***Effectively Scheduling Appointments for Hall Health’s Mental Health Clinic***

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The UW Hall Health’s Mental Health Clinic aims to counteract the occurrences where patients for a scheduled appointment cancel within 24 hours or are absent. To punish these patients, Hall Health have recently instilled a fee system, but this system negatively affects the mental health of patients. Thus, we consider three additional strategies to investigate minimizing the overall loss of all the utility and resources available to patients. In doing so, we use a Monte Carlo simulation, which predicts the outcome of our different strategies from past data. From this, we find that given the limitations of therapist, office space, and time, an overbooking system for appointments from 8am to 10:30am and 1pm to 3:30pm is the most plausible solution that significantly minimizes the loss of utility and resources wasted overall to the current fee system.

1. Introduction

Within UW Hall Health’s Mental Health Clinic from September 2017 to October 2018, 26.9 percent of patients have been absent to their appointments. To be specific, 9.3 percent have had unannounced absences, whereas the other 17.5 percent of patients have canceled ( appointments). This in turn leads to inefficient scheduling overall for the mental health clinic as the time where people do not show up could be used to aid others. Because of this, Hall Health implemented a fee system this past September to penalize no shows and late cancellations.

Specifically, Hall Health currently charges patients 25 dollars for canceling within 24 hours of their appointment and 40 dollars for an unannounced absence. However, most patients in the mental health clinic are suffering from severe mental illnesses and/or struggling financially such that the punishing fee can hinder their willingness to seek further help. Therefore, Hall Health is considering other solutions for scheduling appointments to offer better support for their patient’s mental state.

1.2 Project Motive

When starting off our Math 381 project, we all saw the project as an opportunity to aid others by offering them better access to mental health therapies. As such, we researched and attempted to connect to several different clinics to examine the problems regarding mental health patients. Along this journey, we ended up connecting with UW Hall Health’s Mental Health Medical Clinic.

When we started discussing our project, Patricia Atwater, the current director of Health Promotion at Hall Health, told us about the situation at hand with this no-show problem. There, she tasked us to develop a model to look further into these solutions of maximizing the overall utility of therapists when patients do not show up.

Therefore, our main goal is to consider various methods for mental health staff and patients which maximize the resources given to patients while balancing the concerns for each patient’s situation. We aim to not only improve patient attendance daily but to also make the most use of the therapist’s time.

To accomplish this goal, we will use de-identified patient dataset from the clinic ranging from September 2017 to October 2018 to consider various strategies and methods to make the time scheduling more efficient.

1.3 Previous Works & Solutions

Patient no-show is one of the most common problems in clinical operations within the last half century. Reported reasons for no-shows include lack of transportation, scheduling problems, oversleeping, forgetting, and lack of child care (Campbell, et al., 2000). To mitigate the negative effects and decrease no-show rate, there are many approaches that can improve no shows; one popular example is a reminder system sent to the patients in case they forget about their appointment.

Before texts and smartphones, there were attempts to send patients reminder cards (Rust et al., 1995), calling patients to remind them of appointments, and providing information about public transportation (Bean and Talaga, 1995). Recently, McLean (2016) suggests that all health services should use at least one simple reminder for all patients to effectively decrease no-show rate.

Currently, Hall Health has a text reminder system to notify the patients a day before. However, this method is not ideal for the scheduling issue caused by no shows even though it is a good way to prevent unannounced absences from occurring.

On the other hand, overbooking has not been closely examined as a possible solution for this problem. Shonick and Klein (1977) show how to use the probabilities of patient no-shows to overbook enough patients so that the expected number of arrivals is equal to the target number to be seen. However, they do not consider potential factors such as patient waiting time that could decrease overall satisfaction.

2. Simplifications

When considering the multiple situations for the clinic’s daily schedule, there are many factors including what month we are focusing on, the length of the appointments, how many people will be attending an appointment, and many other aspects. Alongside that, we have other factors for the patient’s situation such as how far they live, what their various schedules are like, individual personality traits, and many others. To control all of this, we will simplify many of these factors to narrow down the focus for our model based on the clinical data we have received.

2.2 Scheduling Simplifications

For scheduling the appointment, we will assume all appointments scheduled are categorized as MH Office Visit Individual appointments lasting 30 minutes long as that was the most common type of appointment (47.40% of all appointments as seen in table 2 in the appendix). Along with that, all appointments will happen consecutively starting at 8am to 5pm on weekdays with a daily lunch break for therapists from 12pm to 1pm.

In addition, we will assume every patient will schedule their appointment with Hall Health within four weeks (83.2% of all appointments as seen in table 3 in the appendix). This assumption is significant as the data portrays some correlation between waiting days and no shows. Hence, this simplification limits that variable as the patients will on average have the same waiting time for their appointment.

2.3 Appointment Simplifications

On the day of the appointment, we will assume all appointments will only consist of one of the four therapist and one patient where the assigned therapist will meet with the patient. If the patient is present to their appointment, both the patient and the therapist will show up on time to eliminate the factor of late-arrivals. In other words, there are only two cases of the patient either showing up on time or not showing up at all.

2.4 Overbooking Simplifications

For the situations where we look to book more patients than the available appointments that day, we will assume that therapists are not willing to work overtime. Along with that, we will assume that all patients have set an hour aside for their appointments, so they have an extra 30 minutes after their scheduled appointment before heading to class.

With these simplifications in place, if there is a worst case scenario of an overflow of patients due to everyone showing up under an overbooking method, we will reschedule their appointment and tell them to return home when checking into their appointment.

3. Mathematical Model

To consider various strategies, we look at minimizing an objective function based on two factors: *resource wasted* to count the wasted time and office space due to no shows, and *concerns for patients and therapists* to factor the disadvantages to patients and therapists of the system implemented. Resources wasted consist of the amount of wasted appointments and therapists that could have been used for aiding other patients when a patient does not show up. Concerns for patients are based on whether the patients are sent home, charged for not coming to appointments, and whether the appointment wait times cut into their free time before class. Then, concerns for therapists include whether there is an overflow of that appointment takes up their lunch time from 12pm to 1pm.

3.2 Determination of Weights

In our model, we used unit weights for each decision variables for *resource wasted* and *concerns for patients and therapist*. When the appointment slot is successfully filled due to the strategy instilled and a patient is served by a therapist, it is assumed to be one positive unit (+1). Whereas, when the appointment slot is unused for either case of no-show and late cancellation, it is assumed to be one negative unit (-1). These two are the fundamental base weights.

Looking at the other weights, it is difficult to perfectly determine each weight as there is no data where the medical clinic has implemented these other methods. Thus, all other weights are estimated based on their relative contributions to the resources wasted and concerns for patients and the therapists. These weights indicate how beneficial and/or harmful the strategy is to our overall goal. Types of weights, their values, and justifications for each weight can be found in Table 1 of the appendix.

Also, we are trying to minimize the resources wasted and concerns, we implement the objective function that minimizes the negative value of the function. In other words, we will maximize the value of the function as we are considering the most negative effects of the strategies and we will label weights in negative terms to show their impact on each situation assigned to the weights. Hence, a higher end value from the objective function shows the better overall strategy.

From this, our objective function is:

Max()

subject to:

Each coefficient and can be roughly translated in Table 1 by the following:

* *a*: the relative effect of no show patients on time wasted; this is base number of relative coefficients
* *b*: the relative effect of fee imposed on unannounced absence
* *c*: the relative effect of fee imposed on late cancellation
* *d*: the relative effect on patients who come up to appointment due to the implemented strategies
* *e*: the relative effect on patients who need to reschedule even if they show up due to their time constraint for overbooking
* *f*: the relative effect on patients who have to wait due to overbooking
* *g*: the relative effect on therapists who have full slots and break time due to too much overflow of overbooking
* *h*: the relative effect on therapists who have relatively full slots and use break time due to overflow of overbooking.

3.3 Monte Carlo Simulation

When looking at various solutions, we will simulate the yearly schedule through the Monte Carlo method. A Monte Carlo simulation looks at the potential scenarios of which we implement one of our proposed methods to see their effects based on the current probability rate of no shows and others we collected from past data (Winston, 2004). To encode the Monte Carlo simulation, we will use Python through Jupyter Notebook provided by Anaconda.

3.4 Current Fee System

For the current method of a fee system, we will factor the potential patients who are going to the appointments due to fear of paying fees. To measure this data, we will look into the difference between no show rates before and after the implementation of the fee system in September 2018. Along with that, we will look at the difference between unannounced absence rates before and after the current system to see if there was a significant change of unannounced absent patients.

The current solution of a fee system is used as a baseline to compare the efficiency of the other strategies based on our objective function.

3.5 Overbooking Model 1:

Full Double Booking

When implementing an overbooking system, we will consider the probability of having two people booking at the same time slot. When considering the different cases, we will let the first person who shows up take the 30 minute time slot and the other patient will wait for the next time slot. We will assume that if the patients wait for more than two slots (1 hour of waiting) without having a therapy session, they will reschedule to the next time. To take into factor of situations where both patients show up, we will leave two appointments from 11:30am to 12pm and 4:30pm to 5pm open that we will call the marginal period.

When Hall Health overbooks a session, they have the risk of having more patients arriving for a session than the available capacity. In that case, a patient will have to wait for a period before meeting with a therapist. To demonstrate the dynamics of patient arrival uncertainty and both benefit and the hazards of overbooking, different cases of arrival are considered (Table 6). The capacity for each therapist is fourteen appointments in a day (N = 14) excluding the marginal time; the patient no-show rate is 26.9% (R = 0.269), and each appointment lasts 1 time unit, 30 minutes session (D = 1). On average about 20 patients show up daily ( 20) which is beyond their capacity N. Four cases are considered to illustrate how overbooking has a large impact on Hall health and their patients (LaGanga, 2017).

**3.6 Overbooking Model 2:**

**Time-Specific Overbooking**

Based on the given de-identified data from Hall Health, we found out correlation between the time of the day and no-show rate that patients tend to have higher chance of being no-show during 8am to 10:30am and 1pm to 3:30pm. This correlation seems reasonable because the most common reason for not showing up for an appointment is oversleeping for the morning, and lunch hours for the afternoon. Since these time slots have higher chance of being empty, we will consider the probability of having two people booking at each of these time slots. At maximum, Hall Health could double book all slots from 8am to 10:30am and 1pm to 3:30pm; that is 10 more appointments available to be made currently. In the case scenario where these slots are fully double booked, on average about 17 patients show up daily , which is 3 more patients than the capacity N. However, the excess can be handled during the marginal time. Thus, this approach seems less exposed to overflow problems.

3.7 Modified Fee System: Fee only on frequent no show patients

Aside from overbooking strategies, an alternative strategy for the current fee system is for Hall Health to charge a fee to patients who have previous no-show history. With our data, we found out that 58.2% of no-show patients are showing repeated no-show history, whereas the other 41.8% not showing up only once.

In this strategy, we will not penalize the first time patients do not show up, but patients who do not show up following that absence will be charged. With this strategy in place instead, we balance the patients` concerns with the punishing fee as the fee can hinder patients` willingness to seek further help.

If implemented, Hall Health should not announce the modified penalty system because if patients know about this, there may be an increase of the no-show rate as they have a grace appointment to not be penalized. Instead, Hall Health should still state the penalty and ask the patients why they were not able to make it to their appointment in exchange for a waive to their fee as this shows Hall Health’s willingness to help and encourage patients to come to their next appointments.

4. Mathematical Solutions

After using the Monte Carlo simulation, we are able to develop a model based on the historical data that enables us to calculate the probability to estimate future projections of when no-show and late arrivals to appointments would occur.

Under the current fee system and the system of fee imposing on the patients who are frequently not showing up to appointments, we focus on the effect from the difference between no show rate before and after the current system.

Under the overbooking systems, we focus on how double booking saves the usage of office time from no show patients and the side effect of having too much patients on limited time slots, such as forcing patients to go home and reschedule for the next.

As described in section 3, we have implemented the system based on the characteristics of each model and have put objective function to compare each other. As a result of over 1000 repeated random simulation for each method, we have obtained these results (figure 3).

Among the strategies, the current fee system is the worst performing in terms of efficient usage of time and concerns of each individual patient's situation. The fee strategy on frequent no show patients has not provided significant difference to the current fee system even if the system only applies to the frequently patients, such patients who do not show only one time would not have to pay.

For overbooking on every time slot, it is very efficient on managing the time slot reacting to the no show patients, and averagely perform well on the enough amount of overflow of patients. However, in the worst case of where every time slot is double booked, this system has performed worse than the current fee system. On the other hand, the time-specific overbooking has performed slightly worse on managing time slots than the full overbooking system yet manages very well on the overflow of patients; an extra 16.67% of patients now have accessed to the appointments under this time-specific overbooking system. However, this system still has the situation where the patients need to go home and reschedule even if they show up..

Based on all of our results, we would suggest that the Hall Health Mental Health Clinic looks to implement the overbooking system at the certain time slots during 8am to 10:30am and 1pm to 3:30 pm, rather than the current fee system.

4.2 Improvements

To improve our current solution of implementing a specified time overbooking system, we will look at changing the current simplifications, such as having time-variant no-show rate based on the data because we are assuming no-show rate to be uniform in the current models. Our next steps would be to consider late arrivals or changing the single sessions and fixed 30 minute appointments to varying factors that are dependent on the appointments made. Along with this, on the overall appointment side, we will ease the assumption of patients having the same time period before their appointment. To find this, we can further analyze past data from the previous years of the mental health clinic.

With either the addition of a variance in arrival time or the duration of the appointment and the time period of patients waiting, we allow our model to take into account cases where times may overlap with one another even without a double booking system in place as some sessions may take longer or some sessions may need to wait on people to be there before starting.

5. Conclusion

With UW Hall Health’s Mental Health Clinic past year consisting of about 26.9% patients being absent to their appointments, we looked at considering different alternatives to the current fee system implemented. For different strategies, we looked at having an overbooking strategy for the whole day, an overbooking strategy for certain times, having a frequency fee system, and the current fee system.

Looking into data about the prior no show rate and late cancellation of appointments from September 2017 to October 2018, we were able to model our strategies through a Monte Carlo simulation. Using this, we conclude a time-specific overbooking system from 8am to 10:30am and 1pm to 3:30pm is the most ideal strategy as we were able to minimize the resources wasted and concerns for patients and therapists.

Hence, with this solution, the UW Hall Health’s Mental Health Clinic will be able to further maximize their utility and resources given to patients while balancing the concerns for each patient’s situation.

5.2 Acknowledgements

This project would not have been possible without having many people and organizations help us along the way. First off, thank you to Professor Sara Billey for tasking us with developing a project from scratch to help a community. Through this project, we were led to talk with Patricia Atwater who allowed us this opportunity to partake in a project to aid mental health care. Through Atwater’s support along with the support of UW Hall Health, UW Medicine Risk Management, the Electronic Health Care System (EHCS), and the IT Department of the UW Medical Center, we were able to delve into the mental health field and aid in the cause of increasing overall welfare for those in need.

6. References

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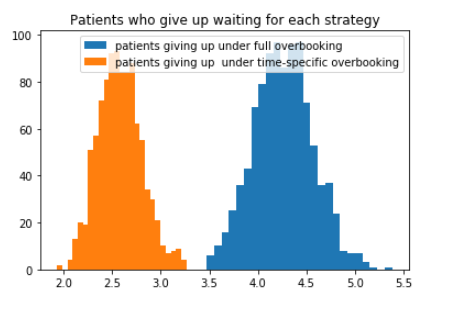
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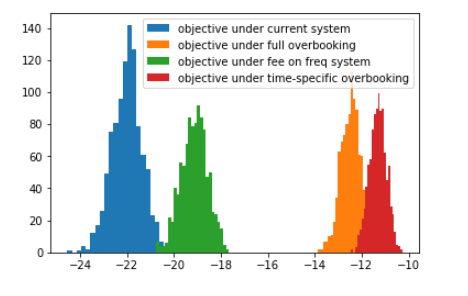
Patricia Atwater, the current director of Health Promotion at Hall Health, writes: “UW struggles to meet the demand for student mental health services. The wait time to see an on-campus therapist for counseling can be up to 4 weeks. Unfortunately, about one-quarter of appointment slots are wasted when students no-show, making it difficult for other students to be seen and for our clinic to run efficiently. This project aimed to examine the best possible solutions to our no show problem. By comparing strategies to improve attendance, students from Math 381 have helped us immeasurably. We can use the team's findings to inform an evidence-based no-show policy.”

7. Appendix

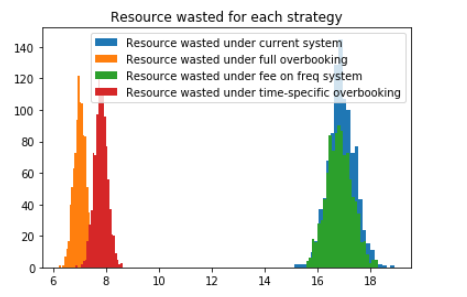
***Figure 1***: Histogram of the number of patients going home and rescheduling in the overbooking strategies modeled.

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***Figure 2***: Histogram of the value of resource wasted for each different strategy used due to patients not showing up.

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**Figure 3**: Histogram of the value of the objective function based on different strategies. The absolute value of the objective function, means that the relative number of patients and therapists who will be discouraged by the system we implemented.



Objective Functions

***General Weighted***:

***Overall***:

***No System***:

***Fee System***:

***Overbooking System***:

**Table 1:** Objective Variable Weight Values and Descriptions

|  |  |  |  |
| --- | --- | --- | --- |
| Meaning | Number of Occurrences | Weights | Values |
| Patient not showing up to appointment |  | a | -1 |
| Absent to appointment |  | b | -0.4 |
| Late Cancellation for appointment |  | c | -0.25 |
| Showing up to appointment |  | d | 1 or 0.5\* |
| Rescheduling Appointment |  | e | -1.5 |
| Waiting for appointment |  | f | -0.25 |
| Too much overflow of patients to appointments |  | g | -0.6 |
| Amount of 30 minute break times therapist use |  | h | -0.15 |

\*if we are looking at an overbooking method, otherwise

***Justification on number of weights***:

*a*: base number (-1) for the system

*b,c*: 40% (25%) of a as it is $40 (assume no show impact $100 on clinic, and patients will pay extra to compensate)

*d*: 1 for fee, 0.5 for overbooking: it is returning the value deducted in a, but for overbooking, it would be halved as it is double booking system

*e*: 50% more than a as going home even if showing up is penalizing wrong patients due to the overbooking -- 50% more is taking account of wrongly discouraging patients

*f*: waiting for up to one hour for patient has similar impact of late cancellation on patients

*g*: therapists taking too much time on patients due to overpacking issue -- it would have been better for therapists to have fee system if that is the case; thus a - b, for not showing up would have been better

*h*: not the worst case but worth noting that it is less stress for therapists than case of g, thus one quarter of the g

**Table 2:** Type of Appointments For Simplification and Further Research

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Count\Type | Clinical Support | MH Assessment and Consultation | MH Med Eval | MH Med F/U | MH Office Visit Individual |
| Count | 2934 | 1235 | 753 | 4050 | 8084 |
| Percentage | 12.20% | 7.241% | 4.415% | 23.75% | 47.40% |

**Table 3:** Table of Patients’ Waiting Days and No Show rate

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Count\Days | Within a week | Within two weeks | Within three weeks | Within four weeks | More than four weeks |
| Count | 5169 | 3463 | 3061 | 2497 | 2866 |
| Percentage | 30.31% | 20.30% | 17.94% | 14.64% | 16.80% |
| No show rate | 20.45% | 26.39% | 26.10% | 28.63% | 38.2% |

**Table 4:** Count of Patient Attendance, Absence, and Cancellation

|  |  |  |  |
| --- | --- | --- | --- |
| Number\Type | Unannounced absence | Late Cancellation | Attended Patients |
| Number of Patients | 1593 | 2987 | 12476 |
| Percentage | 9.34% | 17.51% | 73.15% |

**Table 5:** Weighted Average Loss of Resources and Standard Deviations of All Systems

|  |  |  |
| --- | --- | --- |
| Method | Standard Deviation | Mean (Average) |
| Current System | 0.633 | -22.01 |
| Frequency Fee System | 0.547 | -19.10 |
| Overbooking | 0.471 | -12.45 |
| ***Overbooking at Certain Times*** | ***0.362*** | ***-11.31 (Best)*** |

***Table 6:*** Impact in scheduling with double booking for every time slots

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | Morning time | | | | | | | | | | | | 11:00~12:00 | | |
| Time Slot | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
| Start Time | | 0 | 0.5 | 1 | 1.5 | 2 | 2.5 | 3 | 3.5 | 4 | 4.5 | 5 | 5.5 | 6 | 6.5 | 7 |
| Case 1 | | the early happening of overbook will make patients to wait subsequently | | | | | | | | | | | | No overtime | | |
| Arrivals | | *A1* | *A2* | *A3* | *A4* | *A5* | *A6* | *A7* | *A8* | *A9* | *X10* | *X11* | *X12* |
| Service | | *D1* | | *D3* | | *D5* | | *D7* | | *D9* | | *D11* | |
| Waiting | |  | *W2* | *W3* | | *W5* | | *W7* | | *W9* | |  | |
| Case 2 | | the therapist enters marginal period; concerns for therapists arise | | | | | | | | | | | |  | | |
| Arrivals | | *A1* | *X2* | *A3* | *X4* | *A5* | *X6* | *A7* | *X8* | *A9* | *X10* | *X11* | *X12* |
| Service | | *D1* | | *D3* | | *D5* | | *D7* | | *D9* | | *I* | *D12* | |  | |
| Waiting | | No waiting for patients | | | | | | | | | | | |  | | |
| Case 3 | | multiple late happening of overbook will eventually exceed marginal period | | | | | | | | | | | |
| Arrivals | | *A1* | *X2* | *A3* | *X4* | *X5* | *X6* | *A7* | *X8* | *A9* | *A10* | *A11* | *X12* |  | | |
| Service | | *D1* | | *D3* | | *I* | *I* | *D7* | | *D9* | | *D10* | | *D11* | |  |
| Waiting | |  | | | | | | | | | *W10* | *W11* | |  | | |
| Case 4 | | more patients greater than the capacity N will make patients to wait more and forcing the therapist to work overtime beyond marginal period | | | | | | | | | | | |  | | |
| Arrivals | | *A1* | *A2* | *A3* | *X4* | *A5* | *X6* | *A7* | *X8* | *A9* | *X10* | *A11* | *X12* |
| Service | | *D1* | | *D3* | | *D5* | | *D7* | | *D9* | | *D9* | | *D11* | |  |
| Waiting | |  | *W2* | *W3* | | *W5* | | *W7* | | *W9* | | *W11* | |  | | |

*Ai* : indicates an arriving patient who shows for an appointment for scheduled in time slot *i*

*Xi* : indicates a patient who is a no-show for an appointment for scheduled in time slot *i*

*Di* : indicates a time slot being served for patient *i*

*Wi* : indicates periods during which patient *i* is waiting for service

*I* : indicates periods during which the therapist is idle

***Code and Data:***

Github Link: <https://github.com/warandstar/math381hallhealth>