Proceedings of the 2023 Winter Simulation Conference
C. G. Corlu, S. R. Hunter, H. Lam, B. S. Onggo, J. Shortle, and B. Biller, eds.

MEASURING THE OPERATIONAL IMPACTS OF RIGHT-SIZING PRENATAL CARE USING SIMULATION

Leena Ghrayeb
TJ Bryan
Meghana Kandiraju
Tejas Maire
Yuanbo Zhang
Amy Cohn

Industrial and Operations Engineering
University of Michigan
1891 IOE Building 1205, Beal Ave,
Ann Arbor, MI 48109, USA

Alex Peahl

Department of Obstetrics and Gynecology
University of Michigan
L4001 Women's Hospital
1500 East Medical Center Drive
Ann Arbor, MI 48109, USA

ABSTRACT

Despite high levels of spending on prenatal care, the U.S. has the worst maternal mortality outcomes amongst peer high-income nations. In response to a growing need for modernized prenatal care policies, national prenatal care stakeholders have developed a new model of prenatal care, which moves away from a "one-size-fits-all" model of prenatal care delivery, and instead tailors care to patients' specific needs. In this article, we develop a data-driven discrete event simulation model to quantify the operational impacts of adopting this new care paradigm. We consider a case study of a large academic health center, and derive input parameters for the model from historical data. Our results suggest that when compared with the "one-size-fits-all" model of care, the new tailored care policy leads to reduced patient delays, as well as a reduction in overbooking, implying increased flexibility in the system. This flexibility may help clinics better handle unforeseen changes in patient care plans due to medical or social risk factors.

1 INTRODUCTION

Current prenatal care in the United States is low-value: in spite of spending more and recommending more visits, maternal mortality rates far exceed peer high-income nations, with marked disparities across race, socioeconomic status and urban/rural populations. These disparities are in part driven by the current one-size-fits-all model of care, which does not consider patient-specific risk factors. This traditional model of care recommends 12 to 14 in-person appointments for all patients over the course of their pregnancies, though care for low-risk patients can be safely delivered in 8 to 9 visits (Carter et al. 2016). In sum, for patients, current prenatal care guidelines are simultaneously burdensome for those who don't require 12 to 14 appointments and insufficient for those who may need higher flexibility in their care, while for clinics, unnecessary appointments drive artificial constraints in appointment availability, limiting access (Figure 1).

The COVID-19 pandemic facilitated the largest changes in prenatal care in a century, including implementation of tailored visit schedules based on medical risk factors and the widespread use of telehealth visits. Maternity care leaders including clinicians, researchers, and policymakers have endorsed continuation of these models after the public health crisis to promote right-sized, high-value prenatal care. While there are non-medical needs that contribute significantly to maternal health and well-being, such as anticipatory guidance and social support, the implementation of a *medically* rightsized approach – 1) ensures that each patient receives a care plan based on their unique medical needs and 2) removes unnecessary appointments

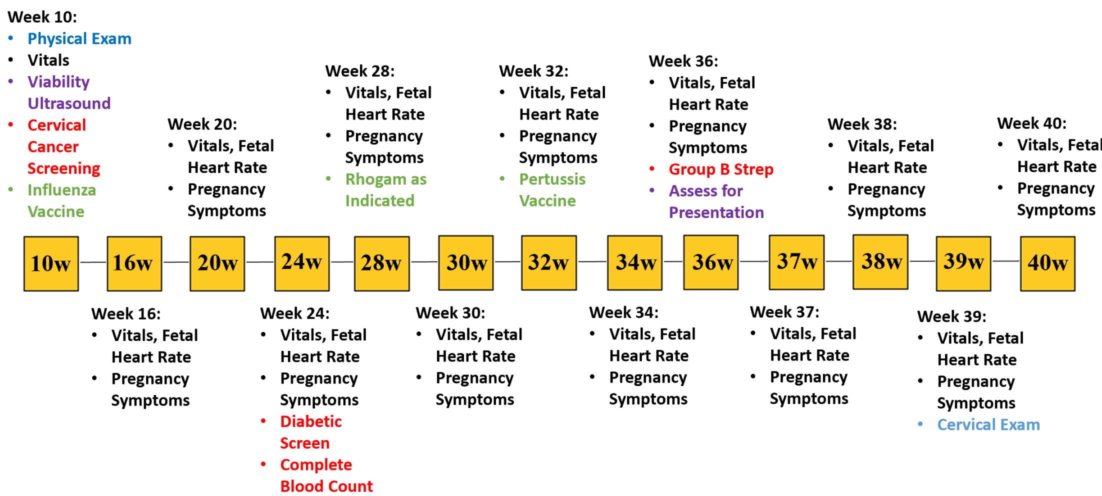

Figure 1: Status-Quo Prenatal Care Pathways (Peahl et al. 2020).

from the system, introducing flexibility for unanticipated changes in patient care plans due to medical or social needs (e.g. an extra appointment needed due to an unexpected health condition or rescheduling an appointment due to a work conflict or lack of transportation). Figure 2 shows the proposed rightsized pathways, where a pathway is a sequence of medical appointments during which patients receive prenatal care. These are further discussed in Section 2.1.

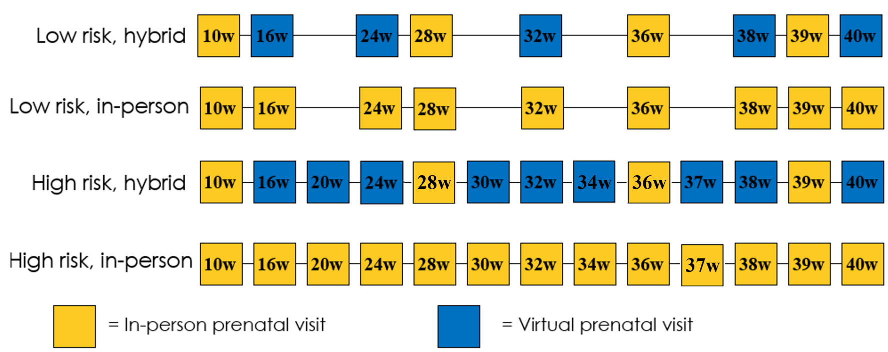

Figure 2: Proposed Prenatal Care Pathways.

Implementation of this new care model requires attention to its operational impacts. While implementing rightsized prenatal care should improve clinic access, it might cause excessive under-utilization of capacity, leading to physician under-utilization/idle time. Specifically, our objective is to develop an accurate, data-driven simulation model to test the operations of the Michigan Medicine prenatal care system under the proposed prenatal care paradigm.

Generally, simulation is a common method used in healthcare to compare different policies, especially when implementing these policies in the real world setting is costly (Vázquez-Serrano et al. 2021). There have been a few simulation studies that model care delivery with a cycle appointment pattern, including obstetrics and gynecology (Ob/Gyn) and chemotherapy. Studies of outpatient Ob/Gyn clinics generally focus on both obstetrics and gynecology, and focus on policies related to clinic operations (e.g. number of physicians on-staff) as opposed to patient care pathways (See Lenin et al. (2015), Ortiz et al. (2016), Fun et al. (2022), and references therein). Outside the scope of Ob/Gyn, the setting most similar to ours is that of chemotherapy. Chemotherapy follows a cyclic appointment pattern, where patients visit the clinic on specific treatment days which are separated by a fixed number of rest days (Condotta and Shakhlevich 2014). Heshmat and Eltawil (2021) consider the problem of both multi-day and intra-day scheduling of chemotherapy patients, and propose a two stage approach. During the first stage, a mixed-integer linear program (MILP) is formulated to schedule patients to a day, taking into account resource constraints (drugs, pharmacists, chairs/beds, and nurses), with the objectives of minimizing the weighted sum of treatment delay and total completion time for all treatments. During the second stage, they develop a discrete event simulation model to determine the optimal daily schedule based on the daily sequence of tasks undertaken by the nurses and pharmacists. Sadki et al. (2010) address only multi-day scheduling of chemotherapy, taking into consideration bed capacity, number of physicians, and physician capacity. They propose a two stage model, in which simulation is used to generate weekly arrivals of patients, and patients are scheduled weekly using a MILP with objectives of best smoothing of the bedload of each week and minimizing overbooking.

To the best of our knowledge, our work is the first to model prenatal care pathways, and more specifically, the first to attempt to quantify the operational impact of shifting to patient-centered prenatal care pathways. This work specifically aims to address the lack of knowledge on the operational impacts of adopting a new prenatal care paradigm.

This article is organized as follows: In Section 2 we provide a description of the problem, including background on prenatal care in the U.S. and a statement of our assumptions. In Section 3, we describe our data analysis and simulation model. In Section 4, we apply our simulation model and present our results. In Section 5, we summarize insights gained from our model and describe future research directions.

2 PROBLEM DESCRIPTION

In this section, we provide a brief background on prenatal care in the United States, and state the specific problem we are considering, as well as our assumptions.

2.1 Prenatal Care Background

Recent figures show that the United States spends approximately $111 billion annually on maternity care, including prenatal care (The Urban Institute. 2018). In spite of these high costs, pregnancy outcomes are not optimal by any definition: maternal morbidity and mortality exceed peer high-income countries, which recommend fewer prenatal care visits than the U.S. and have better pregnancy outcomes (Peahl et al. 2020). Poor access and adverse health outcomes disproportionately affect people marginalized by socioeconomic status, race, and geography, highlighting significant inequities (Hoyert and Miniño 2020).

Prenatal care delivers many evidence-based services, including laboratory tests, vaccinations, and imaging, yet the current delivery model is not evidence based. In 1930, before the American College of Obstetricians and Gynecologists (ACOG) was established, the Children's Bureau published a booklet outlining the recommended frequency of prenatal care visits, with a recommendation for 12 - 14 visits over the course of the pregnancy (Peahl and Howell 2021). Despite significant medical advancements over the past century, these guidelines have remained unchanged, in spite of growing evidence of the equivalence of other care models. In fact, recent observational studies suggest that for medically low-risk patients, more than ten prenatal visits results in additional interventions in pregnancy without improvements in health outcomes (Carter et al. 2016). Additionally, telemedicine provides flexibility for both patients and providers, while also maintaining a high quality of care. For appointments that do not require patients to be in-person (e.g. blood pressure monitoring, which can be done at home by the patient and reported to the clinician in virtual visits), at-home monitoring has been shown to be accurate and feasible for patients (Barrera et al. 2021).

In 2020, in response to growing pressures to modernize prenatal care recommendations, including rapid changes in prenatal care delivery facilitated by the COVID-19 pandemic, national prenatal care stakeholders developed a new model of prenatal care that incorporates reduced visit schedules for low-risk patients and telemedicine for all but 4 visits that require in-person visits (Figure 2). The new Michigan Plan for Appropriate Tailored Healthcare in Pregnancy (MiPATH), first piloted at the University of Michigan, moves away from a “one-size-fits-all” model of prenatal care delivery, and instead tailors care to patients’ specific needs. While this proposed plan also incorporates tailoring based on social factors, for the purposes of this research, we focus on medical appointments only. Through incorporating flexibility into prenatal care, the proposed paradigm aims to improve access and utilization of prenatal care and address significant inequities in care delivery (Peahl et al. 2021).

2.2 Problem Statement and Assumptions

We consider the Michigan Medicine prenatal care system, which is comprised of eight separate ambulatory clinics. We assume that each patient completes the entirety of their prenatal care at the same clinic. At each clinic, physicians have a predetermined number of appointment slots per week, which are split between obstetrics (pregnancy, childbirth, and postpartum care) and gynecology (routine women’s health care and management of issues related to reproductive health). Prenatal care falls under obstetrics, so the simulation only includes obstetrics appointment slots in the clinic capacity. We also do not include services completed outside routine prenatal care appointments (e.g. ultrasounds or antenatal testing). The duration of all appointments is identical, and we assume that all necessary equipment and prenatal care providers are readily available.

We define the arrival of a patient to the system as the week that they call the system to ask to initiate prenatal care (usually within the first 6 - 12 weeks of the pregnancy). We assume that during this call, patients are classified based on their medical risk factors, and are assigned a care pathway. In reality, a patient’s risk level is not known until their first appointment, when their physician can examine their medical history, but since the first appointment is always scheduled as close as possible to this initial call for all patients (within two weeks, both in reality and in the model), we assume that medical risks are known at the time of the call. The pathways are given by a sequence of weeks during which the patient should be seen by an Ob/Gyn physician for routinely scheduled appointments. All prenatal appointments include maternal and fetal assessment (e.g., blood pressure, fetal well being) and counseling. In the MiPATH model of care, all physical exams, laboratory tests, vaccinations and imaging are clustered during 4 key in-person appointments. In the current state, all patients follow the same 13-appointment in-person pathway. In the proposed tailored pathways, medically low-risk patients follow a 9-appointment pathway and both high-risk and low-risk patients can have virtual appointments. Consistent with routine clinical care, patients arrive at varying gestational ages (i.e. week in the pregnancy), and give birth at varying gestational ages, so the number of appointments that are actually scheduled is unique to each patient. For example, a patient could give birth at a gestational age of 38 weeks, meaning they would not have an appointment in weeks 39 and 40 as outlined in the pathway.

While social support resources are an important component of prenatal care, and should be a part of the discussion about addressing disparities and access, we only focus on the scheduling of medical appointments. Social support resources are often external to prenatal care clinics (e.g. social work) so we leave the study of the operational impacts on these resources to future work.

For our model, we assume that at the end of each week, the clinic schedules all patients who have called during that week for all of their pathway appointments (i.e. all appointments they will receive during their pregnancy). We assume that patients are punctual, so we do not consider patient no-shows or tardiness.

Per real-world scheduling policies, for each new patient, if the patient’s assigned clinic has capacity in the target week(s) of the patient’s required pathway appointment(s), the appointment is scheduled in the target week. However, if it does not, the appointment can be delayed for a maximum of 2 weeks for appointments in the first or second trimester (first trimester = gestational age of 0 - 13 weeks; second trimester = gestational age of 14 - 26 weeks) and 1 week for appointments in the third trimester (gestational age of 27 - 40 weeks). If there is no capacity available within these thresholds, then the patient’s appointment is overbooked in its target week.

To quantify the quality of the generated schedules, three metrics are defined:

1. **Patient delay**: this metric captures the average number of weeks that a patient's appointment(s) are delayed past the target dates in their care pathway. Due to the sequential nature of prenatal care appointments, and the importance of receiving prenatal care in a timely manner for both the patient and the baby's health, patients should be scheduled for their appointments as close as possible to these target dates.
2. **Overbooking rate**: each week, we calculate the overbooking rate (Equation 1).

$$max(0, \frac{total\ number\ of\ appointments\ scheduled\ at\ clinic - number\ of\ appointment\ slots\ at\ clinic}{number\ of\ appointment\ slots\ at\ clinic}) \tag{1}$$

3. **Capacity utilization rate**: each week, we capture the percent of the total appointment slots that were actually used (Equation 2).

$$\frac{total\ number\ of\ appointments\ scheduled\ at\ clinic}{number\ of\ appointment\ slots\ at\ clinic} \tag{2}$$

3 METHODOLOGY

To ensure that the model represents the real world as closely as possible, the first phase of this research is a thorough analysis of historical prenatal care utilization data, which is used as inputs to the simulation model. The second phase is the simulation model ideation and implementation, completed in close collaboration with clinical collaborators to ensure the process is captured accurately.

3.1 Data Analysis

To derive input parameters for the simulation model, we obtained a data set from the health system's electronic health record (EHR) system. This data set included patients who gave birth within the health system from March 1st, 2021 to March 31st, 2022 and received at least one prenatal care visit at an ambulatory care clinic affiliated with the health system. This specific time window was chosen to minimize the impact of the COVID-19 pandemic and policies on patient utilization patterns. During this year, the health system allowed in-person visits, with the option of telemedicine for those who preferred it. In total, 4,992 patients were included in our data set.

The data set includes information pertaining to patients' pre-existing conditions (e.g. history of diabetes) as well as socioeconomic factors (e.g. insurance status). As previously mentioned, only medical risk was used in the simulation model to assign care pathways, but having knowledge of social risk will be useful if we incorporate social services in the future. In collaboration with a group of physicians, we identified medical risk factors that would likely lead to an increased appointment frequency (Table 1). For example, if a patient has a history of high blood pressure, they would be classified as high-risk, requiring more appointments.

Using the patient information from the EHR, and these insights, we classified patients in our data set into two categories: medically high-risk or medically low-risk. Of the 4,992 patients, 3,113 (62%) were medically high-risk, and 1,879 (38%) were medically low-risk.

The data also includes information about each patient's pregnancy, including the start and end dates of care, date of birth, the gestational age at birth, and the outcome of the birth, including stillbirth, death of a fetus after birth, and living birth. These fields were used to calculate the arrival rates (number of patients/week) for each patient type, the distribution of the gestational age upon arrival for each patient type, and the gestational age at birth for each patient type. Data related to clinic capacities was obtained

Table 1: Medical Factors Used for Patient Classification.

Medical Factors
Hypothyroidism
Previous C-Section
Pre-Existing Diabetes
Chronic Hypertension
Asthma
Chronic Hepatitis
Connective Tissue/Autoimmune Disorders
Hyperthyroidism
Chronic Kidney Disease
Chronic Ischemic Heart Disease
Congenital Heart Disease
Cardiac Valvular Disease
Cystic Fibrosis

from the Michigan Medicine Ob/Gyn department. Table 2 shows a summary of the input parameters for the model, as well as the source for each.

Table 2: Simulation Input Parameters.

Parameter	Distribution/Value	Source
Arrival Rate (# of high-risk and low-risk patients/week)	Empirical	EHR Data
Gestational Age at Arrival	Empirical	EHR Data
Gestational Age at Birth	Empirical	EHR Data
Delay Threshold (maximum number of weeks an appointment can be delayed in each trimester – [Trimester 1, Trimester 2, Trimester 3])	[2,2,1]	Expert/Health System
Capacity (# of obstetrics appointment slots available at each clinic/week)	See Table 3	Expert/Health System
Telehealth Proportion (% of appointments allocated to telemedicine under the tailored care policy)	20 - 40%	Expert/Health System
Telehealth Preference (% of patients who would be comfortable receiving care virtually under the tailored care policy)	Low-risk patients: 43% High-risk patients: 38%	EHR Data

Table 3: Number of Ob/Gyn Appointment Slots at Each Clinic.

Clinic	Number of Appointment Slots (Ob and Gyn)
Clinic 1	192
Clinic 2	252
Clinic 3	300
Clinic 4	72
Clinic 5	408
Clinic 6	204
Clinic 7	384
Clinic 8	312

For inputs that were modeled using their empirical distributions, the inverse transform method was used to generate the random variable in the simulation model.

3.2 Simulation Model

Given the assumptions stated in Section 2.2 and the parameters from Section 3.1, we developed a discrete event simulation model in C++ to simulate the flow of patients through eight Michigan Medicine locations that provide prenatal care. Figure 3 outlines the simulation logic flow for the tailored care scenarios. For the non-tailored care scenario, we remove the decision point for whether the patient is high-risk or not, and calculate target weeks based on the 13-appointment pathway for all patients.

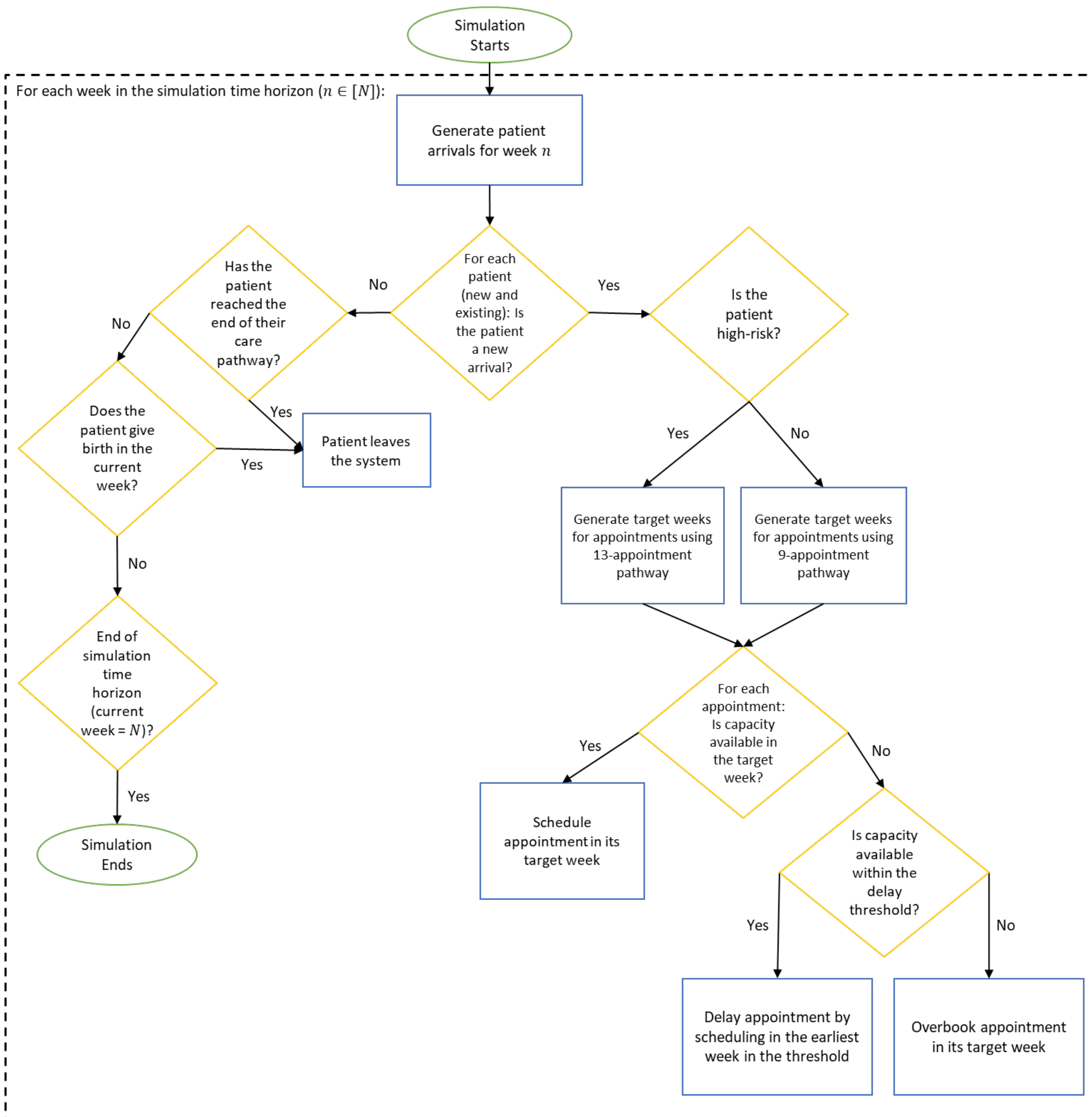

Figure 3: Simulation Logic Flow for Tailored Care Scenarios.

The simulation model captures dynamic weekly patient arrivals, varied patient classifications, and consequently, patient-specific appointment pathways. Every week, based on historical data, a certain number of new patients of each patient-type is generated. These patients "enter" the system and are assigned a pathway according to their patient classification. Patients are assigned to clinics proportional to the number of appointment slots available at each clinic. For example, if a clinic has 30% of the total appointment slots in the system, 30% of patient arrivals will be assigned to that clinic. Each new patient is scheduled for all of their pathway appointments at the end of the week they arrive (i.e. the week they call to initiate care) – for each new patient, the model iterates through their appointment pathway, checking to see if the patient's assigned clinic has capacity in the target week of a patient's appointment, and scheduling/overbooking the appointment based on the scheduling policy outlined in Section 2.2. Each week, the model checks if each patient gives birth in that week; if they do, then all of their future appointments are canceled and the corresponding appointment slots are freed up. Patients can only leave the system if they give birth.We assume that once an appointment is scheduled, it cannot be rescheduled to an earlier or later week.

Note that since appointments are scheduled weeks into the future, and patients give birth at different points in their pregnancies, it is possible that an initially overbooked appointment is never actually completed. Consequently, metrics are captured at the end of the time horizon to ensure that only appointments that actually occur are included.

3.3 Scenarios

One of the main objectives of this work is to determine the effects of adopting the previously mentioned tailored care pathways. Therefore, we considered the following scenarios:

- Scenario 1 (Status-Quo): All patients follow a 13-appointment in-person care pathway, regardless of risk level.
- Scenario 2 (Tailored Care): High-risk patients follow a 13-appointment pathway, while low-risk patients follow a 9-appointment pathway, with the possibility of telehealth for both patient types.

Additionally, clinicians are interested to see how varying the number of appointment slots assigned to obstetrics (i.e. prenatal care) impacts utilization. Currently, the appointments at the clinics in our system are split between obstetrics and gynecology, and the simulation model can be used to provide insights on how best to allocate this capacity. For each of the above scenarios, we considered scenarios where 30%, 40%, or 50% of the total appointment slots at each clinic are allocated to obstetrics appointments. These percentages are chosen based on physician input to ensure that there is still sufficient capacity available for Gyn appointments. We also consider scenarios where 20%, 30%, or 40% of the obstetrics appointments are allocated to telehealth virtual visits (in the tailored pathway scenarios).

4 EXPERIMENTS AND RESULTS

The model was built using C++ and all scenarios were run on a computer with the following specifications – Intel Core i7 2.8GHz with 16GB RAM. Based on ad-hoc experiments using Scenario 1, with a half-width of 1%, 100 replications was determined to be sufficient for this model. The warm-up period was determined to be 40 weeks, so each scenario was run for a horizon of 92 weeks to capture 52 weeks worth of data (per replication).

4.1 Verification and Validation

The model was validated mainly through expert opinion, as granular real-world data regarding utilization, overbooking, and patient delay was not available. Generally, the capacity utilization, overbooking, and patient delay metric values are on-par with what they would expect to see in our problem setting. Additionally, the inputs for the simulation model were derived directly from historical data, ensuring that the number of patients in the system, as well as the number of appointments, was as close to real-world observations as possible.

4.2 Comparison of Scenarios

We present results for the 12 scenarios described in Section 3.3, including capacity utilization rate, overbooking rate, and average patient delay. Metrics are presented as averages across replications. Note that here, utilization simply means the percent of appointment slots filled.

In figure 4, we show the average utilization of all appointment slots (regardless of the appointment modality) across all clinics. If 30% of the appointment slots (i.e. capacity) at each clinic are allocated to OB, tailoring care reduces utilization by an average of 18% when compared to the non-tailored scenario. The reductions in utilization when tailoring care for the 40% OB scenario and the 50% OB scenario are 14% and 12% respectively.

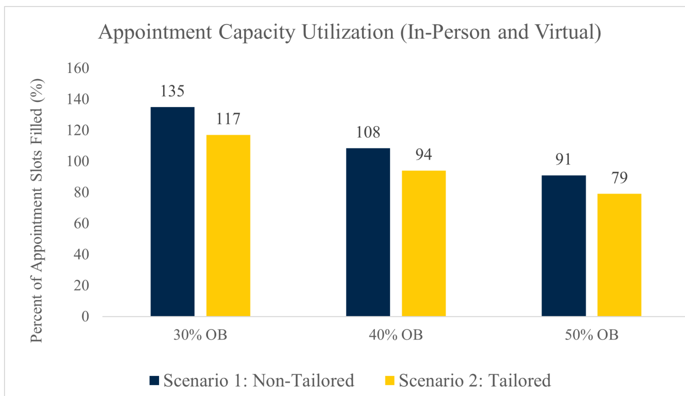

Figure 4: Capacity Utilization Rate (Including In-Person and Virtual Visits).

Generally, for all tailored scenarios, the number of appointments in the system remains relatively constant, as roughly the same number of high and low risk patients arrive, but the number of appointment slots at each clinic (i.e. the clinic capacity) varies depending on the scenario. As the clinic capacity increases, the "utilization" for that scenario will decrease, as the number of appointments booked remains the same. In figure 5, we notice that as more of the clinic capacity is allocated to OB, the number of unfilled appointment slots naturally increases, for both in-person and virtual appointment (i.e. the "utilization" percent decreases). Similarly, as the number of OB appointment slots allocated to telehealth increases, less in-person appointment slots are unfilled, but more virtual appointment slots are unfilled. Note that there is no value for virtual appointment utilization for Scenario 1, as in the non-tailored pathways all appointments are in-person.

A utilization of over 100% implies that the system does not have enough appointment slots to accommodate all of the appointments without overbooking. Generally, clinics would prefer that utilization remains high to avoid idle time, but not high enough to where the clinic has to overbook. Overall, these results suggest that for a balanced utilization rate across in-person and virtual appointments under the tailored care policy, around 40% of a clinic's appointment slots should be allocated to OB, and between 20 - 30% of those slots should be allocated to telehealth. This would lead to an in-person appointment utilization of 88 - 100% and a virtual appointment utilization of 79 - 118%.

Figure 6 shows the overbooking rate for each scenario, which is complementary to the utilization rates shown in figure 5. As the number of appointments allocated to OB increases, the overbooking rate decreases. Additionally, as the number of appointment slots allocated to telehealth increases, the overbooking rate increases for in-person appointments, and decreases for virtual appointments. Note that it is possible to

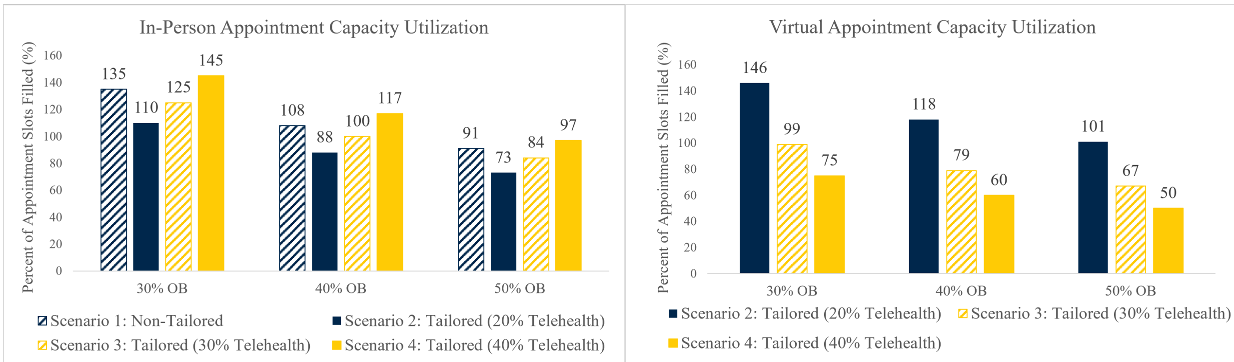

Figure 5: Capacity Utilization Rate Results – Scenario 1 is completely in-person, so it has no virtual capacity utilization.

have an average utilization rate under 100% and an overbooking rate over 0%, as these values are derived by averaging across clinics. Some clinics may experience utilization above 100% and overbooking, while others do not at all. For example, in one randomly chosen replication, clinics 1 - 7 experienced utilization rates less than 100% (implying a 0% overbooking rate), but clinic 8 experienced a utilization of 105% (implying an overbooking rate of 5%). Averaging across all clinics, the average utilization rate is less than 100%, but the overbooking rate is over 0% due to clinic 8's overbooking rate.

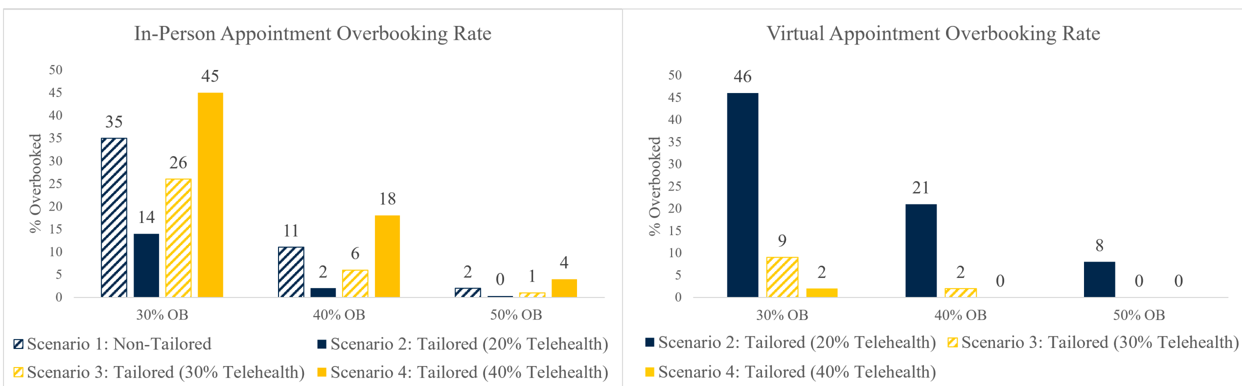

Figure 6: Overbooking Rate – Scenario 1 is completely in-person, so it has no virtual appointment overbooking.

Figure 7 shows the average delay per patient for each scenario. Generally, patient delay is less than one week for all scenarios, implying that most patients are scheduled for their appointments on-time. As the number of appointment slots allocated to OB and telehealth increases, the delay per patient decreases. Since delays are only allowed within the delay thresholds (otherwise the appointment is overbooked in its target week), the amount of delay in the system is constrained by these thresholds.

5 CONCLUSIONS AND FUTURE WORK

As health systems move away from a "one-size-fits-all" model of prenatal care towards a tailored care model, it is important to consider the operational impacts of adopting this new care paradigm. This article presents a simulation model that can be used to quantify these impacts, as well as to draw insights about the allocation of appointment slots based on type (Ob or Gyn) and modality (in-person or virtual) within clinics.

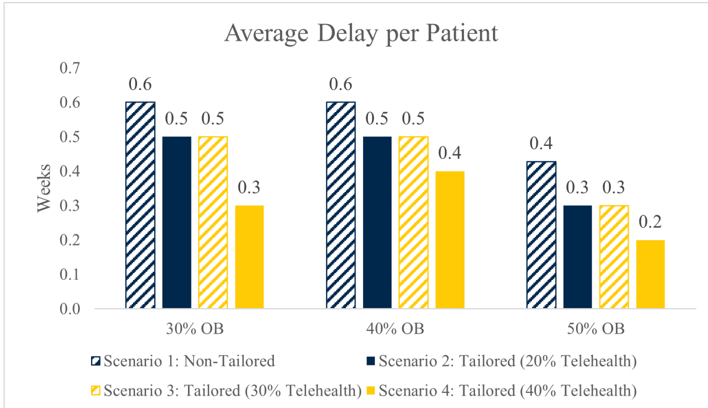

Figure 7: Average Delay per Patient.

Our results suggest that tailoring care, regardless of the appointment allocation policy, reduces overbooking and patient delay. When compared to the non-tailored care model, tailoring care leads to a 12 - 18% reduction in capacity utilization, depending how many appointment slots are allocated to OB. Even with this decrease, utilization remains fairly high, ranging from 79% to 117%, again depending on the allocation policy. This implies that tailoring care can introduce flexibility to the healthcare system that may make it easier for patients to access care. Additionally, patient delay decreases with the tailored care policies.

Our results also imply that in order to be able to accommodate all patients with minimal overbooking, delay, and unused appointment slots, around 40% of appointments should be allocated to OB, and 20% - 30% of those appointments should be allocated to virtual visits.

As with all models, ours is not without its limitations. One major limitation is that we assume patient risk is static over the course of the pregnancy. In reality, low-risk patients can transition to a high-risk pathway during their pregnancies if they are diagnosed with a condition at one of their screening appointments (e.g. gestational hypertension, preeclampsia, gestational diabetes, etc.). A patient may also need additional appointments beyond their pathway appointments due to medical conditions or unexpected symptions that require evaluation. Furthermore, patients may also cancel or not show up to a scheduled appointment. Preliminary analyses show that the no-show rate is 3% for prenatal care visits, but this aspect may still be useful to add to more accurately capture real-world behavior. These patient-related sources of randomness will be incorporated in a future version of this model.

Additionally, this work only focuses on the scheduling of medical appointments, despite the importance of social support in prenatal care. Social support resources are often delivered outside of routine prenatal clinical services through public agencies, community based organizations, and others. In the future, we hope to gain more insights and data regarding additional social services that patients may be referred to, and incorporate them in the model. Extending the model in this way could help decision makers to better understand the current utilization of social resources, and provide insights about how they can optimize the allocation and utilization of these additional services.

REFERENCES

Barrera, C. M., A. R. Powell, C. R. Biermann, Y. Siden, B.-H. Nguyen, S. J. Roberts, L. James, V. Chopra, and A. Peahl. 2021. "A Review of Prenatal Care Delivery to Inform the Michigan Plan for Appropriate Tailored Health Care in Pregnancy Panel". *Obstetrics & Gynecology* 138(4):603–615.

Carter, E. B., M. G. Tuuli, A. B. Caughey, A. O. Odibo, G. A. Macones, and A. G. Cahill. 2016. "Number of Prenatal Visits and Pregnancy Outcomes in Low-Risk Women". *Journal of Perinatology* 36(3):178–181.

Condotta, A., and N. Shakhlevich. 2014. "Scheduling Patient Appointments via Multilevel Template: A Case Study in Chemotherapy". *Operations Research for Health Care* 3(3):129–144.

Fun, W. H., E. H. Tan, R. Khalid, S. Sararaks, K. F. Tang, I. Ab Rahim, S. Md. Sharif, S. Jawahir, R. M. Y. Sibert, and M. K. M. Nawawi. 2022. "Applying Discrete Event Simulation to Reduce Patient Wait Times and Crowding: The Case of a Specialist Outpatient Clinic with Dual Practice System". *Healthcare* 10(2):189.

Heshmat, M., and A. Eltawil. 2021. "Solving Operational Problems in Outpatient Chemotherapy Clinics Using Mathematical Programming and Simulation". *Annals of Operations Research* 298:289–306.

Hoyert, D. L., and A. M. Miniño. 2020. "Maternal mortality in the United States: Changes in Coding, Publication, and Data Release, 2018". *National Vital Statistics Reports* 69(2).

The Urban Institute. 2018. "Strong Start for Mothers and Newborns Evaluation".

Lenin, R., C. L. Lowery, W. C. Hitt, N. A. Manning, P. Lowery, and H. Eswaran. 2015. "Optimizing Appointment Template and Number of Staff of an OB/GYN Clinic–Micro and Macro Simulation Analyses". *BMC Health Services Research* 15:1–17.

Ortiz, M. A., S. McClean, C. D. Nugent, and A. Castillo. 2016. "Reducing Appointment Lead-Time in an Outpatient Department of Gynecology and Obstetrics Through Discrete-Event Simulation: a Case Study". In *Ubiquitous Computing and Ambient Intelligence: 10th International Conference, UCAmI*. San Bartolomé de Tirajana, Gran Canaria, Spain, 274–285. Springer.

Peahl, A. F., M. Heisler, L. K. Essenmacher, V. K. Dalton, V. Chopra, L. K. Admon, and M. H. Moniz. 2020. "A Comparison of International Prenatal Care Guidelines for Low-Risk Women to Inform High-Value Care". *American Journal of Obstetrics & Gynecology* 222(5):505–507.

Peahl, A. F., and J. D. Howell. 2021. "The Evolution of Prenatal Care Delivery Guidelines in the United States". *American Journal of Obstetrics & Gynecology* 224(4):339–347.

Peahl, A. F., C. M. Zahn, M. Turrentine, W. Barfield, S. D. Blackwell, S. J. Roberts, A. R. Powell, V. Chopra, and S. J. Bernstein. 2021. "The Michigan Plan for Appropriate Tailored Healthcare in Pregnancy Prenatal Care Recommendations". *Obstetrics & Gynecology* 138(4):593–602.

Sadki, A., X. Xie, and F. Chauvin. 2010. "Patients Assignment for an Oncology Outpatient Unit". In *2010 IEEE International Conference on Automation Science and Engineering*, 891–896.

Vázquez-Serrano, J. I., R. E. Peimbert-García, and L. E. Cárdenas-Barrón. 2021. "Discrete-Event Simulation Modeling in Healthcare: A Comprehensive Review". *International Journal of Environmental Research and Public Health* 18(22):12262.

AUTHOR BIOGRAPHIES

Leena Ghrayeb is a third year PhD student in Industrial and Operations Engineering at the University of Michigan. Her research is focused on applying operations research techniques, mainly simulation, mixed integer linear programming, and stochastic programming, to guide decision-making in healthcare. Her email is lghrayeb@umich.edu and her website is https://sites.google.com/umich.edu/leena-ghrayeb.

TJ Bryan is a fourth year undergraduate student in Industrial and Operations Engineering at the University of Michigan. His research interests include applying data analysis and simulation tools to improve healthcare delivery. His email is tjbryan@umich.edu.

Meghana Kandiraju is a fourth year undergraduate student in Computer Science Engineering at the University of Michigan. Her research interests include using computational power to solve healthcare access and efficiency issues. Her email is mkandira@umich.edu.

Tejas Maire is a second year undergraduate student in Computer Science Engineering at the University of Michigan. His main research interests are within healthcare engineering. His email is tmaire@umich.edu.

Yuanbo Zhang is a second-year masters student in Applied Statistics at the University of Michigan. With a strong research interest in utilizing cutting-edge technology tools to analyze healthcare data, she aims to enhance the efficiency of healthcare policy. Her email is zyuanbo@umich.edu.

Amy Cohn is the Faculty Director of the Center for Healthcare Engineering and Patient Safety (CHEPS) at the University of Michigan. Her primary research interests are in applications of combinatorial optimization, particularly to healthcare and aviation, and to the challenges of optimization problems with multiple objective criteria. Her email address is amycohn@med.umich.edu.

Alex Peahl is an Obstetrician-Gynecologist, Clinical Lecturer in Obstetrics and Gynecology, and a National Clinician Scholar at the University of Michigan. Her research focuses on how to improve the effectiveness, efficiency and equity of reproductive health care through developing, studying and disseminating high-quality maternity care interventions. Her email address is alexfrie@med.umich.edu.