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TRANSFORMING AMERICAN PRENATAL CARE DELIVERY THROUGH DISCRETE EVENT SIMULATION

Adrianne Blanton[1], Annie He[1], Jillian Uy[1], Krithika Venkatasubramanian[1], Leena Ghrayeb[1], Vincenzo Loffredo[1], Amirhossein Moosavi[1,2], Amy Cohn[1], and Alex Peahl[3]

[1]Dept. of Industrial and Operations Eng., University of Michigan, Ann Arbor, MI, USA
[2]Michigan Institute for Data & AI in Society, University of Michigan, Ann Arbor, MI, USA
[3]Dept. of Obstetrics and Gynecology, University of Michigan, Ann Arbor, MI, USA

ABSTRACT

Formalized models of prenatal care delivery have changed little since 1930, typically including 12-14 in-person visits. Recently released guidelines recommend tailoring prenatal care visit frequency based on patient risk level, potentially integrating telemedicine to increase flexibility for patients. In this paper, we design a discrete event simulation-based approach to study the impact of these new guidelines on healthcare systems, focusing on three main metrics: appointment slot utilization, appointment delays due to lack of capacity, and skipped appointments due to patient cancellations. We find that the tailored approach reduces appointment slot utilization while supporting the same volume of patients as the conventional approach. We also see a decrease in appointment delays and skipped appointments. Our findings suggest that adopting a tailored prenatal care model can reduce provider burnout, allow clinics to accept more patients, and enhance patients' care experience.

1 INTRODUCTION

Global investment in prenatal services continues to escalate, with the U.S. alone allocating approximately \$111 billion annually to cover prenatal and childbirth-related care (Peahl and Howell 2021). Despite this substantial expenditure, pregnancy outcomes in the U.S. persistently lag behind those of peer high-income nations, indicating a disconnect between financial inputs and clinical effectiveness (Peahl et al. 2021). Alarmingly, these suboptimal outcomes are unequally distributed, as marginalized groups bear a disproportionate burden of maternal morbidity and mortality (Hoyert and Miniño 2020). In 2021, according to CDC data, the pregnancy-related mortality ratio for black patients was triple that for non-Hispanic white patients (69.3 vs 24.3 per 100,000 pregnancies), both of which were much worse than those of the European Union (6 per 100,000 pregnancies).

Historically, prenatal services in the U.S. have followed guidelines developed by the U.S. Children's Bureau dating back to the 1930s, which prescribe 12-14 in-person visits for all pregnancies (Peahl and Howell 2021). Contemporary research, together with evidence from European countries, shows that in medically or socially low-risk cases, reducing the number of visits does not lead to poorer health outcomes for the childbearing individual or the newborn, and can lead to a better experience for both the patient, the provider and the healthcare system (Carter et al. 2016). For patients, fewer visits may improve social drivers of health (e.g. reduced need for childcare or transportation support, gaps in employment). This may reduce the number of canceled or missed appointments. For providers, fewer visits may allow for additional time to provide services such as anticipatory counseling or guidance and potentially higher job satisfaction or reduced burnout. For healthcare systems, fewer visits may increase the capacity to see pregnant individuals, improving access to maternity services, which is declining rapidly, particularly in rural regions. Finally, the COVID-19 pandemic catalyzed a rapid expansion of telemedicine, demonstrating that virtual consultations and home monitoring (e.g., blood pressure measurement) can reliably substitute conventional in-person care for most visits, while offering enhanced flexibility (Barrera et al. 2021).

Recognizing the need for modernization, the Michigan Plan for Appropriate Tailored Healthcare in Pregnancy (MiPATH) was instituted in 2020 (Peahl et al. 2021; Peahl et al. 2022). This initiative advocates for a patient-centered approach wherein the frequency and nature of prenatal visits are adapted according to pregnancy risk level, encouraging the use of telemedicine as an alternative for most visits in the pathway, with the exclusion of four "anchor" in-person visits. By replacing a rigid, universal structure with a model that allows flexibility in both the number of visits and the way these visits are conducted (in-person or telemedicine), together with reducing the overall number of visits for low-risk patients, MiPATH aims to narrow systemic gaps in healthcare delivery and improve maternal outcomes (Peahl et al. 2021).

Implementing such a tailored system calls for analytical strategies that account for variations in patient risk profiles, and capacity constraints. Simulation-based methodologies are powerful "what-if-analysis" tools for comparing healthcare scenarios, recently applied as a valuable tool in the analysis of the patient pathway (England et al. 2021; Demir et al. 2018). Such tools enable stakeholders to model how evolving care pathways may influence clinic congestion, patient wait times, and the overall resource efficiency.

The current system creates several hurdles that especially affect marginalized individuals. The conventional "one size fits all" approach with all in-person visits makes it harder for patients with a lack of transportation, childcare, or paid time off to be able to come to every visit. Moreover, this approach forces providers to spend a higher-than-necessary number of visits on low-risk patients, overcrowding the system with unnecessary visits and reducing access to new patients. In this study, we develop a discrete event simulation model, applying it within a Michigan Medicine context to elucidate how risk-adaptive prenatal care protocols can refine healthcare delivery, optimize clinic operations, and potentially redress inequities embedded in the current prenatal care system.

Our primary contributions are twofold. First, we address a relatively understudied area by modeling prenatal care pathways, which have received limited attention in the literature. To the best of our knowledge, ours is only the second study, after Ghrayeb et al. (2023), to quantify the operational impact of tailored prenatal care pathways. Furthermore, we develop a more comprehensive simulation model compared to Ghrayeb et al. (2023), relaxing several assumptions (e.g., patient cancellations), which are all listed in Section 2. This model better captures practical nuances and provides more accurate estimates of the impact of implementing new pathways. Second, we introduce a framework for simulating and modeling healthcare data that mimics the current structure of healthcare databases. Our table-based model reflects real-world systems like EPIC, using interconnected tables to store data efficiently. This modular approach enables seamless scalability and straightforward customization, simplifying integration into diverse healthcare environments and supporting future extensions as clinical requirements evolve.

The remainder of this paper is organized as follows. Section 2 provides a detailed description of the problem, including modeling assumptions and performance metrics. Section 3 outlines our simulation methodology and its settings, and Section 4 presents the numerical experiments. Finally, Section 5 concludes the paper and discusses potential directions for future research.

2 PROBLEM DESCRIPTION

Throughout our analysis, our focus is on the clinic capacity, and for this reason, we make a series of assumptions. When talking about pregnant patients, we focus only on those whose pregnancy goes past the first trimester (i.e., 12 weeks). This is because before that gestational age, the pregnancy can sometimes lead to an early miscarriage. We considered a single prenatal care clinic, as the current practice in our partner health center involves assigning patients to a group of experts rather than a single provider, reducing the importance of individual clinician availability for scheduling purposes. As soon as a patient initiates care for their pregnancy, the booking clerk reserves some of the clinic capacity for the entire sequence of visits for that pregnancy in the following periods (or weeks in our case), subject to capacity constraints and how far along the patient is in their pregnancy. Although some clinics may use this method in reality, while others may choose to schedule one visit at a time, given the time-sensitive nature of prenatal visits and our focus on the week a visit was scheduled, rather than the specific day, both approaches are equivalent when it comes to measuring clinic capacity.

At the time of arrival, each patient is classified as medically and/or socially high-risk based on information available. We assume the clinic's schedulers schedule all the patients arriving in a week at the end of the week during a "scheduling window" on a first-come, first-served basis, with a priority for high-risk patients. In this study, we aim to compare the newly proposed prenatal care approach with the previous existing one. In the conventional approach, all patients are assigned to the same pathway of care, consisting of 14 visits on average, as shown in Figure 1. The new guidelines propose a tailored approach with different pathways of care based on the medical risk of the patient, and suggest that social risk should be considered when addressing telemedicine needs. Medically low-risk patients generally have fewer required appointments, but both groups can include virtual as well as in-person visits. Figure 1 illustrates the pathways designed for medically low- and high-risk patients. These new pathways, referred to as "tailored pathway", are customized to meet the specific needs of patients. In contrast, the conventional pathway mirrors the high-risk patient visit pattern for all patients, requiring more frequent visits, which are all in-person. We call this the "conventional pathway" in the rest of this paper. There are no formal definitions for medical or social risk, despite their common use in obstetric practice.

Note that medical risk typically reflects patient comorbidities, with commonly agreed diagnoses and provider-specific variations. We used criteria from Michigan Medicine (e.g., multiple births) to identify medically high-risk pregnancies. Social risk, a newer concept, includes determinants like food insecurity and domestic violence. As standardized social risk data collection began only recently (2024), we used insurance status as a proxy. Our current analysis prioritizes high social-risk patients for telemedicine appointments, but future approaches may evolve with better understanding.

A patient's gestational age (i.e., the age of the pregnancy, in weeks) at arrival, in combination with their due date (i.e., expected date of delivery), determines the weeks in which prenatal appointments are recommended. Exams, vaccinations, and laboratory tests are generally clustered in four specific in-person appointments. The other appointments mostly consist of routine monitoring (blood pressure, fetal tones, etc.), and we therefore assume they can be safely conducted via telemedicine. Appointments are booked according to each pathway's recommended visit schedule, but exact timing may deviate if the clinic is fully occupied in the target week. The allowed delay (i.e., how many weeks the appointment can be delayed beyond its target week) depends on the patient's gestational age; these guidelines were derived through consultation with Michigan Medicine clinicians:

- For appointments from the beginning of the pregnancy to up to 27 weeks, scheduling may be delayed by up to four weeks beyond the ideal target, as long as it happens before 28 weeks.
- For 28-35 weeks, scheduling may be postponed by up to two weeks, as long as it happens before 36 weeks.
- For 36 weeks onward, appointments must occur within the target week.

In our setting, the clinic's weekly capacity is fixed, and we allow for a limited amount of overbooking. Overbooking slots in a healthy system should rarely be used, as that means overburdening clinicians and having less time to spend on each patient, but overbooking is a necessary tool to deal with emergencies. It is often used in prenatal care to improve access to patients at the expense of the clinician's health. If no appointment slots are available within these delay windows, and there are no overbooking slots either, the appointment is skipped entirely. The delays in care and the number of skipped appointments are especially important to track. Prenatal care is extremely time-sensitive: exams that can be done at 20 weeks cannot be as reliable or effective when conducted at 22 weeks. For this reason, keeping track of how far from the target due date the actual appointment was scheduled can offer insight into the state of the system. Skipped appointments instead capture all the appointments that the system has failed to offer to a patient, and therefore are "infinitely" delayed. Finally, we assume that within each scheduling window, the clinic

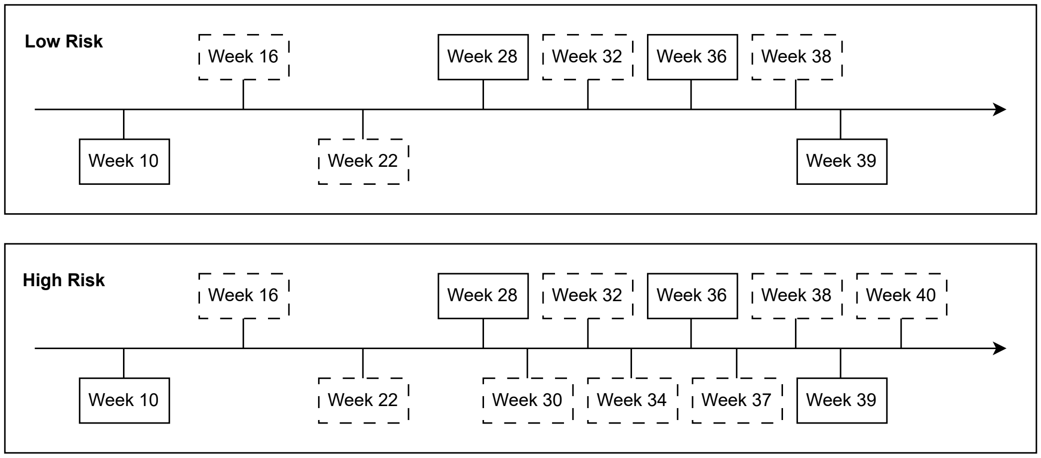


Figure 1: Timeline for tailored prenatal care pathways in medically low- (top) and high-risk (bottom) pregnancies. The conventional pathway mirrors the high-risk pathway, with the only difference being that every visit is conducted in-person. Note: solid-bordered rectangles indicate required in-person visits, while dash-bordered rectangles represent visits that can be either in-person or via telemedicine, depending on patient preference.

prioritizes medically high-risk patients first, then patients with social risk, then all other patients, on a first come, first serve basis.

Uncertainty in this model stems from three sources. First, the number of new patients who initiate prenatal care per week varies on a weekly basis. Second, patients have unique characteristics, including their gestational age at arrival, gestational age at delivery, and risk factors. Third, cancellation and no-show rates cause variation in clinic visit volume, and these rates depend on each patient's visit type and risk level.

An appointment may be canceled or missed (no-show) with probabilities that vary according to the visit type (in-person or virtual) and patients' characteristics (socially high-risk patients are assumed to be more prone to cancellation for in-person visits). No-shows are scheduled appointments where the patient does not come to the clinic for care. The slots for patients who no-show cannot be reallocated to other patients, whereas cancellations are assumed to occur with sufficient advance notice to allow for the redistribution of visits. Consequently, even if an appointment is successfully scheduled, it may not be completed. These events are different from skipped appointments, where instead the system's overcrowding didn't allow the appointment to be scheduled in the first place.

We track a range of performance metrics to gauge the impact of different pathways for prenatal care and telemedicine policies. From the patient's perspective, these include the average delay from the target appointment week, as well as the total number of skipped visits. From the provider's perspective, patient slot utilization reflects how effectively available capacity is used for prenatal care. Specifically, we measure these metrics as follows:

- Utilization: This metric computes the percentage of appointment slots that were used at each period (in our case, week). For a generic week t, we define the utilization rate as:

$$U_t := \frac{\text{Number of used appointment slot in period } t}{\text{Total number of available slots}} \times 100, \tag{1}$$

where a "used slot" is a slot that was assigned to an appointment that was not missed by a patient.

- Delayed appointment: This metric measures the average delay in appointments beyond their target dates due to insufficient capacity (excluding cancellations). For period t:

$$D_t := \frac{\sum_{j=1}^{A_t} \text{Delay of appointment } j \text{ in period } t}{\text{Total number of appointments scheduled in period } t} \tag{2}$$

where A_t is the total number of appointments scheduled for period t.

- Skipped appointment: This metric computes the percentage of appointments that were skipped due to the lack of capacity, and not due to cancellations or no-shows. For period t:

$$S_t := \frac{\text{Number of appointments skipped with a target due date for week } t}{\text{Total number of appointments scheduled in period } t} \times 100 \tag{3}$$

3 METHODOLOGY

This section first provides a detailed description of the data used in our simulation model, followed by an overview of the structure of the model.

3.1 Data Analysis

Working with Michigan Medicine, we utilize data from EPIC, the electronic health record (EHR) system used by our partner providers. In our analysis, we include patients who gave birth between January 1, 2021, and March 31, 2022, and received at least one prenatal care visit in-person or telemedicine format, for a total of 4,992 pregnancies (data available to us at the time of our study). Using the same criteria as described in Ghrayeb et al. (2023), we classify patients as either medically high-risk or medically low-risk.

From this dataset, we also derive distributions and summary statistics for patient arrival rate, gestational age at arrival (GAA), gestational age at birth/departure (GAD), preference for telemedicine, and no-show rates. Arrival rate, GAA, and GAD allowed us to model the overall flow of patients in and out of the clinic, while telemedicine preference and no-show rate informed the way our simulation schedules individual appointments. Finally, in collaboration with providers in Michigan Medicine's Obstetrics & Gynecology Department, we obtained data about weekly clinic capacity for a single Obstetrics & Gynecology clinic, for both in-person and telemedicine visits. These results were used directly in the simulation model as user-inputted parameters, allowing us to replicate the current Michigan Medicine prenatal care system as closely as possible. Historical data also revealed that socially high risk patients have a higher chance of being no-shows compared to socially low-risk patients. Tables 1 and 2 summarize the input parameters for the simulation model.

Table 1: Simulation arrival inputs, by medical risk level.

Parameter	Medical Risk Level	
	High	Low
Arrival Rate	Poisson ($\lambda = 1.5$)	Poisson ($\lambda = 1$)
Gestational Age at Arrival	Poisson ($\lambda = 10$)	Poisson ($\lambda = 10$)
Gestational Age at Departure	Normal ($\mu = 39, \sigma = 2$)	Normal ($\mu = 39, \sigma = 2$)
Social High Risk Percentage	40%	30%

Based on our collaborators' input, we modeled a typical Michigan Medicine provider to have 24 appointment slots per week, with up to three additional slots reserved for overbooking. This was broken up into 18 in-person and six virtual slots. Finally, we assume that a patient's first visit takes double the time of a normal return visit, therefore requiring two slots.

Table 2: Simulation no-show inputs, by social risk level.

Appointment Type	Social Risk Level	
	High	Low
In-Person	1.6%	0.7%
Virtual	1.6%	0.6%

3.2 Simulation Model

Herein, we discuss the logic flow of the simulation model, as well as a more detailed description of the table-based approach.

3.2.1 Table-Based Approach

Our simulation model employs a table-based approach that demonstrates the structure of healthcare databases, such as those used in EPIC, where data is organized into various interconnected tables. This approach is inherently scalable and modular, allowing for straightforward expansion and adaptation as healthcare needs evolve. This compatibility with existing data structures streamlines the adoption and customization of our model across a variety of healthcare contexts, ensuring its practical utility and ease of integration into current systems. We use this approach to process random events, translate them into actionable tasks, and store the results to easily compute metrics.

We use five different tables to assist with the information flow (demonstrated in Figure 2):

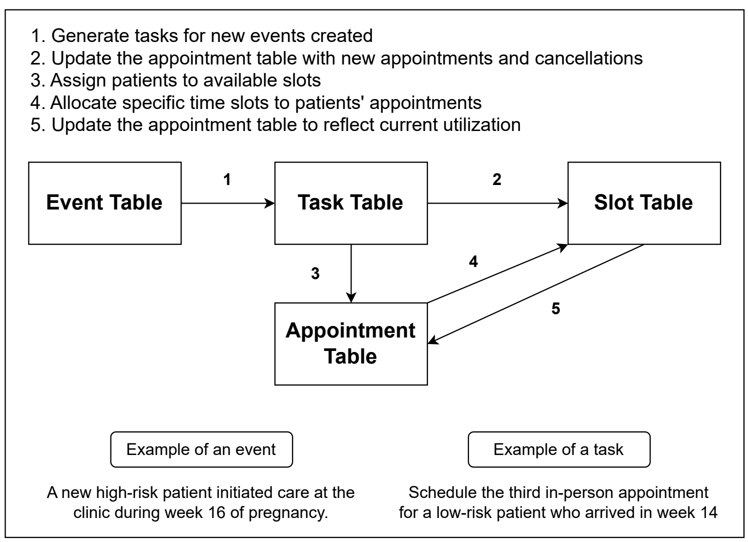


Figure 2: A flow diagram illustrating the table-based simulation approach.

- *Patient Table*: The Patient Table stores all the information related to patients, including their risk level, GAA and GAD, allowing us to keep track of the generated population.
- *Event Table*: The Event Table holds all information concerning all the random events in the simulation, such as new patient arrivals, appointment cancellations, and no-shows. All patient characteristics, such as risk level, GAA, GAD, and preference for visit type, are recorded in the Event Table and stored in the Patient Table upon arrival of the patient into the system. In summary, this table enables us to keep track of cancellations, no shows, and new patient arrivals.

- *Task Table*: All events are translated into deterministic tasks, which are stored in the Task Table. The role of this table is to translate a relatively broad event, like the arrival of a new patient, into a series of specific actionable tasks, like *n* "schedule appointment for week t" tasks.
- *Slot Table*: The Slot Table holds all appointment slots that a clinic (or provider) has available within a period, mimicking the clinic's availability. This table stores all the information about the providers' availability and specialty. Each slot can have different properties: some of them may be only for virtual visits, some only for new patients, etc.
- *Appointment Table*: The Appointment Table stores the information of each appointment, specifically which slot was used to fill which task, connecting the slot to a specific visit of a patient. With this table, we can track changes in the schedule in case of cancellations or of a patient's early delivery.

We now move to describe in detail the overall flow of the simulation.

3.2.2 Simulation Overview

Based on the assumptions described in Section 2, we construct our discrete event simulation model and illustrate its structure in Figure 3. As shown in this figure, the simulation averages results across a number of replications to calculate our performance metrics. Within each replication, we model clinic flow for a user-defined number of periods (or weeks). For each period t, a certain number of new patients P are generated, according to a user-specified distribution for patient arrivals. Attributes for each of the P patients, such as their GAA and GAD and their medical and social risk, are generated at this time.

Once these attributes are generated, individual tasks are created to schedule appointments for each patient. The number and frequency of these appointments are dictated by the patient's risk level and pathway. Each of these scheduling tasks is given a "due date", which is the period in which the corresponding appointment needs to be scheduled. For example, if a task's due date is period 10 and its target period is 12, it should be scheduled sometime between weeks 10 and 12. If capacity constraints prevent it from fitting within that window, the task is skipped.

Tasks are then sorted according to the prioritization policy set by the user. An example of a policy could be to prioritize scheduling appointments for patients in their third trimester over patients in their first trimester. All tasks with a due date of the current period t are then performed. If an appointment is canceled, a cancellation task is generated for the next period. Afterward, tasks are performed in the sorted order. For scheduling tasks, we check the slot table for any free slots in the period specified and update the slot and appointment tables if a suitable slot is found. For cancellation tasks, the number of available slots is incremented. At the end of each replication, we calculate the slot utilization, number of skipped appointments, and average delay in appointments.

4 EXPERIMENTS

The simulation model was built using Python and all scenarios were run on a computer with an Intel Core i7 2.8 GHz CPU and 16 GB RAM. Based on a set of ad-hoc experiments (Figure 4), we determined the warm-up period of our simulation to be 40 weeks. This also aligns with the duration of pregnancy; if the system starts from empty, it takes around 40 weeks for patients to start to deliver and leave the system. To ensure that our metrics in each replication only reflect the system at steady state, we run the simulation for 100 weeks, and only consider the last 60 weeks to compute our metrics. Furthermore, we run the simulation model for 50 replications, and we take the average metric from each period and compare the distribution of those metrics across scenarios. We chose 50 replications as it is sufficient to ensure statistically significant results. Our experiments also confirmed that increasing the number of replications would not significantly impact our conclusions. Finally, we used independent two-sample t-tests with a confidence level of 95% to compare the following scenarios.

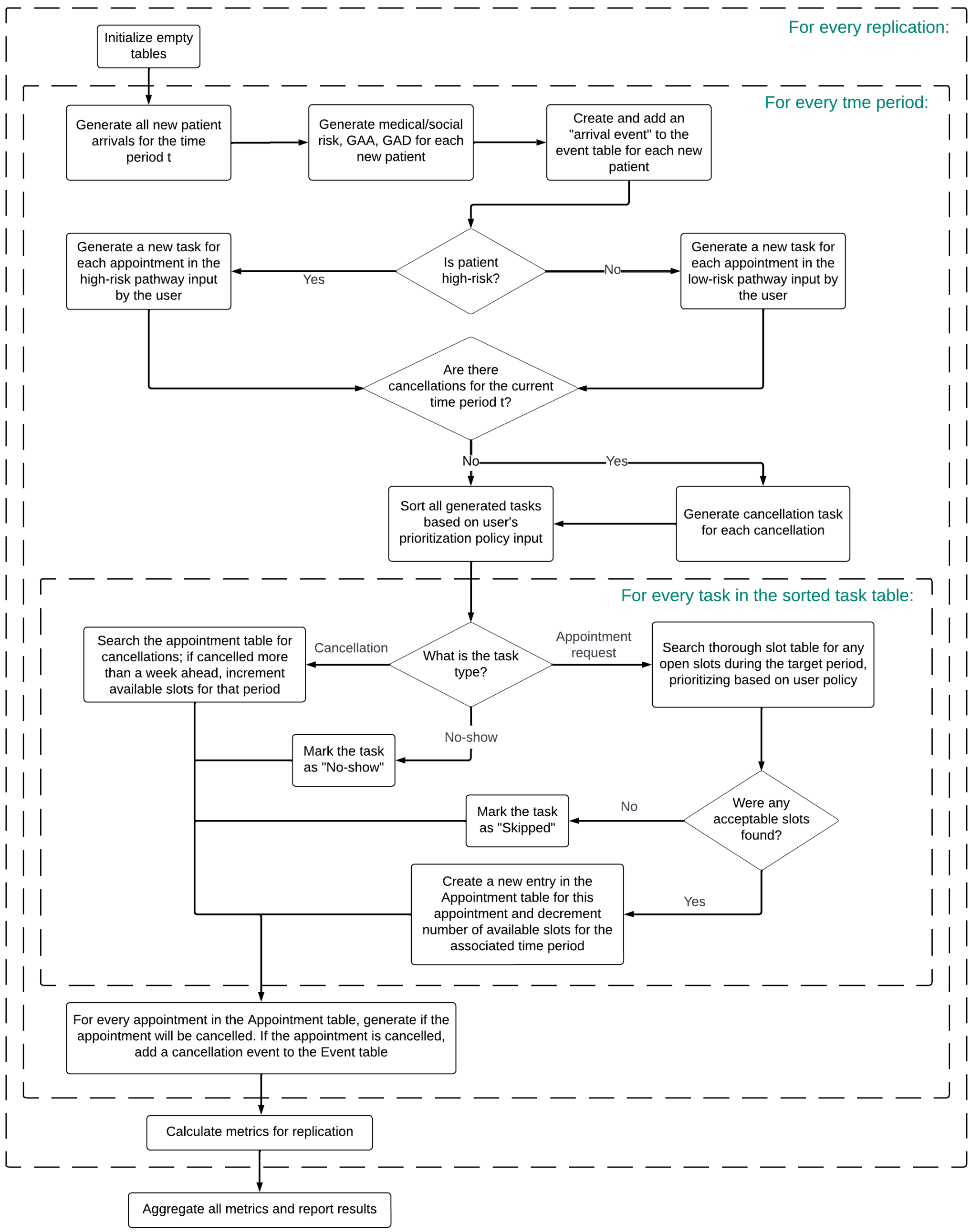
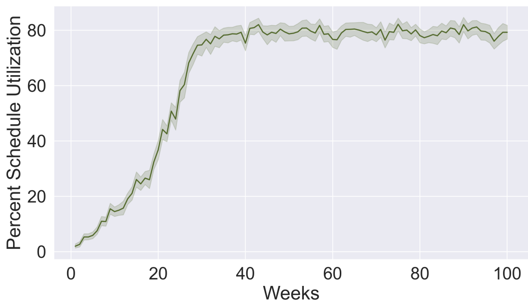


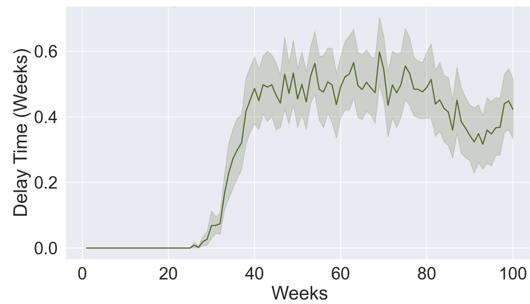
Figure 3: A flow diagram illustrating the simulation model.

4.1 Model Validation

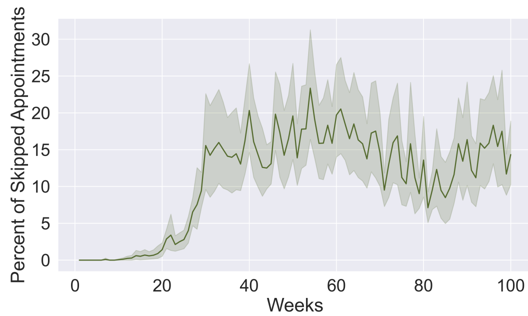
Our simulation was validated primarily through validation sessions with domain experts. Expert panels reviewed the model's structure, input logic, and preliminary output, confirming that projected capacity utilization, overbooking rates, and patient-delay distributions matched the ranges they routinely observe in comparable settings. We calibrated all arrival patterns, service times, and resource counts directly from Michigan Medicine's historical scheduling database (as described in Section 3.1), ensuring that the daily number of patients and appointments reproduced real-world volumes as closely as possible.



(a) Provider utilization



(b) Delayed appointment



(c) Skipped appointment

Figure 4: Warm-up period analysis for the simulation model.

4.2 Scenarios and Results

We consider two levels for our experiments:

- *Conventional vs. tailored pathways*: Following our definition of conventional and tailored pathways in Section 2, we compare these pathways to quantify the impact of adopting the tailored approach.
- *Patient mix*: The proportion of high-risk patients at Michigan Medicine is generally higher than that of non-academic health centers, due to its status as a large academic center. To ensure our findings are generalizable across different settings, we evaluate the tailored pathway under four scenarios, varying the high-risk patient proportion at 25%, 50%, 60%, and 75%. Note that at Michigan Medicine, approximately 60% of the prenatal care population is classified as high-risk.

When comparing the tailored and conventional pathways in terms of provider utilization, tailoring care significantly reduces utilization for all patient mixes (Figure 5). As expected, the greatest reduction occurs for the 25% high-risk patient mix, as a larger proportion of the patient population is low-risk and therefore impacted by the reduced-visit pathway in the tailored paradigm. Note that even in the conventional paradigm, the utilization percentage (i.e., the proportion of appointment slots filled), never exceeds 85%. However, we still observe appointment delays and skipped appointments, implying that overbooking exists in the system. This is due to the heterogeneity in patients' pathways and the subsequent demand for appointments; there may be some weeks in the horizon when the clinic is completely booked or overbooked, and others when the clinic is not utilizing all of its appointment slots.

Tailoring care also significantly reduces the number of skipped appointments for all patient mixes, for both low-risk and high-risk patients (Figures 6b and 6a). Notably, for the 25% high-risk patient population, tailoring care almost completely eliminates the number of skipped appointments. Recall that appointments

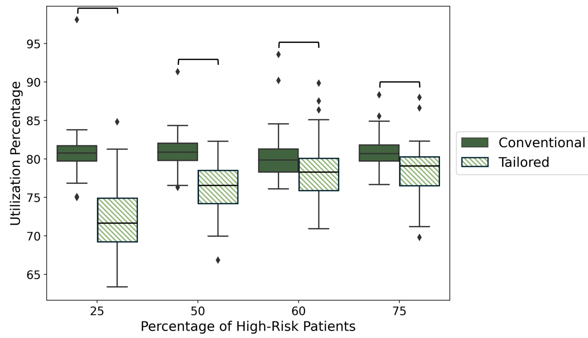
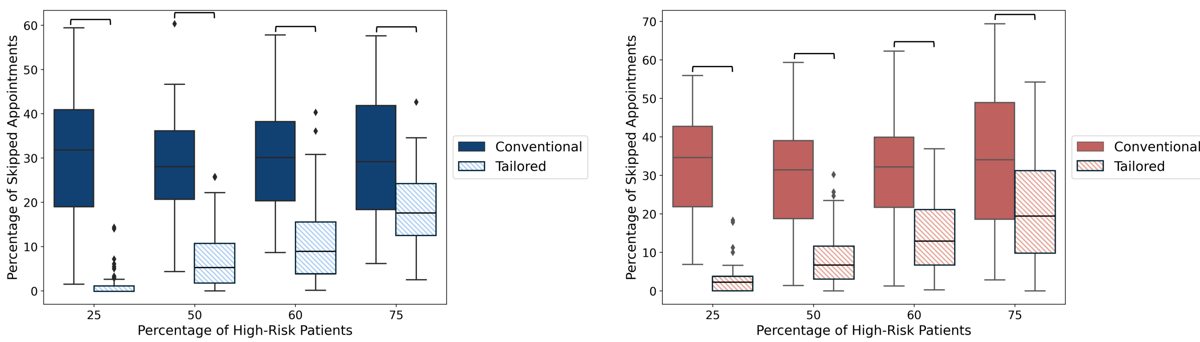


Figure 5: Comparing tailored and conventional pathways in terms of provider utilization. The horizontal bars represent a statistically significant difference between the conventional and tailored care scenarios, based on a standard two-sample t-test.

are skipped if it is not possible to schedule them within a certain threshold of their target week. This implies that appointments that occur in the third trimester, when appointments can only be delayed by one week, are more likely to be skipped.



(a) High medical/social risk.

(b) Low medical/social risk.

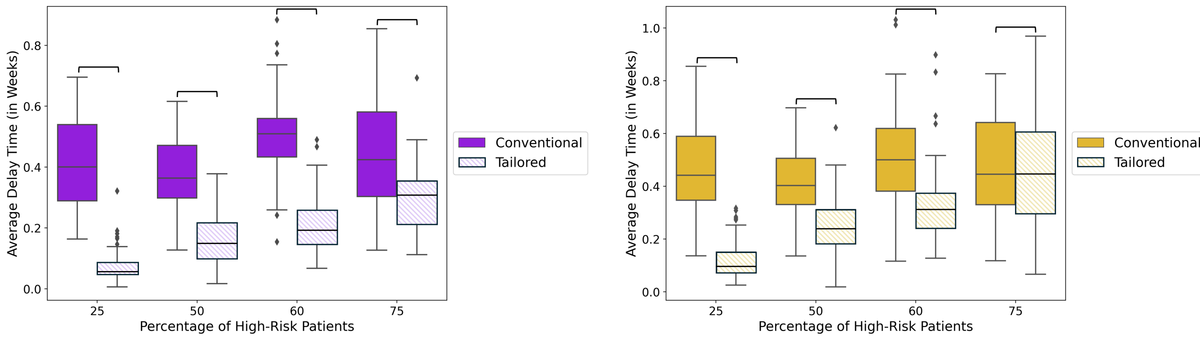
Figure 6: Comparing tailored and conventional pathways in terms of the percent of appointments skipped. The horizontal bars represent a statistically significant difference between the conventional and tailored care scenarios, based on a standard two-sample t-test.

Similarly, tailoring care significantly reduces the amount of delay for all patient mixes, for both low-risk and high-risk patients (Figures 7b and 7a). While the amount of delay is not high for even the conventional paradigm ($<$ 1 week for all experiments), any delay in prenatal care is not ideal. Also note that as capacity becomes more constrained, our scheduling policy is more inclined to skip appointments, as delaying them within an appointment's delay threshold may not be feasible.

Overall, these results highlight the magnitude of the operational savings that result from adopting a tailored prenatal care paradigm. Generally, tailoring care significantly reduces the number of skipped and delayed appointments, ensuring that patients receive prenatal care when they need it. Tailoring care also reduces capacity utilization in clinics, offering providers the flexibility to better adapt to unanticipated changes in their patients' care, and potentially to accommodate more patients.

5 CONCLUSIONS

This study employed discrete-event simulation to model operations at a prenatal care clinic, evaluating the operational efficiency of novel patient pathways compared to conventional practice. We explicitly



(a) High medical/social risk.

(b) Low medical/social risk.

Figure 7: Comparing tailored and conventional pathways in terms of the number of delayed appointments. The horizontal bars represent a statistically significant difference between the conventional and tailored care scenarios, based on a standard two-sample t-test.

simulated various sources of uncertainty, including patient arrivals, cancellations, and no-shows, and assessed performance using three key metrics, such as clinic slot utilization, percentage of delayed appointments, and percentage of skipped appointments. Our numerical results indicate that adopting tailored pathways at Michigan Medicine could significantly enhance clinic performance across these metrics. Moreover, we demonstrated the potential of tailored pathways to yield substantial improvements in diverse healthcare settings.

Medical literature supports that adopting tailored pathways does not negatively impact patient outcomes or service quality. Considering the demonstrated potential for considerable gains in operational efficiency, we recommend that prenatal care providers currently utilizing conventional practices strongly consider transitioning to tailored pathways. To facilitate this shift, our team is developing an accessible, free, and user-friendly dashboard, providing practitioners and healthcare managers with an accelerated version of our simulation model. This dashboard is designed to effectively communicate our findings, allowing providers to evaluate potential benefits tailored specifically to their clinical contexts.

Future research could address certain limitations of our current study. Our simulation does not presently accommodate multiple-clinic scenarios, and adaptations may be necessary to accurately model healthcare systems comprising multiple clinics. Additionally, our approach models capacity at the clinic level rather than individual provider availability. However, given recent trends indicating a reduced emphasis on continuity of care in prenatal settings - where patients routinely consult with multiple providers throughout their pregnancy - this limitation does not substantially affect our conclusions. Nevertheless, a valuable extension of our research would be explicitly considering continuity of care, especially in clinical contexts where it remains critical.

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AUTHOR BIOGRAPHIES

Adrianne Blanton is an undergraduate student in the Department of Biomedical Engineering at the University of Michigan in Ann Arbor, Michigan. Her research interests include policy and ethics in biomedical engineering. Her email address is adriblan@umich.edu.

Annie He is an undergraduate student in Computer Science and Molecular, Cellular, and Developmental Biology at the University of Michigan in Ann Arbor, Michigan. Her research interests include sleep, memory, machine learning, and the applications of simulation optimization in improving healthcare delivery. Her email address is anniehe@umich.edu.

Jillian Uy is a senior studying Industrial and Operations Engineering at the University of Michigan. Her research interests lie in applying industrial engineering principles to problems in healthcare. Her email is jilluy@umich.edu.

Krithika Venkatasubramanian is a senior at the University of Michigan majoring in Computer Science. She is a research assistant at UofM's Center for Healthcare Engineering and Patient Safety, where she has worked on prenatal care projects for the past two years. She is passionate about using computer science to enhance healthcare and patient experience. Her email address is krithiv@umich.edu.

Leena Ghrayeb is a recent PhD graduate from the Department of 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 under uncertainty in healthcare. Her email is lghrayeb@umich.edu and her website is https://sites.google.com/umich.edu/leena-ghrayeb.

Vincenzo Loffredo is a Business Consultant at Michigan Medicine. His research interests include Nonparametric Statistical Modeling, Prenatal Care Delivery optimization, Emergency Department smoothing, and the applications of Machine Learning to clinical settings. His email address is loffredv@med.umich.edu.

Amirhossein Moosavi is a Michigan Data Science Fellow at the University of Michigan's Michigan Institute for Data & AI in Society, where his work centers on data-driven, learning-based healthcare analytics. His email address is moosavia@umich.edu and his website is https://ahmoosavi.github.io.

Amy Cohn is an Alfred F. Thurnau Professor in the Department of Industrial and Operations Engineering at the University of Michigan, where she also holds an appointment in the Department of Health Management and Policy in the School of Public Health. Dr. Cohn is the Faculty Director of the Center for Healthcare Engineering and Patient Safety (CHEPS) and the Chief Transformation Officer for Michigan Medicine. She holds an A.B. in applied mathematics, from Harvard University and a PhD in operations research from the Massachusetts Institute of Technology. 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 is amycohn@med.umich.edu and her website is https://ioe.engin.umich.edu/people/cohn-amy-m/.

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.