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DISCRETE-EVENT SIMULATION WITH CONSIDERATION FOR PATIENT PREFERENCE WHEN SCHEDULING SPECIALTY TELEHEALTH APPOINTMENTS

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ABSTRACT

Healthcare providers have begun providing care to patients via remote appointments using web-based, synchronous video visits. As this appointment modality becomes increasingly prevalent, decision-makers must consider how to incorporate patient preference for an in-person versus virtual care modality when scheduling future visits. We present a discrete-event simulation that models several potential policies that these decision-makers could use to schedule patients, and demonstrate this simulation in the clinical context of patients with gastroesophageal reflux disease. This simulation provides key metrics for decision-makers, including provider utilization, patient lead time, and proportion of appointments that satisfy patients' preferences for appointment modality.

1 INTRODUCTION

Healthcare providers are increasingly using telehealth as an option for interacting with patients (Kane and Gillis 2018). Telehealth can take many forms, including remote monitoring of intensive-care patients' clinical status and physicians phone conferencing to discuss complex patients. In some medical specialties, like gastroenterology, clinicians are beginning to use synchronous video to meet with patients to replace or complement in-person appointments (Siegel 2017). Use of such remote visits increased due to precautions related to the coronavirus pandemic, and continued use of telehealth is expected post-pandemic (Gadzinski et al. 2020).While some appointments may benefit from or necessitate meeting in-person, video visits may be effective alternatives for other appointments. Moreover, some patients may prefer a telehealth visit because an in-person visit may require them to travel a long distance, is more challenging to fit in their schedule, exposes them to risk of infection from other patients and healthcare providers, or other reasons.

Telehealth can improve access to care for patients. Geographic distance is a key barrier to care, especially for people living in rural areas and/or those who do not have access to reliable transportation (Penchansky and Thomas 1981; Kullgren et al. 2012; Fortney et al. 2011). When appropriately implemented, telehealth can reduce the distance patients need to travel in order to interact with the healthcare system. By decreasing travel, patients also save time otherwise spent on getting to and from appointments. This saved time may allow patients to better accommodate visits because they can take less time off of work or do not need to find childcare. In a study of the impact of telehealth in inflammatory bowel disease (IBD), 80% of patients saved at least one half-day of driving by participating in a telemedicine visit (Li et al. 2016). Finally, telehealth has the potential to lower costs for a healthcare system, the savings from which can be passed on to patients (Hafner-Eaton 1993). These savings can mitigate patients' financial barriers to care. Telehealth lowers cost of care by using fewer physical resources and sometimes requiring fewer clinical/nonclinical staff members, including medical assistants, desk staff, and environmental services.

As telehealth has become more common, researchers have sought to understand patients' perceptions of telehealth. In a 2019 patient survey, 66% of patients reported being willing to use telehealth. Telehealth interest varies across age groups with older patients tending to be less interested in using it (American Well 2019). However, the same 2019 survey found that 52% of patients aged 65 or older are willing to use telehealth. Among older adults who have had a telehealth visit, more than half viewed in-person visits to have better overall quality of care compared to telehealth (Malani et al. 2019). In gastroenterology, a study of the effectiveness of telehealth as an option for IBD visits found that 85% of patients reported their care was as good as it would have been in person (Li et al. 2016).

As clinical decision-makers incorporate telehealth options into their systems, simulation can be valuable for understanding how to incorporate this modality (Tang et al. 2017; Gupta and Denton 2008; Zhang et al. 2018; Patrick and Aubin 2013). Simulation is often used to guide healthcare decision-makers in evaluating alternatives, often by incorporating uncertainty. Discrete-event simulation is helpful in scenarios in which patients arrive and interact with a healthcare system via a set of clinical encounters. We add to this literature by applying simulation to a new context area that covers patient preferences for telehealth.

2 PROBLEM STATEMENT

As we demonstrate how simulation can be used to consider patient preference for telehealth, we consider patients with gastroesophageal reflux disease (GERD) as an example. GERD is the most common gastrointestinal (GI) diagnosis in outpatient GI clinic visits in the U.S., with approximately 20% of adults reporting at least weekly GERD symptoms (Richter and Rubenstein 2018). The clinical presentation of GERD primarily involves heartburn and acid regurgitation. GERD symptoms may also indicate more serious diagnoses like Barrett's esophagus and esophageal stricture. These diagnoses may be evaluated using additional testing such as upper endoscopy. Endoscopies occur if a provider determines a patient's symptoms require serious attention and/or if a patient visits a GI provider several times.

We evaluate GERD patients interacting with the Veterans Affairs (VA) Healthcare System gastroenterology clinic in Ann Arbor, Michigan. This care setting is ideal for conducting a simulation because, as an integrated healthcare delivery system, both VA primary care and GI providers belong to the same health system. Thus, patients can more easily be transferred between the two provider types.

GERD patients interact with the VA via several appointments as outlined in Figure 1. Patients tend to treat GERD symptoms at home with over-the-counter therapy prior to seeking clinical care. They then typically visit a primary care provider (PCP) or, less commonly, self-refer to a GI doctor. Regardless of provider type, a patient's first visit will be face-to-face (F2F) so providers can conduct physical examinations and in-person testing . After patients complete each visit they can either exit the system (either because their symptoms have been adequately treated or are lost to follow-up) or move to a future appointment. Most return visits have a specific time range for follow-up (generally 2-8 weeks). We consider appointments scheduled within this range to be "in-range" and those outside of it to be "out-of-range."

Patients visiting a PCP can be referred to a GI doctor after any appointment, and patients can be referred by their provider directly for an endoscopy if their symptoms indicate this would be clinically valuable. Patients may "no-show" for any appointment, in which case they are rescheduled for an appointment with the same provider and of the same type (F2F or telehealth). Patients are dismissed from the system if they "no-show" three times over the duration of care. Aside from the first appointment with each provider type (PCP and GI) and the fourth GI appointment (endoscopy), the simulation assumes that all appointments can be conducted either F2F or via telehealth. Telehealth has been deemed to be an appropriate alternative to F2F visits for the appointments considered here, with no meaningful difference in quality of care.

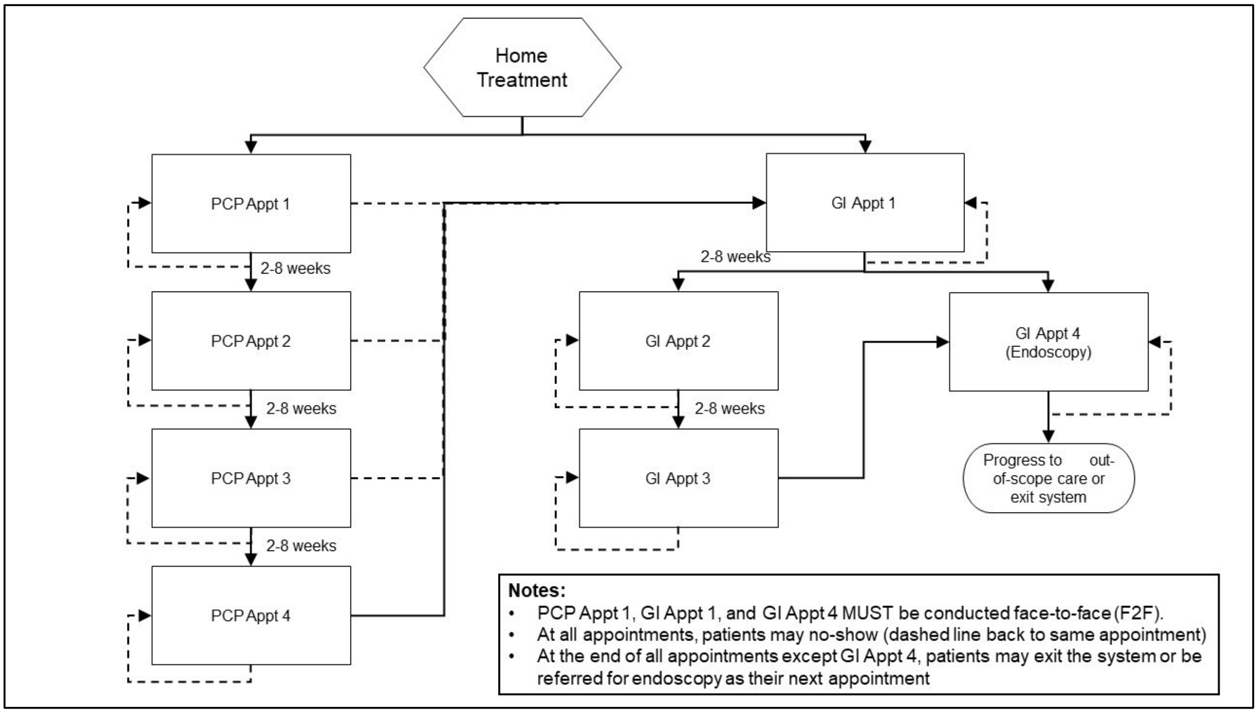

Figure 1: Patient flow through GERD-related appointments.

3 SIMULATION MODEL

We modeled patients flowing through GERD-related clinical visits using discrete-event simulation. The simulation was coded and run in C++. The model is initiated with a set of providers, some of whom are primary care providers (PCPs) and some of whom are gastrointestinal (GI) specialists. Each provider has a given weekly capacity for number of face-to-face (F2F) and telehealth visits. In each replication, we randomly generate a stream of weekly patient arrivals that are Poisson distributed. Patients either seek care from a PCP or self-refer to a GI doctor. Each patient also has a preference for telehealth or face-to-face appointments and the probability of a patient preferring telehealth is based on the patient's geographic distance from the clinic. Patients who live "near" a clinic location (within 40 miles) have a 50% probability of preferring telehealth; 100% of those who live "far" from a clinic location prefer telehealth.

Patients flow through care for GERD and either do not attend a visit and are immediately rescheduled for the same visit (no-show) or do attend the visit. Patients who attend visits are scheduled for their next appointment based on a scheduling policy, as described in Section 3.2. The probability of which appointment is next needed is indicated in a transition probability matrix (example included in Appendix A). The transition probability matrix values are based on historical data from the Ann Arbor VA GI clinic.

Our base unit of time is weeks. The simulation is run over 52 weeks unless otherwise noted. To calculate minimum number of replications needed, we use appointment lead time as our metric of interest, with a standard error of 0.2 weeks, 95% confidence interval, and an initial replication size of 10. With baseline (BL) inputs and scheduling patients without regard for appointment modality preference, we find the minimum number of replications to be 39.8 (Lumina Decision Systems 2020). Our model processes in under one minute with 100 replications in most cases, so we increased to 100 replications for all analyses.

3.1 Model Input Parameters

We include several deterministic and stochastic input values for our model. Input values were derived from historical data, VA operations, and expert clinical opinions. A list of inputs is included in Table 1. Note that weekly provider capacities are specific to GERD patients. That is, we consider providers to only see 3

GERD patients via F2F appointments and 4 GERD patients via telehealth each week, but they may be seeing several other patients not included in this analysis.

Table 1: Simulation model inputs.

Parameter	Baseline Value	Source/Description
Number of PCPs	2	VA operations-Ann Arbor VA GI clinic
Number of GI doctors	2	VA operations-Ann Arbor VA GI clinic
F2F appointment weekly capacity per provider	3	VA operations-Ann Arbor VA GI clinic
Telehealth appointment weekly capacity per provider	4	VA operations-Ann Arbor VA GI clinic
Probability of next appointment type/probability of system exit	Varies based on current appointment	Historical data-Ann Arbor VA GI clinic
No-show rate (includes cancellations)	0.2	Historical data-Ann Arbor VA GI clinic
Weekly patient arrivals to PCP	5	Historical data (Poisson distribution with λ=5)
Weekly patient arrivals to GI providers	7	Historical data (Poisson distribution with λ=7) - Ann Arbor VA GI clinic
Proportion of patients who live far from clinic (defined by VA guidelines for "near" vs "far")	0.014	Historical data-Ann Arbor VA GI clinic, patients who live > 40 miles from clinic are considered "far," all others considered "near"
Probability of patient preference for telehealth vs. F2F visits	0.5 for "near" patients, 1.0 for "far" patients	(Malani et al. 2019; American Well 2019)

3.2 Scheduling Policies

When a patient enters the system, they are scheduled for their first appointment with either a PCP or GI provider. Because all first appointments must be F2F, the simulation finds the first available F2F appointment with the appropriate provider and schedules the patient with a provider of that type. Once a patient has been scheduled with any type of provider, they are always seen by that provider for the appropriate appointments; that is, a patient is seen by at most one PCP and at most one GI provider.

After patients complete each visit, they are scheduled for a next appointment. When determining the patient's next appointment, we follow a policy which considers three parameters: patient's preference for appointment modality (telehealth vs. F2F), a range of time when the next appointment is clinically indicated ("in-range" vs. "out-of-range"), and provider available capacities. Unless otherwise noted, the ideal range of a next appointment is 2-8 weeks. Exceptions to this range include the patient's first appointment with any provider and an upper endoscopy (final GI visit), which are scheduled in the next open slot. Patients who no-show are immediately re-scheduled with the same provider for the next available appointment of the same type they should have attended. Patients see at most one PCP and one GI provider; that is, they are scheduled with the same provider for each visit offered within the set of PCP or GI appointments.

We construct a scheduling policy by combining an in-range policy (lettered A, B, C) and an out-of-range policy (numbered 1, 2) from Figure 2. For example, if we are following policy C2 and a patient who prefers telehealth needs a new appointment, we first attempt to schedule the soonest possible appointment within the next 2-8 weeks with the appropriate provider. If no telehealth appointments are available in this time frame, we then attempt to schedule the soonest possible F2F visit with the appropriate provider. If no appointments of any type are available in-range, we then schedule the patient for the soonest possible out-of-range appointment of their preferred type with the appropriate provider.

If no appointments are available out-of-range or if the patient's next appointment will be beyond the time horizon (e.g., it is week 52 of a 52-week analysis), we assume the patient is scheduled for an appointment beyond the horizon. These instances are tracked, but patients are not considered to have "completed" care.

In-range Policies

A. First available appointment – any modality type (F2F vs. telehealth)
B. First available appointment – preferred modality type only
C. First appointment available of preferred modality type. If no in-range appointment of preferred modality type available, first available appointment of any type

Out-of-range Policies

1. First available appointment– any modality type
2. First available appointment – preferred modality type only

Figure 2: Scheduling policies used in the model.

3.3 Metrics

We track several metrics including lead time to first appointment, percentage of patients' appointment modality preferences met, provider utilization, and number of patients who complete care. Lead time is calculated as the number of weeks between a patient "arriving" in the simulation to their first scheduled appointment. Percentage of modality preferences met considers the number of appointments could be scheduled for either F2F or telehealth (all appointments except the first visit with each provider and endoscopy) as the denominator and the number of those times in which a patient's preferred modality was scheduled as the numerator. Appointments that must be conducted F2F are not included in the denominator of total appointments when considering percent of modality preferences met. Provider utilization is the percentage of providers' available appointment capacities that are used for patient visits.

4 ANALYSES

We present several scenarios in considering patient preference for appointment modality when scheduling GERD patients. For these scenarios, we use scheduling policy C1 unless otherwise noted. Policy C1 indicates that when scheduling a patient in-range, we attempt to schedule the patient for the first available appointment of their preferred type. If no preferred appointments are available in-range, we attempt to schedule the patient for their non-preferred type in-range. If no appointments are available in-range, we schedule the patient for the first available appointment of any type out-of-range.

The four scenarios considered in this analysis include: (1) impact of a higher proportion of patients being far from clinic, (2) impact of patient arrival rates, (3) comparison of changing the number of providers versus changing provider capacity, and (4) comparison of scheduling policies. Additionally, we conduct sensitivity analyses to understand the inputs that have the greatest effect on key metrics. Table 2 lists output metrics when using the baseline inputs listed in Table 1 under policy C1.

Table 2: Baseline metric values, policy C1.

Metric	Value		Metric	Value
Percent modality preference met	99.98%		Telehealth utilization	48.36%
Lead time	2.94 weeks		Overall provider utilization	70.12%
Patients seeking care	355.23		F2F utilization	99.13%
Patients completing care	299.01			

4.1 Scenario 1: Distance to Care

In the first scenario, we vary the percentage of patients who live "far" (>40 miles) from the clinical location. In all analyses, 100% of patients who live far from care prefer telehealth appointments and 50% of patients who live near care prefer telehealth appointments. In our baseline analyses, 1.4% of patients live far from care, based on historical data of GERD patients at the Ann Arbor VA. Given that many other systems will have different proportions of patients who live far from care (or other demographics that influence likelihood of preferring certain appointment modalities), we vary the percentage of patients who live far from 0-50% to understand impact on metrics.

Results from Scenario 1 are included in Table 3. We see that as more patients are far from care, overall (OA) provider utilization increases, largely due to increased telehealth appointment. As a greater proportion of patients are far from care, lead time decreases. This outcome is a result of more patients preferring, and thus being scheduled for, telehealth appointments according to policy C1. The relative increase of telehealth utilization frees more F2F appointments, which patients newly entering the system can use.

In this scenario (also Scenarios 2 and 3), policy C1 accommodates patient preference appropriately, thus the percentage of modality preferences met is greater than 99% in all instances. This occurs because appointment capacity typically exists so patients get their preference for appointments that can be conducted in multiple modalities. Because of this, we do not report on percent preferences met for Scenarios 1-3.

Table 3: Impact of distance to care on utilization and lead time.

	% of Patients who live far (>40 miles) from care					
Metric	**0%**	**1.4% (BL)**	**2.8%**	**10%**	**25%**	**50%**
OA Provider Utilization (%)	69.73 ±2.32	70.12 ±2.03	69.69 ±2.25	71.23 ±2.04	73.86 ±1.96	77.99 ±2.11
F2F Utilization (%)	99.02 ±0.71	99.13 ±0.71	99.08 ±0.81	98.94 ±0.90	98.77 ±0.93	98.01 ±1.45
Telehealth Utilization (%)	47.78 ±3.83	48.37 ±3.44	47.65 ±3.76	50.45 ±3.50	55.18 ±3.28	62.98 ±3.22
Lead Time (weeks)	2.98 ±0.32	2.94 ± 0.34	2.94 ±0.37	2.88 ±0.33	2.78 ±0.35	2.72 ± 0.32

4.2 Scenario 2: Patient Arrival Rates

In our baseline analyses, we model five patients arriving each week seeking care from a PCP and seven each week self-referring to a GI doctor, with each arrival rate being Poisson distributed. To understand how different patient arrival rates impact the system, we vary the PCP patients from 3-9 arrivals per week and the GI patients from 5-9 arrivals per week.

Table 4 shows the results from this scenario analysis. The general relationship between patient arrival rates and utilization is direct; as more patients arrive each week, utilization increases. The number of patients who self-refer to GI has a lesser impact on utilization than the number of patients who visit a PCP first. Lead time and patient arrival rates also have a direct relationship. However, when the PCP patient arrival rate decreases by 2 per week, the difference in lead time is statistically insignificant. All other changes to arrival rates presented here do indicate a significant difference in lead time.

Table 4: Impact of patient arrival rates on utilization and lead time.

	Weekly Patient Arrivals					
Metric	**5 PCP, 7 Self-Refer (BL)**	**3 PCP, 7 Self-Refer**	**7 PCP, 7 Self-Refer**	**9 PCP, 7 Self-Refer**	**5 PCP, 5 Self-Refer**	**5 PCP, 9 Self-Refer**
OA Provider Utilization (%)	70.12 ±2.03	61.91 ±2.75	72.05 ±2.05	72.43 ±1.92	68.77 ±2.17	70.13 ±2.03
F2F Utilization (%)	99.13 ±0.71	89.42 ±3.08	99.76 ±0.27	99.87 ±0.25	98.92 ±0.86	99.16 ±0.78
Telehealth Utilization (%)	48.37 ±3.44	41.27 ±3.67	51.27 ±3.60	51.86 ±3.34	46.15 ±3.69	48.35 ±3.54
Lead Time (weeks)	2.94 ±0.34	2.70 ±0.31	3.86 ±0.45	5.01 ±0.46	1.97 ±0.10	4.17 ±0.33

4.3 Scenario 3: Number of Providers vs. Provider Capacity

As health systems incorporate telehealth into care, they may consider how to adjust staffing. In this scenario we vary the number of providers. At baseline we have two PCPs and two GI doctors. We vary the number of each provider from 1-4. We consider how changing the number of providers compares to changing provider capacities. At baseline each provider has weekly capacity for four telehealth and three F2F GERD visits. We consider instances where both PCPs have a weekly capacity for two telehealth and one F2F visit ("lower capacity"), and where one of the two PCPs have a weekly capacity of seven telehealth and five F2F visits ("higher capacity"). We conduct the same set of capacity changes with GI doctors.

Tables 5 and 6 present analyses of the impact of provider count and capacity, respectively. Logically, as we decrease the number or capacity of providers, utilization and lead time increase; conversely, those metrics decrease when increasing provider count or capacity. When considering lead time, changing the number of providers in these scenarios has a greater impact than changing the capacity of providers. We see the largest impact when going from two to one PCP, with an increase in lead time of over 5 weeks.

Table 5: Impact of number of providers on utilization and lead time.

	Provider Count				
Metric	**2 PCP, 2 GI (BL)**	**1 PCP, 2 GI**	**4 PCP, 2 GI**	**2 PCP, 1 GI**	**2 PCP, 4 GI**
OA Provider Utilization (%)	70.12 ± 2.03	75.01 ± 2.60	58.94 ±1.85	67.41 ±2.58	69.30 ±2.00
F2F Utilization (%)	99.13 ±0.71	99.93 ±0.18	82.46 ± 2.18	98.91 ±0.94	98.54 ±0.77
Telehealth Utilization (%)	48.37 ±3.44	53.65 ±4.83	37.23 ±2.56	43.79 ±4.40	45.38 ±3.45
Lead Time (weeks)	2.94 ± 0.34	8.63 ± 0.56	1.45 ±0.03	4.60 ±0.26	1.75 ±0.07

Table 6: Impact of provider capacity on utilization and lead time.

	Provider Capacity				
Metric	**2 PCP, 2 GI (BL)**	**2 PCP (Low Cap.), 2 GI**	**2 PCP (High Cap.), 2 GI**	**2 PCP, 2 GI (Low Cap.)**	**2 PCP, 2 GI (High Cap)**
OA Provider Utilization (%)	70.12 ± 2.03	68.81 ± 2.15	64.59 ± 1.91	62.00 ± 2.53	70.25 ± 2.34
F2F Utilization (%)	99.13 ± 0.71	99.78 ± 0.39	95.79 ± 2.10	98.82 ± 1.02	99.04 ± 0.61
Telehealth Utilization (%)	48.37 ± 3.44	48.16 ± 3.61	41.61 ± 3.10	37.44 ± 4.01	43.79 ± 3.42
Lead Time (weeks)	2.94 ± 0.34	5.37 ± 0.50	2.64 ± 0.33	4.50 ± 0.23	2.00 ± 0.14

4.4 Scenario 4: Scheduling Policies

In the final scenario of our main analyses, we examine how different scheduling policies impact metrics. We consider the six combinations of in-range and out-of-range policies (A1, A2, B1, B2, C1, and C2). Table 7 indicates metrics for the various policies. We see policies A1 and A2 ("A policies") tend to have different values than B1, B2, C1, and C2 ("B/C policies"). With the A policies, we have approximately 50% of appointments where patient preference for modality are met, because A policies do not consider preference when scheduling. The B/C policies all have 99-100% preferences met. We also see higher overall utilization and telehealth utilization under the A policies versus the B/C policies. We also see a nonsignificant increase in lead time in the A policies compared to B/C.

Table 7: Impact of scheduling policies on patient preferences met, utilization, and lead time.

	Scheduling Policy					
Metric	**A1**	**A2**	**B1**	**B2**	**C1**	**C2**
% Appointment Preferences Met	50.09 ±3.37	50.68 ±3.27	99.97 ±0.09	100 ±0	99.98 ±0.06	100 ±0
OA Provider Utilization (%)	78.49 ±2.60	78.42 ±2.42	70.02 ±1.82	69.73 ±1.98	70.12 ±2.03	69.66 ±2.18
F2F Utilization (%)	99.49 ±0.57	99.50 ±0.46	99.13 ±0.66	99.08 ±0.63	99.13 ±0.71	98.94 ±0.97
Telehealth Utilization (%)	62.74 ±4.47	62.62 ±4.20	48.20 ±3.12	47.72 ±3.31	48.37 ±3.44	47.70 ±3.51
Lead Time (weeks)	3.07 ±0.34	3.06 ±0.30	2.96 ±0.34	2.95 ±0.36	2.94 ±0.34	2.93 ±0.33

4.5 Sensitivity Analyses

We conducted sensitivity analyses to understand which input variables have the greatest impact on two key metrics: lead time and provider utilization for telehealth appointments. For each metric a tornado diagram is created, with each bar of the tornado diagram representing one input variable. The top bar of the diagram indicates the input variable that has the greatest impact on the metric of interest, with subsequent bars included in descending order of impact. Appendix B has abbreviation explanations and full variable names.

Figure 3 shows tornado diagrams for lead time. In all policies, the most influential input variables are the number of PCPs, the number of GI physicians, and the lower-bound of the range of next appointment scheduling. Regarding number of physicians, we see that having fewer physicians, regardless of type, is highly influential on lead time, particularly when moving from two to one PCP.

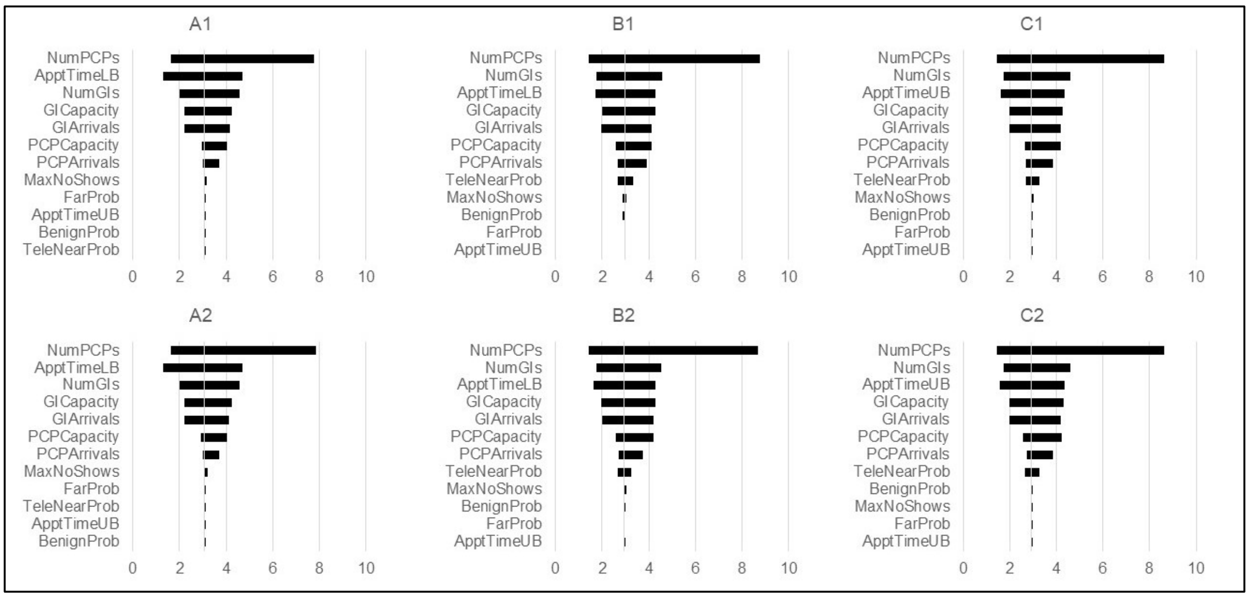

Figure 3: Impact of input variables on lead time across all policies.

Figure 4 shows the influence of input variables on telehealth utilization across all policies. Telehealth utilization under policies A1 and A2 is most influenced by PCP-related input variables, including the number and capacity of PCPs. Telehealth utilization under B/C policies is most impacted by the probability of patients who live near clinics preferring telehealth appointments, which makes sense because these four policies all consider patient preference for appointment modality when scheduling.

5 CONCLUSION

In this paper, we demonstrate how simulation can be used to understand how specialty care clinics can consider patient preference as they offer new ways of providing care to patients, including telehealth. As these modalities are implemented, simulation can be used to help define scheduling policies, such as the ones presented in our case study of GERD patients. Further, simulation helps clinical decision-makers understand the impact of providing telehealth options for patients and providers. Simulation also helps these decision-makers adjust their systems to accommodate patient needs while maintaining operation objectives, such as achieving a given provider utilization or keeping patient lead times under a threshold.

Our simulation models demonstrate that accommodating patient preference for appointment modality when scheduling specialty care appointments can be done with reasonable impact on the system and while incorporating patient preferences for care modality. Across the B/C policies, which take patient preference most into account, we see that patient preferences are met while achieving short lead times (less than 4-5

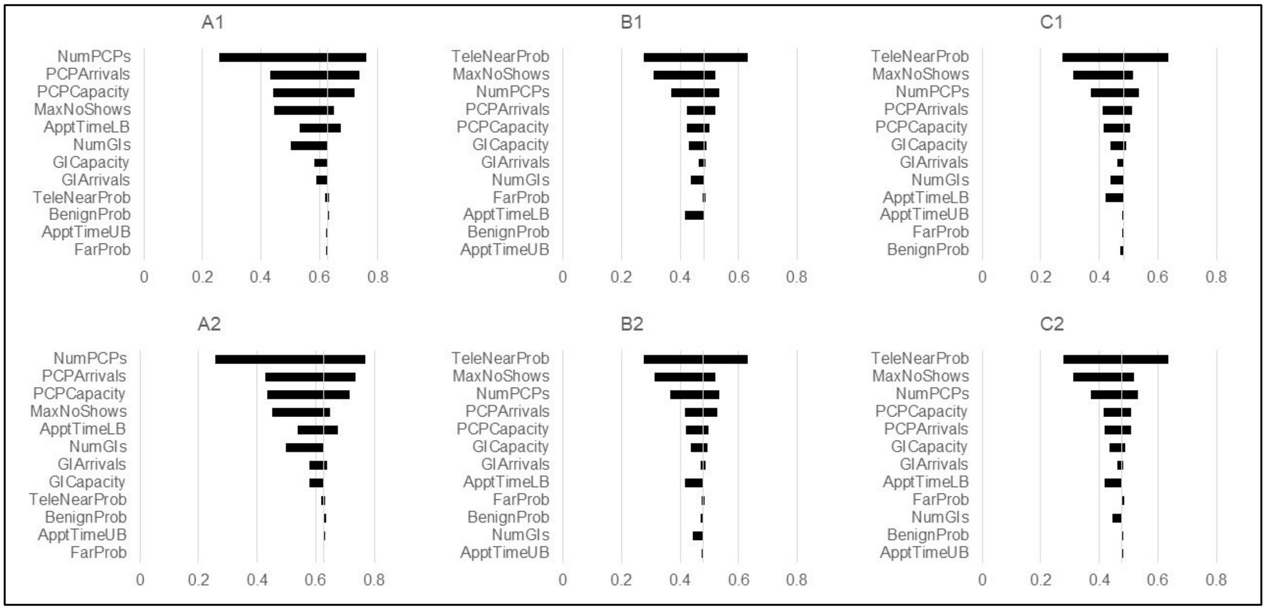

Figure 4: Impact of input variables on telehealth utilization across all policies.

weeks in most scenarios) and appropriate provider utilization. These metrics are maintained under most instances of our sensitivity analyses. In particular, policy C1 indicates a balance between meeting patient needs (scheduling the patient for their preferred appointment modality when one is available in-range), while also offering scheduling flexibility for provider organizations if the patient's preferred appointment modality is not available in a clinically-indicated timeframe. Keeping lead time low will also maintain quality of care because the likelihood of a patient's condition worsening while waiting is smaller.

The discrete-event simulation presented here provides a helpful framework for how to organize models for other clinical institutions or diagnosis groups. Building on the model presented here, future work could include enhancing variable interactions, such as adjusting the probability that a patient is a "no-show" depending on whether their scheduled appointment is of their preferred modality. Additionally, we can extend this simulation to gain additional insight by incorporating financial information to understand impact on costs; imposing maximum lead-time policies; considering endogeneity on patient modality preferences due to scheduling policy changes; and incorporating additional patient attributes, such as age or socioeconomic status, that may impact patient preferences for telehealth.

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A TRANSITION PROBABILITY MATRIX

We determine a patient's next appointment/exit based on a transition probability matrix given their current appointment. Note: if a patient is currently at an appointment, they may no-show, which is indicated by the probability in the matrix of their next appointment being the same as their current appointment.

	Next Appointment								
Current Appointment	PCP Appt 1	PCP Appt 2	PCP Appt 3	PCP Appt 4	GI Appt1	GI Appt 2	GI Appt 3	GI Appt 4 (Endoscopy)	Prob. of Exit
PCP Appt 1	0.2	0.4	0	0	0.1	0	0	0.1	0.2
PCP Appt 2	0	0.2	0.4	0	0.1	0	0	0.1	0.2
PCP Appt 3	0	0	0.2	0.4	0.1	0	0	0.1	0.2
PCP Appt 4	0	0	0	0.2	0.5	0	0	0.1	0.2
GI Appt1	0	0	0	0	0.2	0.5	0	0.1	0.2
GI Appt 2	0	0	0	0	0	0.2	0.5	0.1	0.2
GI Appt 3	0	0	0	0	0	0	0.2	0.6	0.2
GI Appt 4 (Endoscopy)	0	0	0	0	0	0	0	0.2	0.8

B VARIABLE ABBREVIATIONS IN TORNADO DIAGRAMS

The tornado diagrams (Figures 3 & 4) use abbreviated names of input variables. Abbreviations and variable descriptions are listed here, as well as the minimum and maximum values used in our sensitivity analyses:

Abbreviation	Variable Description	Minimum Input Value	Maximum Input Value
NumPCPs	Number of Primary Care Providers	1	4
PCPCapacity/ GICapacity	Capacity of Primary Care/GI Providers	One with 4 telehealth/ 3 F2F appointments per week; one with 2 telehealth/1 F2F	One with 4 telehealth/ 3 F2F appointments per week; one with 7 telehealth/5 F2F
NumGIs	Number of GI providers	1	4
PCPArrivals	Number of patients arriving directly to a PCP each week	3	7
GIArrivals	Number of patients self-referring to a GI provider each week	5	9
apptTimeLB	Lower bound of time range of next appointment	0 weeks	4 weeks
apptTimeUB	Upper bound of time range of next appointment	6 weeks	10 weeks
teleNearProb	Probability that patients who live “near” the clinic prefer telehealth	25%	75%
farProb	Probability that a patient lives “far” from the clinic	0%	2.8%
MaxNoShows	Maximum amount patients can no-show before being dismissed	1	5
BenignProb	Probability patients receives a healthy/benign endoscopy result	85%	95%

REFERENCES

American Well. 2019. “Telehealth Index 2019: Consumer Survey. https://static.americanwell.com/app/uploads/2019/07/American-Well-Telehealth-Index-2019-Consumer-Survey-eBook2.pdf, accessed 12th March 2020.

Fortney, J. C., J. F. Burgess, H. B. Bosworth, B. M. Booth, and P. J. Kaboli. 2011. “A Re-Conceptualization of Access for 21st Century Healthcare". *Journal of General Internal Medicine* 26(S2):639–647.

Gadzinski, A. J., J. L. Gore., C. Ellimoottil, A. Y. Odisho, and K. L. Watts. 2020. “Implementing Telemedicine in Response to the COVID-19 Pandemic”. *Journal of Urology* 204(1):14-16.

Gupta, D., and B. Denton. 2008. “Appointment Scheduling in Health Care: Challenges and Opportunities”. *IIE Transactions* 40(9):800–819.

Hafner-Eaton, C. 1993. "Physician Utilization Disparities Between the Uninsured & Insured: Comparisons of the Chronically Ill, Acutely Ill, & Well Nonelderly Populations". *JAMA* 269(6):787–792.

Kane, C., and K. Gillis. 2018. "The Use Of Telemedicine By Physicians: Still The Exception Rather Than The Rule". *Health Affairs* 37(12):1923–1930.

Kullgren, J. T., C. G. McLaughlin, N. Mitra, and K. Armstrong. 2012. "Nonfinancial Barriers and Access to Care for U.S. Adults". *Health Services Research* 47:462–485.

Li, S., K. Thompson, and T. Peterson. 2016. "Delivering High Value IBD Care through Telemedicine Visits". *Gastroenterology* 150(4):S792.

Lumina Decision Systems. 2020. "Selecting the Sample Size". http://wiki.analytica.com/Selecting_the_Sample_Size, accessed 14th March.

Malani, P., E. Solway, J. Kurlander, D. Singer, S. Saini, M. Kirch, and J. Kullgren. 2019. Virtual Visits: Telehealth and Older Adults. https://www.healthyagingpoll.org/report/virtual-visits-telehealth-and-older-adults, accessed 12th March 2020.

Patrick, J., and A. Aubin. 2013. "Models and Methods for Improving Patient Access". In *Handbook of Healthcare Operations Management: Methods and Applications*, edited by B. T. Denton, 403–420. New York: Springer Science+Business Media.

Penchansky, R., and J. W. Thomas. 1981. "The Concept of Access: Definition and Relationship to Consumer Satisfaction". *Medical Care* 19(2):127–140.

Richter, J. E., and J. H. Rubenstein. 2018. "Presentation and Epidemiology of Gastroesophageal Reflux Disease". *Gastroenterology* 154(2):267–276.

Siegel, C. A. 2017. "Transforming Gastroenterology Care With Telemedicine". *Gastroenterology* 152(5):958–963.

Tang, J., Y. Chiu, P. Chiang, M. Su, and T. Chan. 2017. "A Flow-Based Statistical Model Integrating Spatial and Nonspatial Dimensions to Measure Healthcare Access". *Health & Place* 47:126–138.

Zhang, C., T. Grandits, K. P. Härenstam, J. B. Hauge, and S. Meijer. 2018. "A Systematic Literature Review of Simulation Models for Non-Technical Skill Training in Healthcare Logistics". *Advances in Simulation* 3(15):1-16.

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