 ratio. We use case-table 6 to establish these guidelines. However, in the simulation, daily schedules are randomly produced within these parameters. Appointments are set from 8:00 to 11:15 for shift 1, and 12:00 to 15:15 for shift 2. With five doctors each working two weekly shifts, we have two shifts daily.

Show-up rate: The paper states that 10% of all patients miss their appointments. We must account for them since these patients do not enter the system.

Resident cases: On average six patients (new, return) per shift are chosen as resident cases (2 cases * 3 residents). The cases are assigned randomly, and we choose the resident show-up-rate arbitrarily at 70% to leave room for answering Q3, since no numbers are specified in the case. Consequently, $6 * 0.7 = 4.2$ patients per shift are seen by a resident. This means that if a resident does not show up, the only consequence is that the patient proceeds with the "attending" step. For this step, we assume attending service times from the private clinic.

PA and Attending: For 50% of the follow-up patients, the PA has to consult with the attending. This takes on average three minutes (see assumptions).

Other resources: Not to be neglected are four examination rooms as resources, of which one is always used by the PA. Furthermore, there is only one PA, one attending, and we assume one CA and unlimited front desk capacity.

Parametric distributions: For all other activity times, the case provides sample data. To simulate the process, we need to determine the distributions these times follow. We conduct this analysis in R (see attachment 18), using mainly the 'fitdistrplus' package. The procedure is as follows:

1. First, we inspect the histograms of all variables to determine which distributions could potentially be a good fit.
2. We define a set of parametric distributions for fitting. We choose only continuous distributions available in JaamSim. Uniform, Triangular, Normal, Exponential, Erlang, Gamma, Beta, Weibull, Log-Normal and Log-Logistic.
3. We fit the set of distributions to all available variables and inspect the fit. An example is displayed in figure 1. Included in the plot are all variables from case-table 1.
4. The goodness of fit is evaluated based on the Kolmogorov-Smirnov (ks) statistic. The ks statistic assumes no specific distribution. Therefore, it should apply to all distributions we fit.
5. We select the best fitting distribution for the input in the simulation model.

Table 1 in the case-descriptions contains sample times of the activities labeled Registration, Vitals, Physicians Assistant and Check-Out. All values are positive integers, thus we have a wide selection of distributions to evaluate. The results of the distribution fitting of these activities is presented in figure 1.

Both the Log-Logistic and the Gamma distributions follows that data closely for the Registration data. However, the Log-Logistic overestimates the density around the mean, and the Gamma overestimates the right-tail values. Based on the ks stat, the Log-Logistic provides a better fit, implying that the ks test values the fit to the tails more than around the mean in this case. Based on this, we assume that the times of this activity follows a Log-Logistic distribution with a shape parameter of 2.94 and scale of 3.7.

The Log-Logistic and the Weibull provide good fits to the Vitals data. However, the number of bins in the histogram makes it difficult to determine the best fitting distributions on visual inspection alone. Relying on the ks statistic, we assume that this activity follows a Weibull distribution with a shape parameter of 2.11 and scale of 3.98.

For the physician assistant times, both the Log-Logistic and Log-Normal follows the data closely. However, the ks statistic is lower for the Log-Logistic, likely due to a better fit to the right-tale values. It is thus assumed that the time it takes the physicians assistant to service the follow-up patients follow a Log-Logistic distribution with shape parameter of 3.29 and scale of 19.16.

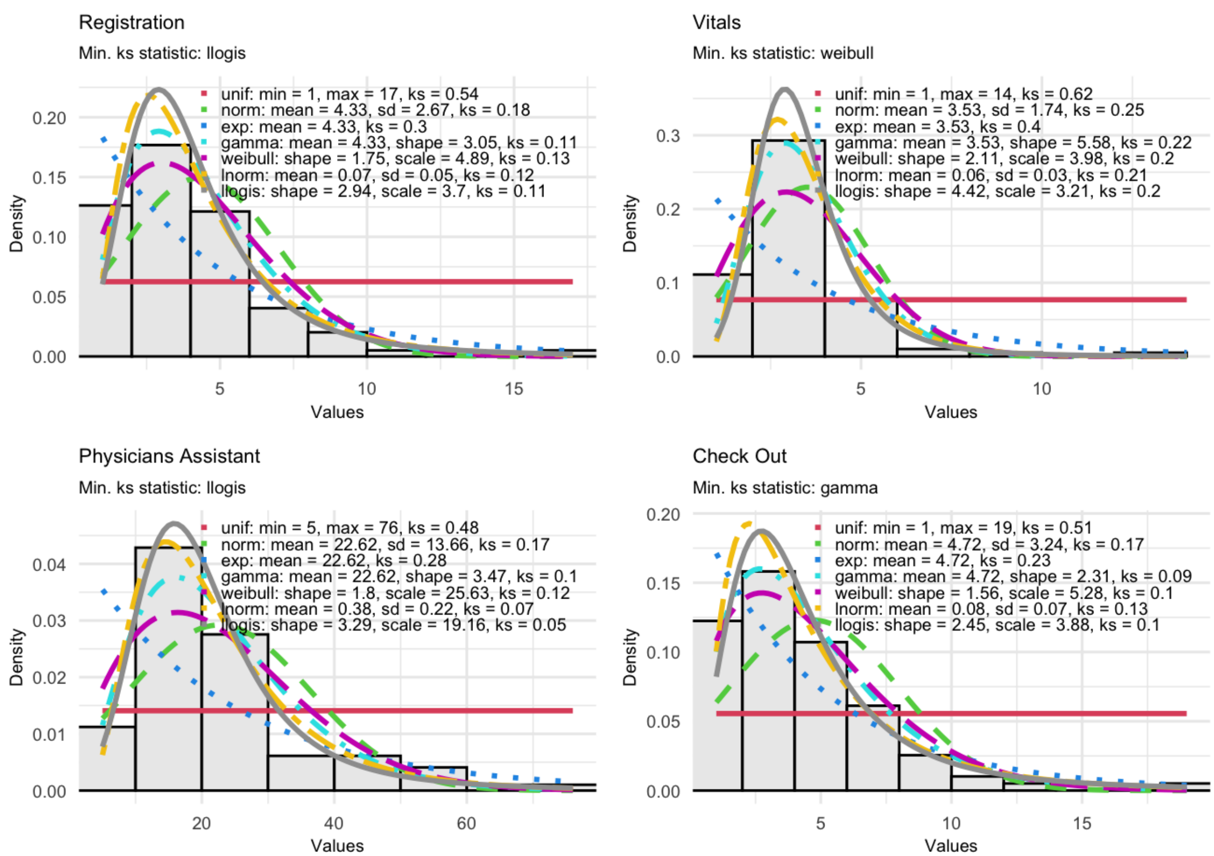

Figure 1: Fitted distributions to the variables in case-table 1 with corresponding input parameters for JaamSim and ks statistics.

The Weibull and Log-Logistic distribution also appear to provide good fits for the check-out activity times. However, the Gamma follows the data more closely both around the mean and the tail values, resulting in a slight improvement in the ks statistic. Thus, we assume that this activity follow a Gamma distribution with mean of 4.72 minutes and shape of 2.31.

Fitting distributions to the other activity times follows the same procedure as for figure 1. To see the remaining plots, we refer to the appendix (see figure A1 – A4). The distributions we use in the simulations with corresponding parameters and ks statistics is presented in table 1.

Table 1: Best fitting parametric distributions by KS stat.

Activity	Best Distribution	KS stat
Attending time new	LogLogistic(scale = 29.15, shape = 4.88)	0.09
Attending time return	Weibull(scale = 19.13, shape = 2.35)	0.1
Arr - app time before	Normal(mean = -24.09, sd = 24.64)	0.11
Arr - app time after	Normal(mean = -25.55, sd = 16.03)	0.1
Resident review new	Exponential(mean = 10.44)	0.17
Resident review return	LogNormal(NMean = 9.38, Nsd = 12.39)	0.07
Resident and patient new	LogNormal(NMean = 20.31, Nsd = 12.23)	0.09
Resident and patient return	Weibull(scale = 14.65, shape = 1.74)	0.07
Teach new	Normal(mean = 7.85, sd = 5.59)	0.2
Teach return	Normal(mean = 5.17, sd = 4.04)	0.13
Resident and attending new	LogLogistic(scale = 10.67, shape = 2.78)	0.07
Resident and attending return	LogNormal(NMean = 9.15, Nsd = 7.8)	0.09

Simulation Models

The following makes remarks about the most important components of the JaamSim benchmark model, and the modifications to simulate Q1 – Q5.

Patients are simulated entities. Doctor, CA, and PA are resource units. All patients for one day are generated at the same time, separating follow-up and new or return patients. This occurs every 24 hours, always with the same number of patients. Each new or return patient is assigned one of the 28 15-minute time slots between 8:00 and 11:15, and 12:00 and 15:15 using a ValueSequence object. The same happens for follow-up patients, except that only 43% of the 28 slots are assigned. This is the patient's appointment time. Next, a value from the early-delay-distribution is added to the appointment time, resulting in the actual arrival time, and the patient is delayed by this arrival time before entering the actual system. Additionally, 10% of the patients exits immediately due to the now-show-rate, and some are rejected due to late arrival. If the assigned arrival time is before 8:00, an entity gate is blocking the patient before proceeding to registration, which is controlled by a time series threshold. Furthermore, important attributes assigned during the arrival process are "ResidentCase" (True, False), "NeedsAttendingConsultation" (True, False), "PatientType", "Rejected" (True, False), and

"WaitingTime". Figure 2 displays this arrival process in JaamSim.

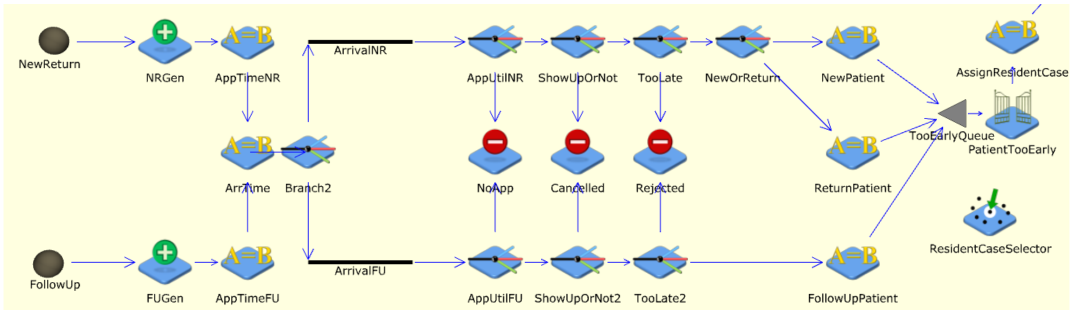

Figure 2: JaamSim arrival process for the benchmark model.

Two separate waiting room queues for different patient types in conjunction with entity gates make sure that the correct patient type is released to the examination rooms depending on whether room 1-3 or room 4 (PA room) becomes available. A patient may enter a room when the CA is ready to take vitals, signaled by an expression threshold. We model rooms in separate lines, where occupation is signaled by a signal threshold. After vitals, the "Rejected"-attribute on the patient determines whether he is a resident case or not. If not, the patient passes through resident review and resident & patient with 0 service time and just waits for the attending ("WaitDoc"-queue). Otherwise, the service time is drawn from the respective distributions. When the attending is available, "DocEnters1" seizes the "Doctor"-resource, and the patient is attended. After teaching (only resident case), and attending is finished, the "Doctor"-resource is released and the patient passes through a signal threshold "opening" the respective room, and to an entity conveyor simulating the check-out. For follow-up patients, we model a separate room without the resident-servers. For patients where the PA does not consult with the attending, the follow-up passes through a signal threshold immediately to leave the room, and is routed to the "WaitDoc"-queue to wait for the doctors signature. In consultation cases, PA and patient wait in the room for the doctor. The PA resource is then released and the room opened after PA and attending leave. We assign states at all steps in the process, including the waiting times at the "TooEarlyQueue", "WaitingRoom", "WaitingRoom2", "ResidentReview", and "WaitDoc". Especially the total waiting time, summing up the above, is important for our output analysis. We assign the sum of the waiting times to each patient as an attribute at the end of the process and collect this total waiting time at a statistics object. We use the "RenegeCondition" in the waiting room queues to simulate when patients are sent home because the clinic is closing and they could not be accommodated. Importantly, in the waiting room queues and the doctor queue, the priority input is used to sort patients by appointment time.

In the following, all adjustments of the benchmark model to simulate Q1 – Q5 are described.

M1 simulating Q1: We carry out a minor process change after the TooEarly-EntityGate. The gate now opens at 7:30. However, patients arriving before 8 are routed to a single server (PSC), since only one PSC is working between 7:30 and 8:00. The PSC is working with the same service time distribution as the registration EntityConveyor. An EntityGate after the PSC server then stops the patients from proceeding further until the rest of the clinical staff starts work at 8:00. After 8:00, patients are routed normally to the registration.
M2 simulating Q2: Merely the resident-review distributions and the teaching distributions are adjusted. Since Dr. W. estimates that time could be cut in half for these activities, we simply divide the means stated in the input analysis by two for resident review and teaching. We assume that Dr. W. has expert knowledge about this, and that his estimates are correct.
M3 simulating Q3: We run three scenarios increasing the show-up rate of residents to 0.8, 0.9, and 1. Consequently, there are $6 * 0.8 = 4.8$, $6 * 0.9 = 5.4$, and $6 * 1 = 6$ resident cases in the respective scenarios. We choose this method to evaluate whether better predicting resident show-up, and thus adjusting schedules to reduce missed clinic session, results in a better process flow.
M4 simulating Q4: Two changes are conducted. First, in determining the actual arrival time, the distribution from case-table 3 "after policy change" replaces the distribution "before policy change". Second, at the "TooLate"-branch (figure 2), patients are routed to "Rejected", if their arrival time is greater than their appointment time.
M5 optimizing scheduling: Before optimizing the schedule using a simulation approach, we prepare multiple randomly (following the guidelines given and assumed from the case) assembled schedules for a day (two shifts). We create 50 schedules for each utilization of 26, 27, and 28, meaning 26, 27, or 28 of the daily 28 15-minute slots are allocated with new and return patients respectively. This results in 150 scenarios to simulate. The creation of these schedules is conducted in R and available in attachment 14. The output from the R file, which is the input data to the JaamSim simulation, is split into two files, one containing the time slot sequences, and one containing the patient type sequences for each scenario (see attachments 15 and 16). We now change some technicalities in the JaamSim arrival process. Since the input files contain 42 time slots or patient IDs (some of them being 0), 42 patients are generated at the beginning of each day and are subsequently assigned the values from the FileToMatrix objects "Times" and "PatientTypeID". This way, the patient type is "merged" with the according appointment time as attributes on each patient-entity. Patient-entities with 0s in these attributes leave the system immediately (they are not scheduled). We record

metrics for each replication and scenario to determine the optimal schedule (scenario) in the output analysis.

All model configuration files are included in attachment 1 – 6

Output Analysis

As stated in the objectives and desired outputs that all our models output cycle and waiting times to enable further analysis. We are thus able to test if the average times for M1 – M5 deviate significantly from the benchmark model performance. To provide statistical proof of differences in simulated times, we rely on Welch's and Student's right-tailed t-tests. These tests make different assumptions about the sample variances. Welch's assume differences in sample variance, Student's t-test do not. Therefore, we conduct F-test to statistically determine which t-test to use. All output analysis is conducted in R and available in attachment 17.

We simulate 10 replications of 500 days. The number of replications is chosen to reduce the variance of the simulation estimates. Additionally, with this number of simulation days, we believe that the estimates of the average cycle and waiting times provide reliable estimates for an average day at the clinic under the modeled conditions.

In the following, the results of testing differences in average cycle and waiting times for all patients is presented.

Simulations of Q1 show that employing one PSC to register patients from 7:30 to 8:00 has a significant effect on the performance measures. Average cycle times are reduced by 2.4 minutes, and average waiting times are reduced by 3.6 minutes. The t-statistic is greater for waiting times than for cycle times, indicating that opening the doors earlier for registration likely has a greater effect on waiting time than on cycle time.

Dr. Weems' proposal of resident pre-processing shows great promise in reducing the time patients spend in the clinic. Both cycle and waiting times are reduced by approximately 4.8 minutes on average in the simulation. We compute t-statistics of 8.81 for average cycle times and 9.45 for average waiting times. The larger t-statistic for average waiting times suggests that resident pre-processing might have a greater effect on this measure.

To address Q3, we simulate reductions in the assumed probability of a resident missing a session from 30% to 20%, 10%, and 0%, respectively. The average cycle times are reduced by 3.0 minutes, 6.0 minutes, and 8.4 minutes for these probabilities, while waiting times decrease by 3.0 minutes, 5.4 minutes, and 7.8 minutes, respectively. The differences between the t-statistics within each prediction probability are small, suggesting that an increased probability of residents showing up has a similar effect on both average waiting and cycle times.

Simulating Q4 with M1 results in reduced average cycle times by 7.2 minutes and reduced average waiting times by 7.8 minutes. T-tests on the estimated averages for the cycle and waiting times output t-statistics of 13.20 and 14.72, respectively. The difference in the statistics indicates that denying access to late patients likely has a greater impact on waiting times. However, both statistics provide significant evidence of this policy's effect on average cycle and waiting times at the clinic.

Lastly, we simulate the operations with different scheduling policies. We are interested in the effect of both varying the number of appointments, as well as the order in which patient types are scheduled. The 150-scenario model identifies one optimal schedule for each utilization level. The three optimal schedules are displayed in table A1. Remarkably, the simulated schedules range from 1.27h cycle time to 1.9h cycle time. Similar intervals are observed for waiting time. Even for full utilization of 28 appointments, the optimal schedule reduces the cycle time from 1.67 hours to 1.42 hours and the waiting time from 1.14 hours to 0.86 hours. As expected, if a smaller utilization is chosen, times are reduced further.

We assume that patient satisfaction is determined by both time spent in the center and if they are being accommodated. Furthermore, comparability to the benchmark model is only given for full utilization rate of 28. Consequently, we will limit the testing to 28 daily appointments. Nevertheless, the smaller utilization rate can be an additional insight for Dr. W. to consider in the future. T-statistics of 29.15 and 36.20 for the average cycle time and waiting time respectively greatly exceed the critical value of 1.64 for both tests. Thus, we are confident in saying that optimizing the scheduling order will likely reduce both average cycle times and waiting times.

We did additional tests for the average cycle times for the different types of patients and differences in the average rejection rate. All averages and the results of all conducted tests is presented in table 2.

Conculsions and Recommendations

This report set out to answer five questions related to process changes in the AMC. The questions were raised by Dr. W., and evidence was needed to convince management and staff of partly disruptive process adjustments. Through a clear objective definition, elaborate assumptions, and statistically supported input analysis of important clinical activities and processes, we were able to create simulation models that resemble the real process to the necessary extent. Staying within reasonable boundaries for the simulation, we believe that the well reasoned models are necessary to provide meaningful insights for Dr. W.

Table 2: Average values in all simulations for selected measures.

Model	**CT**	**WT**	**CT-N**	**CT-R**	**CT-FU**	**RejRate**
Benchmark	1.67	1.15	1.71	1.48	1.9	0.068
Early Opening of Front Desk	1.63*	1.09*	1.68*	1.44*	1.86*	0.066*
Late Arrival Policy Change	1.55*	1.07*	1.6*	1.36*	1.76*	0.046*
Resident Preprocessing	1.59*	1.1*	1.61*	1.4*	1.84*	0.058*
Resident Scheduling Accuracy 100	1.53*	1.02*	1.56*	1.32*	1.8*	0.049*
Resident Scheduling Accuracy 90	1.57*	1.06*	1.6*	1.37*	1.83*	0.056*
Resident Scheduling Accuracy 80	1.62*	1.1*	1.66*	1.42*	1.86*	0.061*
Schedule Optimization (28)	1.42*	0.86*	1.57*	1.24*	1.54*	0.044*

* significant at the 95% confidence-level
All measures except for rejection rate in hours.

Our findings clearly indicate that the process changes proposed by Dr. W. lead to statistically significant improvements in overall cycle and waiting times. We can now answer all the questions raised in the introduction and give recommendations to Dr. W. for process changes. As table 2 evidently shows, all proposed measures lead to process improvements.

The greatest improvement is achieved by the schedule optimization. We are aware, however, that sticking to a policy of strictly scheduling patient types in specific time slots, may not always be possible. In worst case, it may lead to patient dissatisfaction because patients are not offered their preferred appointment time. However, we believe that Dr. W. can utilize his experience in explaining the necessity of certain policy changes to patients to counteract this. Additionally, the 150 scenarios offer insight and flexibility in choosing schedules. It must not always be the optimal schedule, but there are multiple "good" schedules, and a further analysis may uncover patterns that should be avoided. The models and material we provide may be utilized for further process improvement proposals, as they offer great flexibility for adjustments or adding components.

Importantly, we do not recommend Dr. W., even if possible, to employ and enforce all process changes at the same time. We did not simulate or test a model incorporating all five process changes against the benchmark model. Although it is likely that this model may reveal great results, the true outcome remains unclear until simulated or tested. Dr. W. should employ one change at a time for a certain period of time and assess the effect in the real world, before implementing further policies.

Nevertheless, the evidence of simulation models, supported by statistically significant measures, should be enough for Dr. W. to convince staff, more experienced fellow doctors, and clinic management, to realize process changes in the AMC.

Appendix

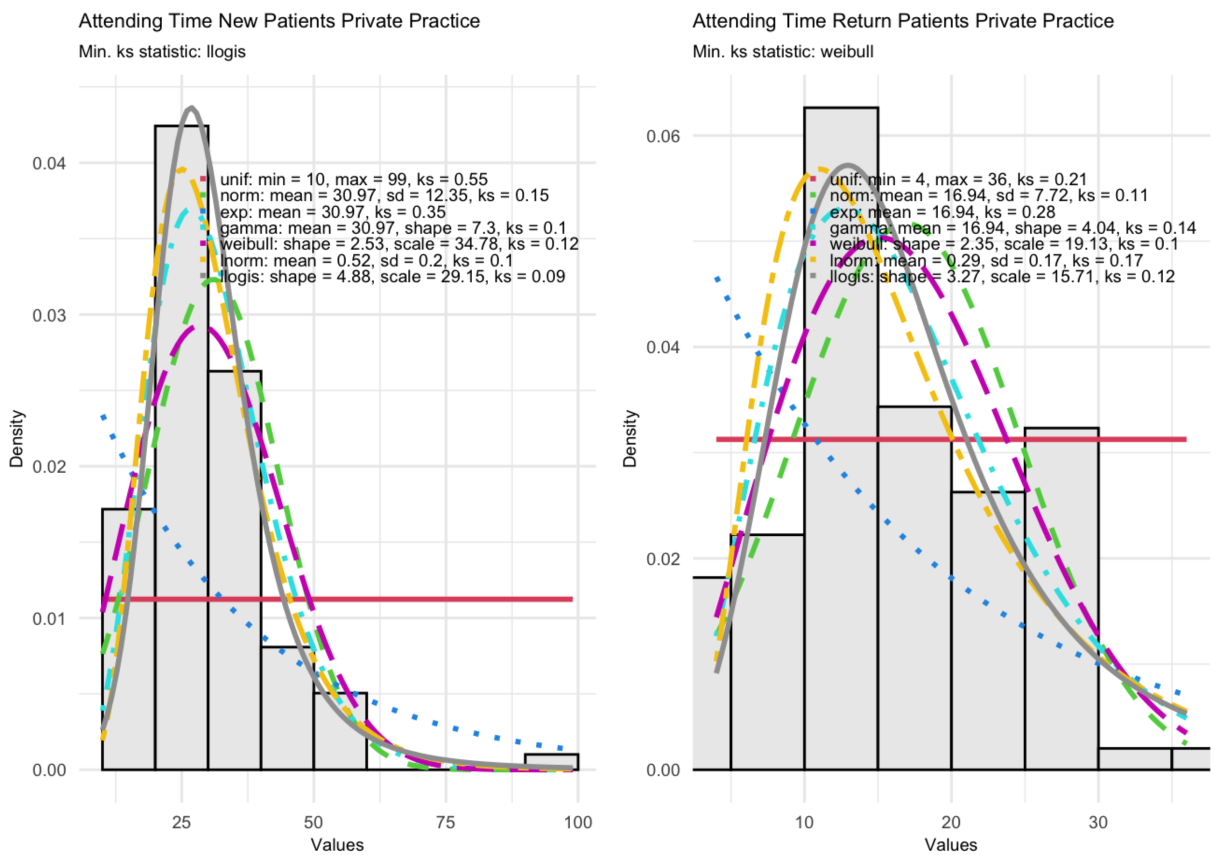

Figure A1: Fitted distributions to the variables in case-table 2, parameters, and ks stat.

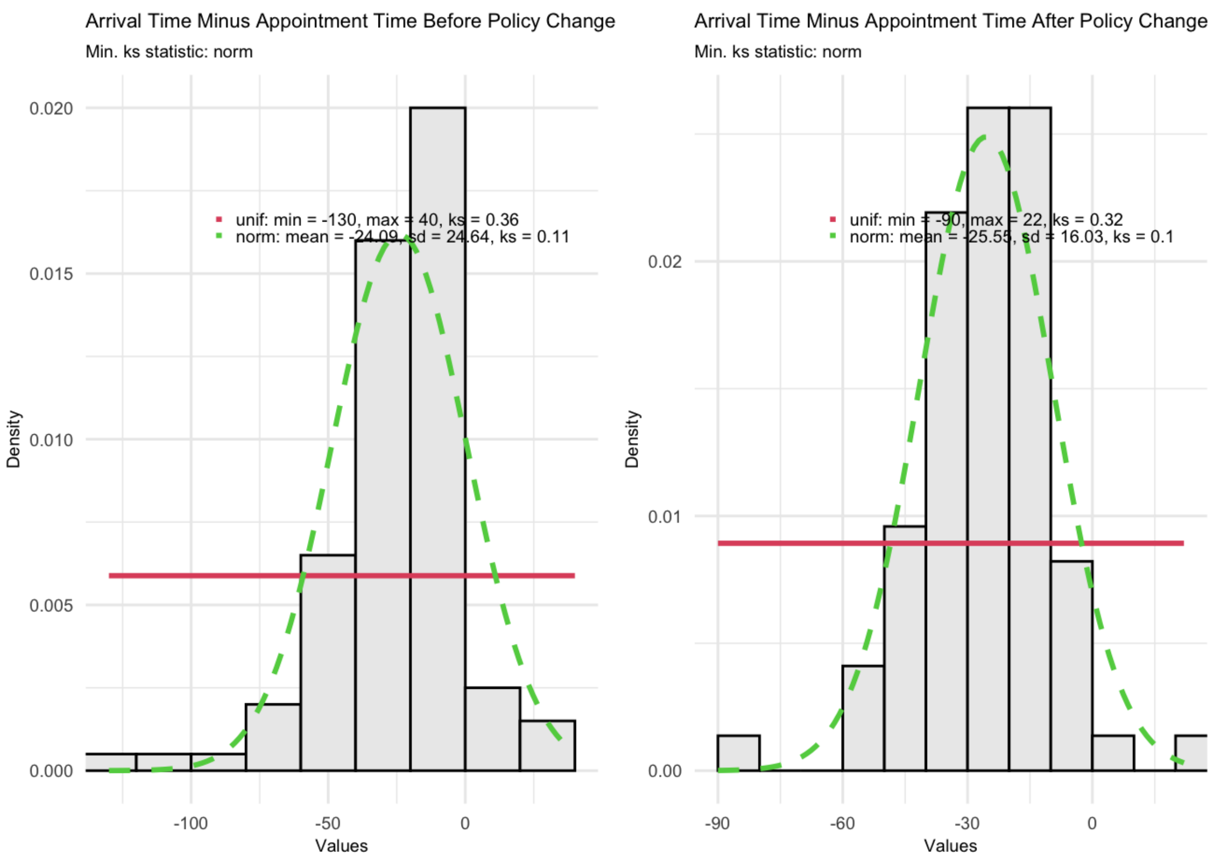

Figure A2: Fitted distributions to the variables in case-table 3, parameters, and ks stat.

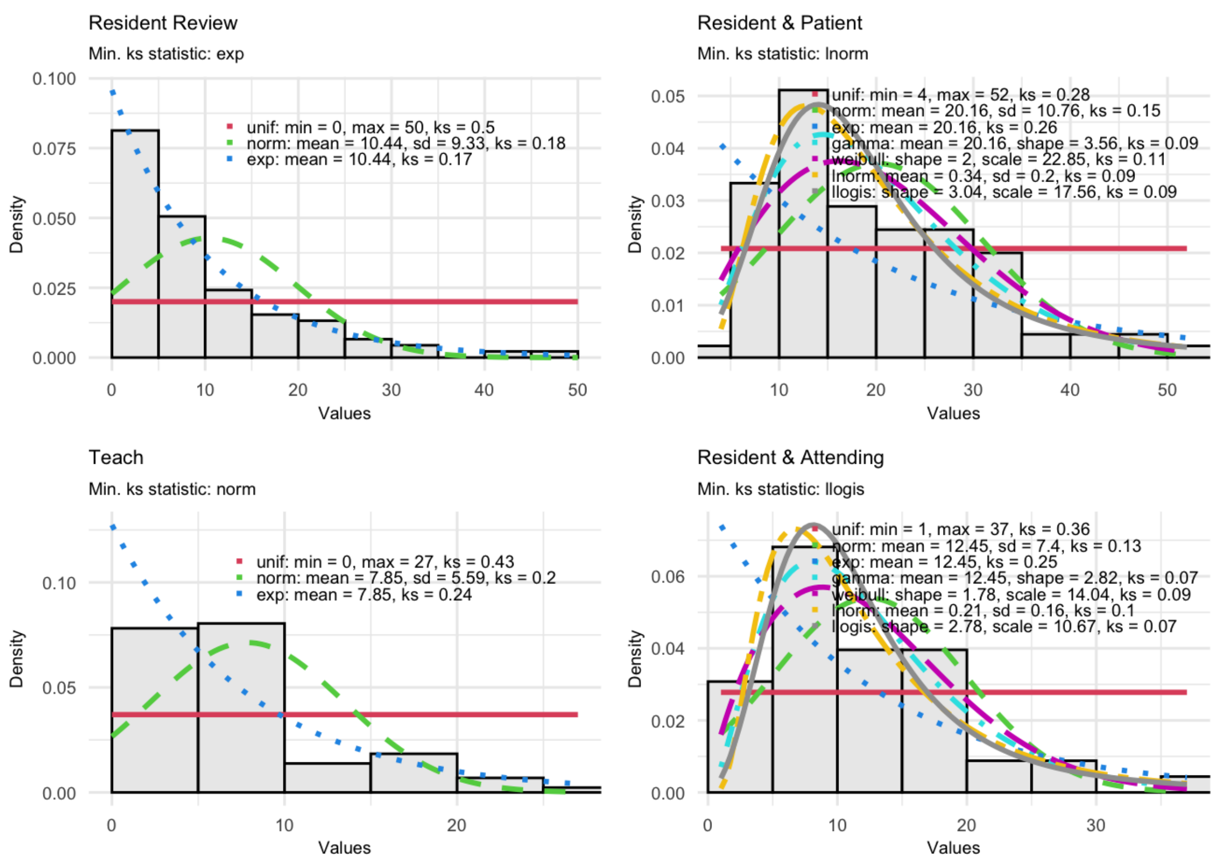

Figure A3: Fitted distributions to the variables in case-table 4, parameters, and ks stat.

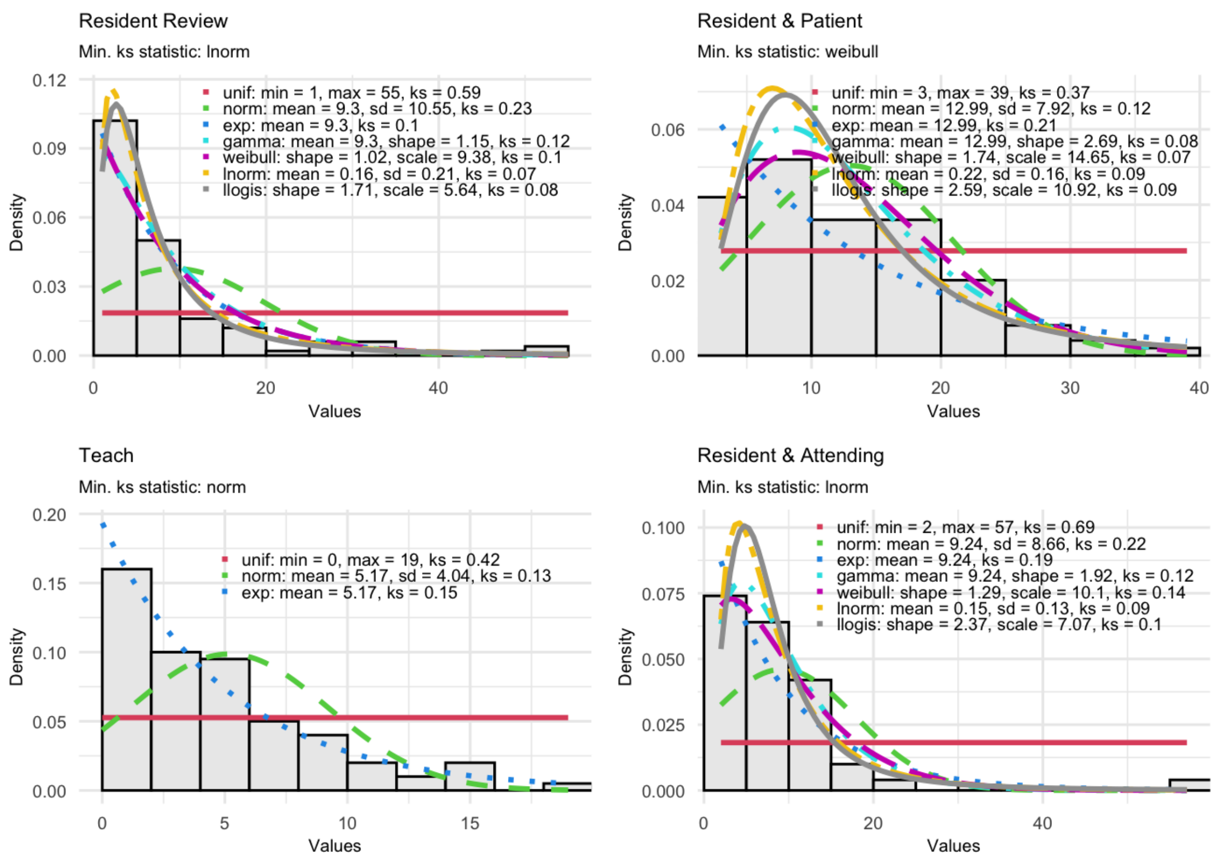

Figure A4: Fitted distributions to the variables in case-table 5, parameters, and ks stat.

Table A1: Optimal schedules determined by simulation.

26*		**27***		**28***	
Time	**Patient**	**Time**	**Patient**	**Time**	**Patient**
8:00	New	8:00	Return	8:00	Return
8:15	Return	8:00	FollowUp	8:15	Return
8:30	New	8:15	Return	8:15	FollowUp
8:30	FollowUp	8:30	Return	8:30	Return
8:45	Return	8:45	Return	8:45	New
9:15	Return	9:00	Return	8:45	FollowUp
9:45	Return	9:00	FollowUp	9:00	Return
9:45	FollowUp	9:15	Return	9:15	Return
10:00	New	9:15	FollowUp	9:30	Return
10:00	FollowUp	9:30	New	9:30	FollowUp
10:15	Return	9:45	Return	9:45	New
10:30	Return	9:45	FollowUp	10:00	Return
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10:45	FollowUp	10:15	New	10:30	Return
11:00	Return	10:15	FollowUp	10:30	FollowUp
11:15	Return	10:45	Return	10:45	New
12:00	New	11:00	Return	10:45	FollowUp
12:00	FollowUp	11:15	New	11:00	New
12:15	Return	11:15	FollowUp	11:15	New
12:30	New	12:00	Return	12:00	New
12:30	FollowUp	12:15	New	12:15	Return
12:45	Return	12:30	Return	12:30	Return
13:00	New	12:30	FollowUp	12:30	FollowUp
13:15	Return	12:45	Return	12:45	Return
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13:30	Return	13:00	Return	13:15	Return
13:30	FollowUp	13:15	New	13:15	FollowUp
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14:00	New	13:45	New	13:45	New
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14:30	New	14:00	New	14:00	Return
14:45	New	14:15	New	14:15	Return
15:00	New	14:30	New	14:30	New
15:00	FollowUp	14:30	FollowUp	14:30	FollowUp
15:15	Return	14:45	Return	14:45	New
15:15	FollowUp	15:00	Return	15:00	New
		15:15	New	15:00	FollowUp
		15:15	FollowUp	15:15	New
				15:15	FollowUp

*26, 27, and 28 refers to the number of 15-minute slots with new or return patients.
28 is the maximum in our assumed shifts.

Attachments

Attachment 1: 15-proj2-att-Benchmark.cfg. JaamSim config file for benchmark model.

Attachment 2: 15-proj2-att-EarlyOpening.cfg. JaamSim config file for early front desk staffing model.

Attachment 3: 15-proj2-att-ResidentPreProcessing.cfg. JaamSim config file for resident pre-processing model.

Attachment 4: 15-proj2-att-ResidentScheduling.cfg. JaamSim config file for resident scheduling model.

Attachment 5: 15-proj2-att-LateArrivalPolicyChange.cfg. JaamSim config file for late arrival policy change model.

Attachment 6: 15-proj2-att-ScheduleOptimization.cfg. JaamSim config file schedule optimization model.

Attachment 7: 15-proj2-att-Benchmark.dat. JaamSim output file for benchmark model.

Attachment 8: 15-proj2-att-EarlyOpening.dat. JaamSim output file for early front desk staffing model.

Attachment 9: 15-proj2-att-ResidentPreProcessing.dat. JaamSim output file for resident pre-processing model.

Attachment 10: 15-proj2-att-ResidentScheduling.dat. JaamSim output file for resident scheduling model.

Attachment 11: 15-proj2-att-LateArrivalPolicyChange.dat. JaamSim output file for late arrival policy change model.

Attachment 12: 15-proj2-att-ScheduleOptimization.dat. JaamSim output file for schedule optimization model.

Attachment 13: MillerPainTreatmentCenterData.xlsx. Data provided by the case.

Attachment 14: 15-proj2-att-ScheduleSimulations.R. R file to create 150 random schedules.

Attachment 15: 15-proj2-att-OptimizationScheduleInput.txt. 150 random schedules containing sequences of appointment times.

Attachment 16: 15-proj2-att-OptimizationPatientInput.txt. 150 random schedules containing sequences of patient types.

Attachment 17: 15-proj2-att-OutputAnalysis.qmd. Quarto file containing statistical tests and other analysis for the output analysis.

Attachment 18: 15-proj2-att-InputAnalysis.qmd. Quarto file containing procedure for distribution fitting.