NHH

BAN403 - Project 2

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Candidates: 213, 221 & 278

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1 Introduction

This report is based on the case study of the Miller Pain Treatment Center (MPTC) (Chambers and Williams, 2017). We will assist Dr. Keith Weems in providing evidence to his colleagues that his approach is worth considering. We will begin by defining the problem and our assumptions, followed by a description of our input analysis. After that, we will outline the different models and key implementations in JaamSim. Subsequently, we will analyze the results from each scenario and compare them against the base case. We will then summarize our findings and provide Dr. Weems with some recommendations.

1.1 Problem assessment

Dr. Weems successfully managed a satellite pain clinic focused on customer satisfaction within the Eastern system. Following the clinic's integration into the Eastern Health Operations Center (E-HOC) due to organizational restructuring, Dr. Weems was appointed Director of Operations. The E-HOC, an Academic Medical Center (AMC), prioritizes teaching and incorporates additional steps and resources in patient care compared to the satellite clinic. This transition is likely to impact cycle times, waiting times, and throughput. Dr. Weems plans to implement new strategies to enhance clinic efficiency and profitability, based on previous measures implemented in his private clinic. Figure 1 outlines our understanding of the clinic's workflow:

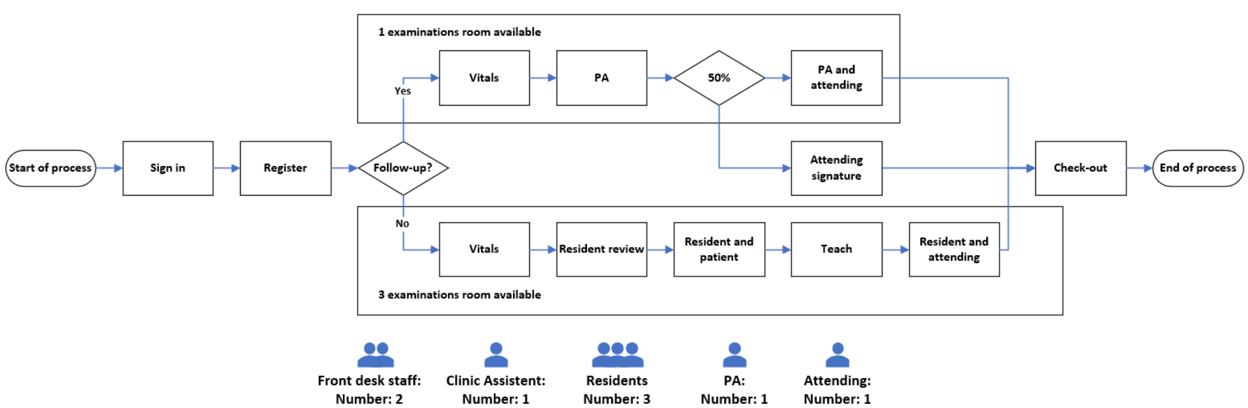

Figure 1: Process Flow

1.2 Assumptions

Based on our understanding of the problem and our experience with clinics, we have made several assumptions. The clinic opens at 8 AM, and no patient can register before this time. We assume the clinic operates two client sessions: one from 8 AM to 12 PM, and another from 1 PM to 5 PM. We assume the staff has a lunch break in between these sessions; however, if a patient arrives at 11:30 AM and the consultation lasts an hour, the assigned staff's break will only be 30 minutes.

Further, we assume there are two patient service coordinators (PSC), both capable of handling both registration and check-out. There will be one Clinical Assistant (CA), who will escort a patient from the waiting room to one of the four examination rooms. There is one room designated solely for the PA and follow-up patients; this room will only serve this type of patient, and these patients can only be placed in this room.

Additionally, we have assumed that a patient stays in the same room and have the same resident through the visits. Although an attending signing the reception virtually takes no time, it must be done. To avoid unnecessary and lengthy queues, the attending will prioritize these patients.

1.3 Goals and desired output

The main goal of this report is to provide Dr. Weems with arguments to persuade other staff members on how to run the clinic more efficiently. Dr. Weems has identified five ideas he wants to propose:

1. Open the front desk from 7:30 AM so that the first scheduled appointment of the day is ready by 8 AM.
2. Implement a late arrival policy requiring patients to reschedule or notify the next patient of reduced appointment time due to their delay.
3. Optimize the way patients are scheduled throughout the day.
4. Assign a resident to a patient the day before, allowing them to prepare overnight and reduce time spent on reviewing and teaching.
5. Investigate how varying the number of residents per day affects clinic flow.

Dr. Weems has had positive experiences with many of these ideas at his previous clinic. However, since E-HOC has roots going back over 100 years and considers itself one of the best, it could be challenging to change established practices. Through simulation models and their outputs, we aim to validate these ideas and provide Dr. Weems with arguments and evidence. Key performance indicators such as cycle time, waiting time, and throughput are the desired outputs that will reflect customer satisfaction.

2 Input data analysis

In this section, we present the input data analysis conducted for building and validating our simulation model, using field data provided by Dr. Weems and his team.

The data includes sample activity times from a private clinic and AMC, essential for our simulation but limited by sample size (approximately 100 observations per activity) and potential omission of extreme real-life values. To mitigate these limitations, we will fit a probability density function (PDF) for each activity based on this data. Our JaamSim simulation will utilize these PDFs to generate random variate.

2.1 Methodology and results

To analyse our field data and fit a suitable PDF, we will use the *Fitter* library in Python (Fitter, n.d.). This uses the *fit* method of SciPy, using the maximum likelihood estimation (MLE) method.

We will utilize a modification of the approach described by Marklund and Laguna (2019). We plot a histogram of the field data, while applying the fitter function to the data. The fitter function automatically returns statistics for the model fits, including metrics for SSE, AIC, BIC and the Kolmogorov-Smirnov (KS) test. We will therefore not do a separate KS test after this step.

Since our field data is of a small sample, we have done these operations in tandem, as just choosing distributions from a visual analysis alone is difficult. When choosing bins for our histogram and model fitting, we have chosen 15 as standard, using 10 or 20 bins on a case to case basis as recommended by Marklund and Laguna (2019). We will primarily use the KS test statistics to rank the different fits. We then pick the best candidates and perform an additional parametric bootstrap based goodness of fit (GOF) test (SciPy, n.d.-c). If a candidate distribution is rejected by the GOF, we will discard it. If the KS and the goodness of fit tests don't give conclusive results, or tests discard all available distributions, we further assess AIC, BIC and the SSE given by the fitter library, together with another visual assessment to determine which distribution to use.

Upon selecting the optimal PDF fit, our code outputs the parameters used in our JaamSim simulations. Several distributions were excluded due to their constraints: the beta distribution is limited to $[0,1]$ (SciPy, n.d.-a) and unsuitable for our data without modification; the Erlang distribution requires integer shape parameters (SciPy, n.d.-b), reducing its flexibility compared to gamma; the Weibull, log-normal, exponential, and gamma distributions are only defined for $x \in (0, +\infty)$, and thus inappropriate for negative data values. For the "PA and attending" times, lacking specific data, we assumed a triangular distribution with a minimum of 1 minute, a maximum of 6 minutes, a mean of 3 minutes, and a mode of 2 minutes, following Law's approach when data is absent (2015).

Activity	**Patient Type**	**Distribution**	**Parameter Values**
Arrival before policy	All	Normal	loc = -24.09, scale = 24.6443
Arrival after policy	All	Normal	loc = -25.5479, scale = 16.0266
Register	All	Lognormal	loc = -0.3418, scale = 4.0488, shape = 0.5385
Vitals	All	Gamma	shape = 3.7514, mean = 3.5252
Resident & Review	New	Weibull	loc = 0.9889, scale = 9.6487, shape = 1.0476
Resident & Review	Return	Exponential	mean = 9.3000
Resident & Patient	New	Gamma	shape = 2.3064, mean = 20.1556
Resident & Patient	Return	Weibull	loc = 2.8993, scale = 10.4922, shape = 1.1297
Teach	New	Weibull	loc = 0.9180, scale = 7.5634, shape = 1.3014
Teach	Return	Weibull	loc = -0.0942, scale = 5.6699, shape = 1.2799
Resident & Attending	New	Lognormal	loc = -3.7373, scale = 14.6787, shape = 0.4440
Resident & Attending	Return	Exponential	mean = 9.24
PA	Follow-up	Lognormal	loc = 1.5346, scale = 17.6551, shape = 0.5940
Attending & PA	Follow-up	Triangular	Min = 1, Max = 6, Mode = 2, Mean = 3
Check-out	All	Exponential	mean = 4.7245

Table 1: Distibutions, loc = location

By using the described method on our field data, we have determined distributions to generate random variates. Our findings are displayed in table 1. Additional details is provided in the attached *Input Analysis.ipynb* notebook.

3 Simulation Models

In this section, we will describe the different simulation models and key elements in JaamSim. We will begin by describing the base case model, which will be used as a benchmark against the various scenarios. Following this, we will detail Dr. Weems' different scenarios.

3.1 Base case

Our base model generates patients four hours prior to their scheduled appointment times. This is done using a *FileToMatrix* element, with the schedule from the *EntityData.txt* file. As part of the system's logic, 10% of patients are sent directly to the *No-Show* sink. The remaining 90% undergo a procedural delay: they are directed to an entity delayer that adjusts their registration time based on the four-hour early generation and a predetermined arrival distribution.

Upon generation, each entity is assigned a patient type and an appointment time based on the schedule template. This assignment ensures that no patient can be seen before their appointment time, that they are sent to the correct room, and that they have the appropriate distribution.

To manage various resources and staff, we utilize resource pools that include rooms, CA, physician assistants (PAs), attendings, and PSCs. Throughout the model, these resources are assigned to a patient and then unassigned once their task is completed. Two entity gates, one for *New* and *Return* patients and another for *Follow-Up* patients, ensure that a patient cannot be seen before their appointment time, that an examination room is available, and that a CA is available to escort the patient from the *Waiting Area* to an examination room.

3.2 Scenario 1: Opening hours

To simulate this scenario, we adjusted the *OpeningHours* from 8 A.M. to 7:30 A.M., ensuring that one PSC was available for registration starting at 7:30 A.M. A similar adjustment was made for the second clinic session, where one PSC was available from 12:30 P.M. These changes were necessary because the clinic sessions are identical in terms of schedule and patient type. Modifying only the first session would have affected only half of the sample and the change would therefore not be reflected in statistics like throughput or WIP. This scenario assumes that the hospital agrees to the additional cost of having one PSC arrive 30 minutes earlier each day and that the rest of the staff is ready to receive patients by 8 A.M. sharp.

3.3 Scenario 2 : Policy change

Introducing a late arrival policy necessitated two modifications in the model. The first modification was to adjust the arrival distribution to fit the data from Dr. Weems' old clinic after he tested the policy there. The policy offered the late patients two options, but virtually all chose to reschedule their appointments. Based on this, the second modification was to add a branch after the arrival delay, which checked whether a patient was late. If the patient was late, they were sent directly to a *Late* sink.

3.4 Scenario 3: Schedule

To test different schedule templates, we first needed to know how patients were affected by different patient-types at the same or previous appointment. To do this we performed a 15 scenario simulation(*PenaltySimulations.cfg*) with different combinations of 2 patients. We then created a penalty score based on the total time used waiting for resources in the scenario. These penalty scores were then utilized in a Monte Carlo Simulation(*MonteCarlo.ipynb*) to rank 1,000,000 randomly generated templates, before selecting the five best templates for further investigation through simulation. In the Monte Carlo simulation, we have assumed that the number of patient-types must be the same as in the original template, that the two 4 hours shifts must have the same template, and that the time between two appointments could either be 0 minutes or 15 minutes.

3.5 Scenario 4: Pre-processing

To model this scenario, we added a third column to our *EntityDataAssignedResidents.txt* file, which indicates which resident was assigned to each patient. Since *Follow-Up* patients do not interact with residents, they were assigned a dummy resident, represented by the number 0. The remaining patients were assigned to residents 1, 2, or 3, based on the order of their scheduled appointments for the day. Additionally, each of the three resident resources were changed to only accept patients with their number as an attribute. In this way we ensured that residents could only treat their assigned patients. The last modification involved adjusting the distribution such that the new mean was 50% of the old mean. This was done by dividing our existing observations by two and fitting new distributions.

3.6 Scenario 5: Variability in the number of residents

To accommodate the variability in the number of available residents throughout the day, we ran the base model with different numbers of resident resources. We tested new variations with 1 and 2 available residents, to compare with the basecase of 3 residents. Although the case stated that 1 to 2 residents could be absent for a clinic session (lasting 4 hours), we simulated this over an entire day, to easier be able to compare the results to the basecase. To implement this in Jaamsim, ran two scenarios with the number of resident matching the scenarionumber.

4 Output analysis

Since the inputs in our model are random within their respective distributions, we must also treat the outputs as stochastic variables, and therefore we need to analyze the outputs (Laguna and Marklund, 2019). Our model operates as a terminating process, running precisely from 00:00 to 23:59 (24 hours). To obtain a sufficient sample size, we have decided to run the scenarios for 1000 days(1000 replications). This will also enhance the precision of our estimates and reduce the width of our confidence intervals. Each run will be independent, with different random variables drawn from the distributions, thereby guaranteeing the independence of each simulation run.

To evaluate Dr. Weems' different ideas, we began by running the base case model to establish some benchmark numbers. Regarding these numbers, we are most interested in cycle time, throughput, and waiting time, as we believe these are essential for ensuring customer satisfaction. Furthermore, we have excluded any consideration of resources (except for variations in the number of residents working) as we assume these were beyond the scope of the case. Our model will provide confidence intervals at the 0.05 level for the the cycle time and time spent in the different queues. We will strictly adhere to the criteria of non-overlapping confidence intervals when assessing whether any changes in our model behavior is statistically significant. (Laguna and Marklund, 2019)

To gather the different numbers from the models, we have utilized a range of methods. For collecting *Cycle Time* and *Queue Time*, we used *RunOutputList* in JaamSim and *Read_data.ipynb*, while for throughput, we employed an *ExpressionLogger* that logged the *Estimated Throughput* (E.T), *Actual Throughput* (A.T), and *Work-in-Process* (WIP) for every replication at 17:00, 18:00, 19:00, and 20:00 each day. To aggregate these numbers, we used the *get_WIP* function found in *Read_data.ipynb*.

4.1 Base case

As Table 2 displays, the average cycle time for our patients is 90.74 minutes. Furthermore, we can observe that *New* patients have significantly higher times in the system than the mean, while *Follow-up* patients experience significantly lower times.

Patient Type	Mean	St.dev	Confidence Interval
All	90.742	33.469	[90.068, 91.416]
Follow-up	74.546	27.791	[73.776, 75.316]
Return	92.309	31.216	[91.367, 93.251]
New	104.667	31.787	[103.748, 105.587]

Table 2: Cycle time by patient type

From Table 3, we see that there are, on average, 2.33 patients in the system after the clinic's planned closing time. Additionally, it can take up to two to three hours after closing time (17:00) before all scheduled patients are done with their treatment.The WIP after 17:00 necessitates overtime for the staff, which might induce strain on the AMC staff and lead to increased costs.

Time	E.T	A.T	WIP
17:00	30.677	28.348	2.329
18:00	30.677	30.468	0.209
19:00	30.677	30.662	0.015
20:00	30.677	30.677	0.000

Table 3: Throughput and WIP

It's important to note that E.T is derived from observed data rather than calculated estimates. Theoretically, if each session serves 17 patients and accounts for a 10% no-show rate, the calculated throughput would be 30.6. However, with sufficient replications, the observed throughput, currently 30.677, would likely converge to this value. From Table 4, we can see that the average waiting time is approximately 41 minutes, with the majority of this time spent in the *Waiting Room*. This is natural since the patients are expected to meet 30/15 min before their appointment. Furthermore, we observe that there are small differences in the average waiting time among the different patient types.

Measure	Mean	SD	Confidence Interval
Waiting Room	26.559	24.393	[26.15, 26.969]
Total	40.927	27.152	[40.357, 41.497]
Follow-up	38.063	24.457	[37.45, 38.677]
Return	42.972	27.682	[42.154, 43.79]
New	40.802	26.277	[40.04, 41.564]

Table 4: Different Queue Measures

4.2 Scenario 1: Opening hours

From Table 5, we can see that there are only minor changes in the average cycle times for the different patient types, and all confidence intervals(C.I) overlaps with the base case indicating that the change is not statistically significant. When assessing queue statistics the confidence intervals, we observe there is a statistically significant increase in waiting time at the *Waiting Room*. This is natural since the patient now can enter the clinic earlier, but the treatment doesn't start before 8 AM or 01 PM. On the other side, the *Total Queue* time has significant reduced, and we also seeing a small change in the WIP. This indicates that the revised opening has a slight positive effect on the patient flow.

Patient Type	Mean	St.dev	Confidence Interval
Total	89.772	33.325	[89.114, 90.429]
Follow-up	73.731	27.917	[72.98, 74.482]
Return	91.809	31.092	[90.882, 92.737]
New	102.892	31.804	[101.988, 103.796]

Table 5: Cycle times after new opening hours

Time	E.T	A.T	WIP
17:00	30.677	28.388	2.289
18:00	30.677	30.477	0.200
19:00	30.677	30.664	0.013

Table 6: WIP after changes in opening hours

Measure	Mean	SD	Confidence Interval
Waiting Room	29.185	23.456	[28.783, 29.587]
Total	38.409	26.815	[37.867, 38.952]
Follow-up	35.488	24.179	[34.897, 36.078]
Return	41.401	27.202	[40.618, 42.184]
New	37.022	26.051	[36.295, 37.749]

Table 7: Queue Measurements

4.3 Scenario 2 : Policy change

There is a slight reduction in observed processing time for patients for all categories, viewed in Table 8. However, these are not statistically significant for the follow-up and new patients. From Table 9 we can see a reduction in WIP, from 2.329 to 1.803, which indicates that the system on average is more efficient at processing patients. However, there are still patients left to be processed at the end of the last shift. There is also a statistically significant, albeit small, reduction in total waiting time, view in Table 10. Overall, the policy change does not seem to have a large impact on the system as a whole.

Patient Type	Mean	St.dev	Confidence Interval
Total	89.092	28.814	[88.46, 89.723]
Follow-up	73.742	22.657	[73.042, 74.443]
Return	89.822	26.275	[88.964, 90.68]
New	103.167	27.170	[102.324, 104.011]

Table 8: Cycle-time after policy change

Time	E.T	A.T	WIP
17:00	28.974	27.171	1.803
18:00	28.974	28.840	0.134
19:00	28.974	28.966	0.008

Table 9: WIP after policy change

Measure	Mean	SD	Confidence Interval
Waiting Room	25.380	19.267	[25.031, 25.73]
Total	39.241	21.264	[38.725, 39.758]
Follow-up	37.327	18.414	[36.79, 37.864]

Table 10: Queue after policy change

4.4 Scenario 3: Schedule

We have chosen to only compare the best of the 5 simulated schedule-templates with the base-case(Scenario 5). This template is shown in Appendix A. From Table 11, we observe that the average total cycle time for patients has decreased from approximately 90.7 minutes to 87.6 minutes, a reduction that is statistically significant. Additionally, there is a statistically significant reduction in the average cycle times for *Return* patients. Although the change is not statistically significant, the cycle time for *New* patients has actually increased. This indicates that the algorithm favors *Return* patients or that they have the greatest potential for improvement. This is also shown in the queue times, as shown in Table 12, where *Returning* patients are the only group that experience an statistically significant reduction in queue times of approximately 8 minutes. This does however also cause a significant reduction in the total average of 3 minutes. We observe an overall increase of the WIP in our system, as seen in Table 13. This suggests that while some patients experience reductions in cycle times and queue times, the overall throughput of the system is not improved. This might be due to grouping of *New* and *Return* patients towards the end of the shift, as our penalty does not take WIP into account.

Measure	Mean	SD	Confidence Interval
All	87.630	32.806	[87.046, 88.213]
Follow-up	74.286	28.279	[73.485, 75.087]
Return	84.273	29.247	[83.586, 84.96]
New	105.472	31.184	[104.551, 106.394]

Table 11: Cycle time new schedule

Measure	Mean	SD	Confidence Interval
Waiting Room	24.815	23.192	[24.473, 25.157]
Total	37.827	26.119	[37.347, 38.306]
Follow-up	37.834	25.043	[37.183, 38.484]
Return	34.899	24.850	[34.356, 35.441]
New	41.665	26.081	[40.847, 42.483]

Table 12: Queue time with a new schedule template

Time	E.T	A.T	WIP
17:00	30.677	27.927	2.750
18:00	30.677	30.313	0.364
19:00	30.677	30.656	0.021
20:00	30.677	30.674	0.003

Table 13: WIP with a new schedule template

4.5 Scenario 4: Pre-processing

Table 14 shows a significant reduction in the average processing time for all patient types, with notable improvements for *New* and *Return* patients. *Follow-up* patients also see reduced waiting times, likely because the *Attending* spends less time on others, easing the *Signature* and *AttendingPA* steps. These time reductions are statistically significant. Despite the improvements, 0.068 patients on average remain in the system an hour after closing, suggesting that reprocessing alone cannot eliminate overtime. Additionally, the overall waiting time drops by about 5 minutes, which is statistically significant, with *Follow-up*, *Return*, and *New* patients reducing their waiting times by approximately 3, 7, and 5 minutes.

Patient Type	Mean	St.dev	Confidence Interval
All	79.841	30.096	[79.285, 80.398]
Follow-up	71.442	26.979	[70.721, 72.162]
Return	78.487	28.838	[77.724, 79.25]
New	90.177	29.179	[89.373, 90.98]

Table 14: Cycle time with pre-processing

Measure	Mean	SD	Confidence Interval
Waiting Room	22.730	21.676	[22.421, 23.039]
Total	35.736	25.278	[35.276, 36.195]
Follow-up	34.982	23.576	[34.426, 35.537]
Return	36.370	25.527	[35.716, 37.023]
New	35.583	24.674	[34.921, 36.245]

Table 15: Queue time with pre-processing

Time	E.T	A.T	WIP
17:00	30.677	29.238	1.439
18:00	30.677	30.609	0.068
19:00	30.677	30.677	0.000

Table 16: WIP with pre-processing

4.6 Scenario 5: Variability in the number of residents

With only one resident available, we can see that there is a large increase of 125 minutes in total average processing time for patients. This is due to *Return* and *New* patients taking much longer to be processed by our model, with an increased average time usage of 201 and 158 minutes respectively, as viewed in Table 17. There is also a statistically significant reduction in processing time for follow-up patients. The reduction might be due to attending doctors having more time at hand, since patients are stuck at the resident review, leaving attending free to handle signatures and assist the PA.

Scenario	Patient Type	Mean	St.dev	Confidence Interval
2 Residents	All	101.489	40.188	[98.67, 104.308]
	Follow-up	73.378	27.763	[70.768, 75.989]
	Return	110.087	36.885	[105.797, 114.376]
	New	117.051	37.238	[113.608, 120.493]
1 Resident	All	215.624	135.941	[213.636, 217.612]
	Follow-up	68.888	26.851	[68.19, 69.585]
	Return	293.300	108.813	[290.391, 296.208]
	New	262.333	113.055	[259.27, 265.395]

Table 17: Cycle Time by Resident Count

A similar pattern is evident for the queue times, showed in Table 19. There is a big uptick in average total waiting time for waiting rooms. There is also a very large increase in WIP at the end of the day, from an average of 2.329 to 10.13 patients not processed by our system by closure at 17:00, viewed in Table 18. Our simulation indicates that having only one resident available creates a significant bottleneck in our system. This would certainly be a unacceptable situation for the clinic.

From table 17, we can see that having two residents available also negatively affects the average total processing time by almost 10 minutes. Returning patients and new patients have an average increase in processing time by 20 and 14 minutes each. There are no statistically significant increase in time usage for follow-up patients. Here, we can also see an increase in WIP compared to the base case, from 2.329 to 9.89.

The largest increase in queue waiting times for both the scenarios with less than three residents is in the waiting room queue. This is due to patients holding up examination-rooms while waiting for a resident, which blocks people from leaving the waiting room.

Scenario	Time	WIP
2 Residents	17:00	3.555
	18:00	0.994
	19:00	0.129
	20:00	0.013
1 Resident	17:00	10.218
	18:00	8.648
	19:00	7.273
	20:00	5.925

Table 18: WIP by Resident Count

Scenario	Measure	Mean	SD	Confidence Interval
2 Residents	Waiting_Room	31.941	28.740	[31.33, 32.551]
	Total	52.768	33.623	[51.945, 53.591]
	Follow-up	36.890	24.413	[36.284, 37.495]
	Return	62.738	34.326	[61.481, 63.995]
	New	54.444	32.078	[53.435, 55.453]
1 Resident	Waiting_Room	107.464	102.206	[105.821, 109.107]
	Total	165.884	129.990	[163.996, 167.772]
	Follow-up	32.387	23.379	[31.846, 32.929]
	Return	244.040	109.103	[241.241, 246.840]
	New	198.450	112.695	[195.570, 201.329]

Table 19: Cycle Time Metrics by Resident Count

5 Conclusion and recommendations

This report utilizes field data to simulate issues and recommendations at MPTC as proposed by Dr. Weems. We developed several JaamSim simulations to evaluate these proposals. The simulations showed that a change of opening hours slightly improved waiting times. A proposed policy change effectively reduced unfinished appointments by shift's end. Adjusting patient schedules had a positive impact on waiting times but did not boost clinic throughput. Implementing a pre-processing routine positively influenced patient flow. Having fewer than three residents available significantly worsened waiting times and throughput, potentially reducing customer satisfaction.

As we have observed, all the proposed changes impact at least one measure. Our recommendation to Dr. Weems depends largely on what the Miller Pain Treatment Center (MPTC) prioritizes most. If cycle time is of paramount importance, we recommend emphasizing the introduction of pre-processing, which also enhances throughput. It is worth noting that while this strategy significantly reduces *Cycle Time*, it relies heavily on the assumption that residents are adequately preparing the night before. Additionally, residents and attending must conduct teaching sessions when patients are not present, which could increase overall costs and stress on the staff. Optimizing the schedule also had a significant impact on the *Cycle Time*, but saw a small increase in the WIP. The policy change can be introduced without severe negative consequences for the staff, and we recommend implementing this. If the goal is to reduce average waiting time, then adjusting the opening hours appears to be a viable option. Lastly, our analysis reveals that all measures are heavily influenced by having fewer than three residents available per day; thus, the MPTC should strive to have at least two residents available, preferably three.

A word of caution. Since we have performed a discrete event simulation, we have not explored how the different ideas might interact with each other. Therefore, it is possible that implementing multiple strategies could successfully meet the MPTC's goals. However, there is also the possibility that combining measures could yield negative results.

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A Appendix

Appointment	Patient Type
08:00:00	Follow-up
08:00:00	Return
08:15:00	Return
08:30:00	Return
08:45:00	Follow-up
09:00:00	Return
09:15:00	Follow-up
09:15:00	Return
09:30:00	New
09:45:00	New
10:00:00	New
10:15:00	New
10:30:00	Follow-up
10:45:00	Return
11:00:00	Follow-up
11:15:00	Return

Table 20: Optimized Schedule