# Access and Utilization: Methods for Analyzing Appointment Scheduling in Outpatient Specialty Care Clinics

**Running Title:** Methods for Analyzing Access and Utilization

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**Abstract**

OBJECTIVES:

Timely access to outpatient healthcare, particularly specialty care, is a significant challenge nationally. Although insufficient numbers of providers/appointments can contribute to this, existing capacity may also be scheduled inefficiently. Our objective was to evaluate the relationship between scheduling practices, patient cancellation behaviors, and capacity utilization.

STUDY DESIGN:

A longitudinal data set was compiled of appointment data from 7/15/14 to 7/11/17, containing three providers, 3,866 unique patients, and 31,189 appointment slots. Daily schedule "snapshots" allowed us to study how appointments were scheduled, changed, cancelled, and completed.

METHODS:

Analyses were conducted using an SQL ("structured query language") database specially designed to track schedule changes longitudinally. Each record in the database corresponds to an appointment slot (defined by a provider, date, and time) and its status on a specific date (available for schedule or assigned to a specific patient).

RESULTS:

Key observations from the analysis include: 1) few appointments are available for short-term scheduling, 2) appointments are frequently cancelled and rescheduled, 3) rescheduling takes place close to the appointment date and increases in frequency as a function of lead time (i.e. how far into the future the appointment was booked), and thus 4) patients are often seen far later than their originally-requested date because rescheduling incurs significant additional delays while, nonetheless, 5) appointments often go unfilled.

CONCLUSION:

Results suggest the potential value of modified scheduling practices, including scheduling closer to the desired time of appointment and better wait-list management, to ensure that patients are seen closer to the desired date of appointment.

Timely access to outpatient specialty care is an important aim of the U.S. healthcare system[1]. A study by Forrest et al[2] estimated that roughly one in three primary care patients are referred to a specialist annually. Barnett et al[3] showed that the rate of referrals was growing in a study tracking referrals from 1999 to 2009. Similar trends of increasing visits to specialty care physicians are seen in the CDC report *Health, United States, 2016*[4]. Many referrals are associated with chronic conditions; an AHRQ study[5] found that 25% of the adult population in 2012 were being treated for two or more chronic conditions.

Associated with these specialty referrals are often significant delays in time to be seen. A 2017 survey by Merritt Hawkins, *Survey of Physician Appointment Wait Times and Medicare and Medicaid Acceptance Rates*[6], considered time to first available appointment in several major cities. They found a lead time of 24.1 days on average across all cities considered, and that this has increased by 30% since 2014. Other studies have focused on more conservative metrics, recognizing that the lead time to the next available appointment may be a reflection of last-minute patient cancellations and thus overestimate available capacity. For example, Bush et al[7] focused on the time until the third next available appointment (i.e. the time until there are three slots to choose from). They observed a 38-day wait in an obstetrics and gynecology clinic system. A report by the Commonwealth Fund[8] finds that 6% of patients wait two months or longer to be seen by a specialist.

Delays in waiting to be seen impact satisfaction, as reported in Pizer et al[9], Prentice et al [10], and the literature review of Rittenmeyer et al[11], as well as patient outcomes. For example, McComb et al[12] studied primary care appointment behavior for 7,586 adult patients with diabetes, showing a 26.0% increase in ED visits for patients who cancelled a scheduled visit and did not reschedule a new visit until after the original date. The negative impact of delays to appointment on veterans' health outcomes has been extensively studied[13-16].

**We hypothesize that the delays observed in gaining access to specialty outpatient care are not solely an issue of capacity (i.e. number of providers and number of appointment slots) but also an issue of scheduling practices and patient behaviors. Better understanding of these practices and behaviors can lead to new methods for improving both the utilization of capacity and the appropriate matching of capacity to patients.**

To gain this understanding, it is not sufficient to look at static snapshots but rather to study how appointment schedules evolve over time. Therefore, we have developed and implemented an SQL ("structured query language") database specially designed to track schedule changes longitudinally. Each record in the database corresponds to an *appointment slot* (defined by a provider, date, and time) and its status on a specific date (available for schedule or assigned to a specific patient). Each appointment slot is 15 minutes, therefore each *appointment* is comprised of 1 to 3 appointment slots with the appointment slated for 15, 30 or 45 minutes. This database then enables us to ask questions such as how often do patients cancel and reschedule, when does this happen relative to the original scheduling date, when does it happen relative to the date of appointment, and what are the implications of this for timeliness of visit and utilization of clinic capacity. Our goal was to develop a method for studying scheduling behaviors longitudinally. This method is demonstrated in the following case study of a particular clinical environment.

## METHODS

### Database Design

Our case study is based on the Metabolism, Endocrinology, and Diabetes (MEND) clinic at the University of Michigan. MEND has more than twenty-eight physician providers, eight diabetes educators, diabetes nurses, and other support personnel. It operates an endocrine testing suite for advanced and specialized testing for common and rare endocrine disorders and for fine needle aspiration biopsy for thyroid nodules.

For the case study, we considered three providers ("Provider A", "Provider B", and "Provider C") who typically spent one full day, one full day/one half day, and two full days/two half days, respectively, in the MEND clinic during the study period. A standard half-day clinic is four hours long comprised of fifteen-minute slots, design to include two new patient visits of three slots, six return visits (one slot), and two buffer slots. Thirty-minute (i.e. two-slot) visits are occasionally scheduled for patients returning but seeing a new provider.

Our intent was to understand how appointment schedules evolve over time, and the implications of this with respect to access and utilization. We collected schedules from 7/15/14 to 7/11/17, compiling this data into a longitudinal SQL database to assess these changes.

On each weekday within the study horizon, we received a schedule snapshot from Cadence (Epic Systems Corp, Verona, WI), a scheduling module for outpatient and specialty clinics. This contained the schedules of the three providers under consideration six months forward from that date. It was collected with approval from the University of Michigan Institutional Review Board (HUM00087998).

This data was then added to an SQL database table, where each record in the table includes:

- **Date received** (i.e. the date of the "snapshot")
- **Appointment date**
- **Appointment time**
- **Provider**
- **Patient ID** (i.e. a masked medical record number (MRN) allowing us to track individual patients' scheduling, re-scheduling, and cancellation behaviors over time)

Table 1 depicts an example of this database, showing how it can be used to track both appointment slots and patients as their status evolves over time.

After constructing the database, we focused on the following three key questions:

- **Availability**: How many open appointment slots are available as a function of lead time? Specifically, for each "snapshot date" in our database, we counted the number of available appointment slots for each provider one week into the future, computing associated statistics accordingly. We repeated this for open appointment slots two, four, twelve, and twenty-four weeks into the future.
- **Utilization**: What percent of appointments are filled/unfilled on the actual date of appointment, and how does the status of these appointments change in the short-term leading up to the appointment date? Specifically, for each appointment date we looked at the percent of appointment slots that were filled on the date of appointment, on average, for each provider. We also looked at the percent of appointment slots that were filled one, two, three, four, and five days in advance.
- **Patient Behavior**: How often are appointments changed and/or cancelled, and when do these changes occur, relative to the scheduling date, to the date of the appointment, and to

the length of time in between? To address this, we calculated the frequency of cancellation and rescheduling. We also determined the impact of rescheduling on increases in time-to-visit relative to the original scheduled appointment.

RESULTS

**Availability**

Table 2 depicts the availability of appointment slots as a function of provider and how far into the future the appointment is requested. Specifically, we looked at week-long intervals one, two, four, twelve, and twenty-four weeks into the future. For example, the first row of the table considers patients requesting an appointment one week into the future with Provider A. The mean number of appointments available was 3.32. This is skewed, however, by a small number of high values – e.g., the maximum number of appointments available one week into the future from any individual date was twenty-two. We hypothesize that these high values typically occur when the clinic was closed with fairly short notice (but was still captured in our query because there *had* been patients scheduled on that date who were subsequently cancelled). The median value is only one open appointment in the upcoming week. In addition, the mode is 0, i.e. the most common occurrence is to have no available appointments in the upcoming week.

More broadly, Table 2 shows that all three providers have minimal capacity one or two weeks into the future and that there are many dates with no capacity for a patient wanting to be seen as far as four weeks into the future.

## Utilization

Table 2 seems to suggest an inadequacy in capacity, with patients having to wait for several weeks for an available appointment. As we get close to the date-of-appointment, however, a more detailed study of the longitudinal data shows us that scheduled utilization of capacity is actually *decreasing*, i.e. appointments are being cancelled and the associated slots not re-filled.

Specifically, we queried on the number of available slots for each of the providers five, four three, two, and one day ahead of time and computed summary statistics. For Provider B, we observed that by five days in advance of an appointment date, a median value of 92% of the day's appointment slots had been assigned to patients. This value remained the same four, three, and two days in advance of date-of-appointment. But one day in advance, the median percent of slots filled dropped to 88% and on the day-of, we observed only 84% filled.

For Providers A and C, the values of scheduled utilization from five days in advance through day-of-appointment behave similarly (91%, 91%, 91%, 92%, 91%, 87%, and 92%, 92%, 92%, 92%, 91%, 87%, respectively), with most slots filled by five days in advance and remaining filled until the day before, when there was a significant drop-off. This suggests that late cancellations were frequently not being re-filled, either from new requests, from waiting lists, or by moving up patients scheduled further into the future than is medically appropriate.

Similar results are found in a study[17] in which appointment data from an outpatient cardiology clinic was collected for 18 months. They observed that there were nearly eight surplus slots per clinic on average, with the majority of cancellations having lag times that may have been sufficient for recovery, i.e. booking a new patient.

**Patient Behavior**

Within the time period under consideration, our analysis of the longitudinal data shows that approximately 20% of patient appointments were cancelled and rescheduled at least once, with 5% rescheduled twice or more. The percent of appointments cancelled increased as the appointment lead time grows, as shown in Table 3. For example, of those appointments scheduled 0 to 3 days in advance, only 3% cancelled, while more than 42% of those scheduled at least 319 days in advance cancelled. Note that as the lead time from scheduling date to date of appointment exceeds five weeks, the percentage of appointments cancelled is consistently 30% or higher.

Related behavior is noted in Cohen et al[18], which focuses on patient no-shows. In their study of an adult otolaryngology clinic, they observed that long lead times are correlated with patient no-shows. McCullen and Netland[19] also investigated the link between long lead times and no-shows in an outpatient ophthalmology clinic and showed positive correlation (i.e. longer lead times correlated to higher no-show rates). In a similar study of patients with diabetes, McComb et al[12] showed lengthy delays to be seen when an appointment is cancelled (e.g. 28.8% of their patients experiences more than 30 days' delay from the date of the cancelled appointment to the date of the re-scheduled appointment), and 59.9% did not reschedule until the day of the original appointment or later.

To more deeply explore how and when patients schedule, cancel, and re-schedule, we identified the appointment lead time and when the cancellation occurred, relative to both the appointment date and the creation date. For example, a patient who scheduled on 4/14/14 for 7/21/14 and then cancelled on 7/18/14 had a lead time of 37 days, held the appointment for 29 days, and cancelled eight days prior to the appointment. Table 4 shows, as a function of appointment lead time, the percent of appointments that were cancelled at most three or at most seven days before the date of the appointment. Although these percentages increase over time (for example, a patient scheduling one month into the future and then cancelling is more likely to do so within a week of the scheduled appointment than a patient scheduling a year into the future is), they are nonetheless at least 10% for all categories. This has significant implications for the ability to reschedule another patient into these slots, given the limited new lead time.

Finally, given that it is often the case that patients reschedule at the time of cancellation, we explored the implications of the above on delays to being seen. For example, if a patient schedules an appointment for three months into the future and then reschedules close to the date of appointment, because of limited short-term capacity, their new appointment may be scheduled for several weeks or even months into the future beyond the original three month lead time, thus greatly increasing the time from original request until the patient is seen.

To study this, we calculated for each rescheduled appointment the change in lead time for the new appointment relative to the lead time for the original appointment. For example, if an appointment was scheduled on January 1 for January 31 (a lead time of 30 days) and then cancelled and rescheduled for January 16 ( a lead time of 15 days), this would represent a 50% reduction in lead time ((15 – 30)/30). If it were rescheduled for February 15 (a lead time of 45 days), this would represent an increase in lead time of 50% ((45 – 30)/30).

Figure 1 shows the lead time for re-scheduled appointments as a function of the initial lead time. Each set of bars corresponds to a set of rescheduled appointments, grouped by the original lead time (0 – 7, 8 – 14, 15 – 30, 31 – 90, 91 – 180, and 181 days or more). Within these groups, the individual bars represent the number of re-scheduled appointments as a function of new lead time, relative to the original scheduling date (decreasing by 50 – 100%, i.e. moving earlier;

decreasing by 0 to 50%; increasing by 0 to 50%, increasing by 50 to 100%; and increasing by more than 100%).

For example, for all appointments that were originally scheduled with 31 – 90 days' lead time and subsequently cancelled and rescheduled, 16 of these moved earlier by 50 - 100% of the original lead time, 47 moved earlier by 0 - 50%, 173 moved later by 0 - 50%, 102 moved later by 50 - 100%, and 116 moved later by more than 100% (i.e. more than doubled the original lead team). We observe that the majority of rescheduled appointments move later, often considerably so, often adding months to the lead time of the original appointment.

## DISCUSSION

In the above case study, we were able to study in detail the utilization of an outpatient specialty clinic, looking not only at a single snapshot in time but watching how appointments and patient scheduling behavior evolved over time.

The first observation is that a non-trivial amount of slots go unscheduled. In and of itself, this may not be an undesirable characteristic of the system. In fact, it could correspond to necessary and appropriate buffer to ensure that patients flow smoothly throughout the day given inevitable delays, as well as providing valuable time for charting and other provider tasks.

What is more concerning is the use of the filled appointment – are these appointment slots going to the most medically-appropriate patients? Three areas of concerns are raised by the remainder of the analysis. First, given the limited number of appointments available in the short-term, patients may be getting scheduled farther out than is medically requested. Second, when appointments are scheduled well into the future (either because of lack of capacity or because a long lead time is medically appropriate), they have a high probability of cancelling. Because these cancellations happen close to the time of appointment and because of limited short-term appointment availability, patients in this situation are almost always adding delay, sometimes substantial, to the time to be seen. Finally, the fact that very few appointments move earlier when rescheduled suggests that newly-freed capacity due to cancellations is rarely used to reduce delays for patients with inappropriately long lead times but rather to accommodate new patient requests, although those patients may be of lower priority to be seen.

More broadly, this research helps to demonstrate the opportunities presented by a longitudinal data study that cannot be captured by a single, static snapshot.

Limitations

Our data only includes scheduling data and not completion data. We do not have data on patients who no-show (or cancel on the day of appointment). Therefore, we over-state utilization. We also do not know which cancellations were patient-driven versus provider-driven. In addition, we have no data as to the medically-appropriate interval for scheduling a given patient's appointment. For example, if a patient scheduled an appointment for three months into the future, this may have been at the request of the provider or the provider requested may have requested an earlier visit but no earlier appointment could be found for that patient.

Finally, our study only focuses on a single institution. While the methods that we present are applicable in other clinical environments, the results (and thus the associated conclusions) may vary significantly.

## CONCLUSIONS

A dynamic, longitudinal approach to evaluating patient scheduling can provide greater insights than a single static snapshot. In this case study, our insights include the observations that patients are scheduling far in advance (partially due to limited short-term capacity). This leads to a high cancellation/rescheduling rate. Not only do these last-minute cancellations often leave the original appointment slots unfilled, but those patients are not able to reschedule in the near-term, and thus their date of visit extends even further into the future. This could potentially be mitigated both by scheduling patients closer to the desired date of visit (e.g. by reserving appropriate amounts of appointment time and sending reminders to patients to schedule closer to the appropriate date of appointment) and by developing patient-focused wait lists that prioritize reassigning cancelled slots to patients who are scheduled later than is clinically appropriate.

REFERENCES


1. Institute of Medicine. 2001. Crossing the Quality Chasm: A New Health System for the 21st Century. Washington, DC: *The National Academies Press*.
2. Forrest CB, Majeed A, Weiner JP, Carroll K, Bindman AB. Comparison of specialty referral rates in the United Kingdom and the United States: retrospective cohort analysis. *BMJ : British Medical Journal*. 2002;325(7360):370-371.
3. Barnett ML, Song Z, Landon BE. Trends in physician referrals in the United States, 1999-2009. Arch Intern Med. 2012 Jan 23;172(2):163-70.
4. National Center for Health Statistics. Health, United States, 2016: With Chartbook on Long-term Trends in Health. Hyattsville, MD. 2017.
5. Soni, A. Specialist Need and Access among Adults with Multiple Chronic Conditions, U.S. Civilian Noninstitutionalized Population, 2012. Statistical Brief #482. November 2015. Agency for Healthcare Research and Quality, Rockville, MD.
6. Merritt Hawkins. 2017. Survey of Physician Appointment Wait Times and Medicare and Medicaid Acceptance Rates. Dallas, TX.
7. Bush SH, Lao MR, Simmons KL, Goode JH, Cunningham SA, Calhoun BC. Patient access and clinical efficiency improvement in a resident hospital-based women's medicine center clinic. *Am J Manag Care*. 2007;13(12):686–690.
8. Schoen C, Osborn R, Squires D, Doty MM. Access, affordability, and insurance complexity are often worse in the United States compared to ten other countries. *Health Aff (Millwood).* 2013 Dec;32(12):2205-15.
9. Pizer SD, Davies ML, Prentice JC. Consult Coordination Affects Patient Experience. *Am J Manag Care.* 2017. 3(17):23-28.
10. Prentice JC, Davies ML, Pizer SD. Which outpatient wait-time measures are related to patient satisfaction? *Am J Med Qual.* 2014;29: 227–235.
11. Rittenmeyer, L, Huffman, D, Godfrey, C. The experience of patients, families and/or significant others of waiting when engaging with the healthcare system: a qualitative systematic review. *JBI Database of Systematic Reviews and Implementation Reports*. 2012 12(8):193-258.
12. McComb S, Tian Z, Sands L, Turkcan A, Zhang L, Frazier S, Lawley M. Cancelled Primary Care Appointments: A Prospective Cohort Study of Diabetic Patients. *J Med Syst*. 2017 Apr;41(4):53.
13. Pizer SD, Prentice JC. What are the consequences of waiting for health care in the veteran population? *J Gen Intern Med.* 2011 Nov;26 Suppl 2:676-82.
14. Prentice, J.D. and Pizer, S.D. Delayed access to health care and mortality. *Health Services Research.* 2007;42: 2, 644–662.
15. Prentice, J.D. and Pizer, S.D. Waiting times and hospitalizations for ambulatory care sensitive conditions. *Health Services Outcomes & Research Methodology*. 2008; 8: 1.

16. Prentice JC, Fincke BG, Miller DR, Pizer SD. Outpatient wait time and diabetes care quality improvement. *Am J Manag Care.* 2011 Feb 1;17(2):e43-54.

17. Monahan K, Fabbri D. Schedule-based metrics for the evaluation of clinic performance and potential recovery of cancelled appointments. *Int J Med Inform.* 2018 Jan;109:49-54.

18. Cohen AD, Kaplan DM, Kraus M, Rubinshtein E, Vardy DA. Nonattendance of adult otolaryngology patients for scheduled appointments. *J Laryngol Otol.* 2007 Mar;121(3):258-61.

19. McMullen MJ, Netland PA. Lead time for appointment and the no-show rate in an ophthalmology clinic. *Clinical Ophthalmology (Auckland, NZ)*. 2015;9:513-516.

TABLES AND FIGURES

**Table 1:** Example Records from Longitudinal SQL Database

| Date_received | Appt_date | Appt_time | Provider | Patient_ID | Notes |
|---|---|---|---|---|---|
| 3/1/2015 | 7/1/2015 | 9:00 AM | Dr. A | -1 | Appointment slot available |
| 3/2/2015 | 7/1/2015 | 9:00 AM | Dr. A | 123456 | On 3/2/15, Pt 123456 is scheduled to be seen on 7/1/15 |
| 3/3/2015 | 7/1/2015 | 9:00 AM | Dr. A | 123456 | |
| 3/4/2015 | 7/1/2015 | 9:00 AM | Dr. A | 123456 | |
| 3/5/2015 | 7/1/2015 | 9:00 AM | Dr. A | 123456 | |
| 3/6/2015 | 7/1/2015 | 9:00 AM | Dr. A | 123456 | On 3/6/15, Pt 123456 is cancelled |
| 3/7/2015 | 7/1/2015 | 9:00 AM | Dr. A | -1 | …making the 7/1/15 slot available |
| 3/7/2015 | 8/4/2015 | 2:00 PM | Dr. A | 123456 | …and rescheduled for 8/4/15 |
| … | … | … | … | … | … |
| 3/20/2015 | 7/1/2015 | 9:00 AM | Dr. A | 689012 | On 3/20/15, Pt 689012 is scheduled to use the 7/1/15 slot |

| |
|---|
| Changes to pt #123456 |
| Changes to appt slot 7/1/15 9:00 Dr. A |

**Table 2:** Available Number of Appointments by Provider and Time into the Future

| Available Future Appointments in…. | | Min | Max | Mean | Median | Mode |
|---|---|---|---|---|---|---|
| **Provider A** | 1 week | 0 | 22 | 3.32 | 1 | 0 |
| (1 full day clinic per week) | 2 weeks | 0 | 21 | 4.07 | 2 | 0 |
| | 4 weeks | 0 | 22 | 5.91 | 6 | 0 |
| | 12 weeks | 0 | 22 | 11.49 | 11 | 11 |
| | 24 weeks | 0 | 22 | 16.50 | 20 | 20 |
| | | | | | | |
| **Provider B** | 1 week | 0 | 56 | 8.13 | 7 | 0 |
| (2 full, 2 half day clinics per week) | 2 weeks | 0 | 52 | 9.36 | 8 | 0 |
| | 4 weeks | 0 | 41 | 10.29 | 9 | 7 |
| | 12 weeks | 0 | 55 | 26.18 | 26 | 20 |
| | 24 weeks | 0 | 67 | 39.11 | 42 | 45 |
| | | | | | | |
| **Provider C** | 1 week | 0 | 26 | 5.33 | 2 | 0 |
| (1 full, 1 half day clinic per week) | 2 weeks | 0 | 25 | 6.73 | 5 | 0 |
| | 4 weeks | 0 | 27 | 9.53 | 11 | 0 |
| | 12 weeks | 0 | 32 | 18.71 | 21 | 22 |
| | 24 weeks | 0 | 35 | 12.81 | 10 | 0 |

**Table 3:** Percent of Appointments Cancelled as a Function of Number of Days' Lead Time

| Lead Time (Days) | Percent Cancelled |
|---|---|
| 0 to 3 | 3.0% |
| 4 to 10 | 10.9% |
| 11 to 24 | 15.0% |
| 25 to 38 | 21.5% |
| 39 to 66 | 30.3% |
| 67 to 94 | 34.0% |
| 95 to 150 | 35.3% |
| 151 to 206 | 41.6% |
| 207 to 318 | 41.6% |
| >= 319 | 42.1% |

**Table 4:** For Cancelled Appointments, Probability of Cancelling within 3/7 Days of the Appointment Date

| # Days from Scheduled Date to Appointment Date (Lead Time) | # Appointments Cancelled/ Rescheduled | # Days from Cancellation Date to Appointment Date | # Appointments Cancelled/ Rescheduled | Percent Rescheduled < 3/ <7 days from Appointment Date |
|---|---|---|---|---|
| 0 to 30 | 465 | ≤ 3 | 224 | 48.2% |
| | | ≤ 7 | 321 | 69.0% |
| 30 to 60 | 847 | ≤ 3 | 265 | 31.3% |
| | | ≤ 7 | 387 | 45.7% |
| 60 to 90 | 1173 | ≤ 3 | 237 | 20.2% |
| | | ≤ 7 | 388 | 33.1% |
| 90 to 120 | 1666 | ≤ 3 | 364 | 21.8% |
| | | ≤ 7 | 613 | 36.8% |
| 120+ | 2222 | ≤ 3 | 367 | 16.5% |
| | | ≤ 7 | 583 | 26.2% |

Figure 1. Extending Time to Be Seen When Rescheduling