A quantitative simulation–based modeling approach for college counseling centers

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Abstract
College counseling centers in various universities have been tasked with the important responsibility of attending to the mental health needs of their students. Owing to the unprecedented recent surge of demand for such services, college counseling centers are facing several crippling resource-level challenges. This is leading to longer wait times which limit access to critical mental health services. To address these challenges, we construct a discrete-event simulation model that captures several intricate details of their operations and provides a data-driven framework to quantify the effect of different policy changes. In contrast to existing work on this matter, which is primarily based on qualitative assessments, the considered quantitative approach has the potential to lead to key observations that can assist counseling directors in constructing a system with desirable performance. To demonstrate the benefit of the considered simulation model, we use data specific to Texas A&M’s Counseling & Psychological Services to run a series of numerical experiments. Our results demonstrate the predictive power of the simulation model, highlight a number of key observations, and identify policy changes that result in desirable system performance.

Keywords
College counseling, mental health, modeling, discrete-event simulation, system performance, access time

1. Introduction and motivation
Since the advent of the COVID-19 pandemic and its impact on our everyday lives, mental health–related problems have seen a sharp increase across the population.1,2 with a notable negative impact on students.3–5 Today, student mental health in higher education is considered one of the primary hurdles in the path to academic success. Studies have shown that students experience their first onset of mental health problems, as well as an increase in pre-existing symptoms, during their college years.6 Unfortunately, over the past few decades, there has been an alarming increase in psychological issues that college students exhibit. For example, according to the 2006 National Survey of Counseling Center Directors, almost half of college-aged individuals were reported to have some kind of psychiatric disorder.7 More recent reports from the 2019 annual survey by the Association for University and College Counseling Center Directors (AUCCCD) demonstrate that college students suffer from a multitude of mental disorders, with anxiety, depression, and stress being the most prevalent psychological issues reported by counseling centers.8–10

To combat this worrying trend, higher education institutions have set up university Counseling and Psychological Service (CAPS) centers to provide preventive and remedial counseling to help students identify and attain personal, academic, and career goals.11 However, the increasing ethnic, racial, and social diversity within the student population, as well as the changing trends in students’ needs, has altered the traditional mission of these centers, with student mental health support being one of the primary services.12 These challenges have been

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stress, anxiety, and depression—leading to a drastic increase in psychological needs. This surge in demand has imposed additional strains on counseling centers, and the current model is unable to meet the growing mental health needs of students and is resulting in staff burn-out, thus calling for a major transformation in the delivery of CAPS at university campuses. Counseling centers in universities are different from counseling centers that cater to the general population in two ways: first, the demand for CAPS services on college campuses follows a cyclical nature related to the student academic calendar, and second, the set of mental health disorders experienced by students, and their prevalence, are different from those of the general population. As such, CAPS facilities need to tailor their services and resources to cater to this need. Given these unique characteristics of CAPS, we focus the analysis on college counseling centers.

College counseling centers face a myriad of challenges, which can be broadly categorized into two classes: resource-level and patient-level challenges. Patient-level challenges pertain to the relationship between patient improvement and the treatment plan they undertake, while resource-level challenges involve resource planning and allocation. Patients have unique needs and hence are assigned tailored treatment plans which are often a combination of various treatment options. The main challenge lies in identifying a treatment plan that yields the best possible improvement. Studies have shown that a patient’s improvement tends to increase with the number of attended sessions. However, the study also reveals that there are no clear pathways to construct treatment plans for patients based on their specific case. Hence, there is no guarantee that the treatment plan they receive maximizes improvement. In addition, although there is a direct relation between the number of sessions and patient improvement, it may be infeasible—on a resource level—to provide every patient with as many sessions as they might need. Therefore, counseling centers also face challenges with regard to resource planning.

The increase in demand has negatively affected the waiting time for patients to receive care. According to the 2019 survey by AUCCCD that included 562 counseling centers, the average wait time for a first triage appointment (which we refer to as access time) was 6.1 days, while the average wait time for the following clinical appointment was 8.7 days. These numbers are expected to be much higher during the pandemic. The most straightforward solution to this issue is to hire more counselors as the most frequently reported barrier to meeting demand is understaffing issues. However, limited funding availability, which is the root cause of understaffing, prevents the adoption of such solutions. The study in this paper focuses on addressing the resource-level challenges facing CAPS with the aim of providing recommendations that do not impact the current staffing structure and strategy for deciding on treatment plans.

A number of attempts have been made by counseling centers to meet the surge in demand. One example is the external referral of patients where students are referred to off-campus providers whenever they require a higher level of specialization. For example, Iarussi and Shaw propose a model consisting of four phases. The first phase provides patients with all the information about the services provided and the possibility of a referral. In the subsequent phases, the patient’s case is assessed, and a personalized referral is identified and implemented. Owen et al. suggest a similar referral process that entails meeting the patient and then following up with them. In such models, the patient’s involvement in the process increases the likelihood of a successful referral (i.e., patients successfully transfer to off-campus providers). However, the proposed approaches require extra follow-up sessions from the counselor which is not optimal from a resource-allocation perspective. In addition, such models do not tackle one of the challenges that counseling centers face, access time. Because the initiation of the process begins with the first phase during the first appointment with the patient, such models do not affect the expected access time. Another example of an attempt made by counseling centers is to set an upper bound on the number of sessions that a student can utilize. This decision was driven by the fact that a considerable number of students end up utilizing a large number of treatment sessions which prevents other students from accessing the services. While such a policy has the potential to reduce the load on CAPS, it is still not clear how such a change will impact the overall performance. Moreover, no framework currently exists to help CAPS facilities determine an appropriate maximum number of sessions.

In this paper, we build a discrete-event simulation (DES) model to study and analyze college counseling centers’ performance. The main objective is to provide a quantitative framework to help answer fundamental questions about CAPS’s operations so as to propose data-driven solutions and recommendations that improve system performance. By utilizing the DES model, this paper aims to address three key research questions: (1) what is the effect of external referrals on the performance of the system and what proportion of referrals is needed to attain desirable performance? (2) what is the impact of a maximum session policy on the system performance and what bound provides good performance? (3) how does the scheduling policy impact system performance and what policies lead to favorable performance? Addressing these research questions is of importance as doing so can result in significant performance improvement. This will positively impact students by increasing access to critical
mental healthcare. To measure system performance, we use two key performance indicators (KPIs) which are the average wait time for the first appointment (access time) and the average wait time of crisis patients (referred to as crisis time). These KPIs were chosen based on discussions with our collaborator Texas A&M University (TAMU) Counseling & Psychological Services (CAPS). In addition to these two primary KPIs, we also monitor the average wait time for subsequent appointments (referred to as ongoing wait time) to ensure that patients in the system can have their periodic sessions with counselors at the desired planned frequency. Our collaboration with TAMU CAPS provides domain expertise and valuable real-life data. This is of value as it enables us to construct and validate a realistic simulation model. The contributions of this paper are twofold. First, to the best of our knowledge, this paper is the first to present a DES model that is specifically tailored to CAPS. The model serves as a quantitative platform to help CAPS facilities identify ways to improve system performance. The simulation model will be publicly available for other counseling centers to benefit from it. Second, we conduct a case study using data specific to TAMU CAPS. Our simulation results provide insights into the impact of external referrals, maximum session policy, and scheduling policy on system performance.

The remainder of this paper is organized as follows. Section 2 presents a comprehensive review of the literature. Section 3 provides an overview of the scheduling system implemented at CAPS centers. Then, section 4 presents a high-level description of the operational flow at CAPS centers. Section 5 details the different elements of the DES model and their implementation. Section 6 discusses findings and results from a series of numerical experiments conducted on TAMU CAPS. Finally, section 7 concludes this paper and provides future research directions.

2. Review of literature

Due to the ever-growing complexities of healthcare systems, quantitative methods that attempt to enhance services and reduce costs are being increasingly utilized. Of particular note are appointment scheduling problems, which is the primary focus of this study. These problems have received significant attention from the literature, and various quantitative tools have been used to address such problems. An example is optimization which is one of the most commonly adopted tools for appointment scheduling. For instance, Began and Queyranne discuss an efficient method to solve a single-server appointment scheduling problem. Their objective is to design an optimal schedule for a given sequence of jobs with the assumption that job durations are integer random values. Denton and Gupta also consider a single-server scheduling problem using a two-stage stochastic linear program, solving it using a modified L-shaped algorithm, with the objective of minimizing waiting time and service overtime. Other examples consider the problem of allocating surgery blocks to operating rooms (e.g., Denton et al. and Charnetski). While these optimization approaches can provide a mathematical basis for scheduling policies, they exhibit difficulty capturing the complexities of most healthcare settings. For instance, analytical models are often limited to Exponential or Erlang arrivals and service times. In addition, as seen in Begen and Queyranne and Denton and Gupta, such optimization models are typically formulated for a single server. While multi-server approaches have been considered (e.g., Alaeddini et al., Granja et al., Liu et al., and Sickinger and Kolisch), existing studies often impose unrealistic assumptions, such as identical servers and stationary arrival processes, in an effort to maintain analytical tractability.

Another commonly utilized analytical approach in healthcare systems is simulation modeling. Simulation has been extensively used to study various problems in the field of healthcare (e.g., Long and Meadows) as it overcomes many of the aforementioned drawbacks of an optimization approach. Several different modeling techniques exist such as Monte Carlo simulation (MCS), agent-based simulation (ABS), and DES. Each of these techniques has been applied to address various problems in healthcare, and they are best suited for specific types of problems. For example, MCS is appropriate for static systems that do not involve the passage of time and has been used to estimate the incidence of mental health disorders and survey analysis. ABS, however, is best suited for systems that consist of autonomous agents who interact with each other and with the environment and has been used to model the dynamics of infection transmission in hospitals and assess intervention policies to improve community mental health. Although these methods have been successfully used in a variety of settings, they are not ideal for modeling problems that are based on queuing systems. For such systems, DES is the most appropriate choice, since it has certain distinct advantages. First, DES models provide the ability to capture real-life complexities (e.g., patient cancelations and no-shows, and dynamic schedule adjustments in the context of healthcare systems). As a result, DES is commonly used to model different kinds of facilities that involve complex operations with uncertainty such as manufacturing units and healthcare clinics. Such complicating factors, which are often neglected in optimization models for tractability reasons, can play a crucial role in governing the performance of the system and hence should not be ignored. Second, DES models allow us to perform what-if analysis and evaluate the impact of policies on the system before they are implemented in the real world. Various different aspects of the system can be tested without actually committing...
resources. Third, DES models are very useful when the state of the system changes at specific discrete points of time as a result of a specific sequence of events. This is true for the operations at college counseling centers since the state of the system only changes when specific events occur such as a patient’s arrival, end of a counseling session, and cancelation of a session.

Given their distinct advantages, DES models have been extensively used to model the operations of various healthcare settings such as intensive care units, emergency departments, mass vaccination centers, and operating rooms. While some of the existing work study problems that are similar to ours, there are certain differences between the specifics of operations at CAPS centers and the setting of other healthcare appointment scheduling problems in the literature. For example, within the context of operating room scheduling, the number of operating rooms is often a decision variable, while, for our study, the analogous variable, i.e., the number of counselors, is fixed. Similarly, the length of the surgeries is usually the main source of uncertainty in the context of operating room scheduling, while the length of a counseling session is usually constant. Another important factor is that, in the context of counseling, after a triage session, patients potentially need to continue follow-up sessions with a certain frequency for the rest of the semester, but such follow-up sessions are not typically required in operating room scheduling settings. Given these discrepancies, it is challenging to extend existing work to model mental healthcare facilities.

There has been a rising popularity in constructing simulation models that are tailored to mental healthcare facilities. For example, Kuno et al. develop a DES model for the Philadelphia County Mental Health System to assess possible impacts of changes in arrival rates, service times, and bed capacity on the system performance. Subsequently, there have been several studies to aid with capacity planning and resource allocation. For instance, Kim et al. develop a DES model for the White River Junction Veterans Affairs Medical Center and recommend increasing service hours by two and employing an extra psychiatrist. More recently, Howells et al. construct a DES model of a psychology clinic in the United Kingdom, and analyze the impact of different staffing configurations on reducing patient waiting times. They conclude that employing additional dedicated care-coordinators can improve patient flow. Although such studies have the potential to provide valuable insights, there are some major shortcomings in their analyses. First, most of the studies provide a high-level description of their model without providing too much detail on their modeling approach, nor do they provide access to their DES models. As such, it is difficult to assess whether these can be applied to our problem. Second, most of these studies recommend employing additional resources to improve their current operations, which involves an extra financial investment from the clinics. Consequently, it is difficult to apply these recommendations in the context of university counseling centers, which are underfunded. In these settings, it is more important to identify policies that reallocate the existing resources in a way that improves the current performance. Third, the existing literature does not consider counselor schedules in their analyses, which is an important aspect of studying patient appointment allocation. Finally, none of these studies focus their analyses on university counseling centers, which have a host of unique challenges. This leads to a critical gap in the literature which this paper aims to address.

3. Overview of CAPS scheduling system

College counseling centers are equipped with a wide range of employees, including clinical staff, trainees, and support staff. The clinical staff (hereafter collectively referred to as counselors) includes licensed psychologists and psychiatrists who provide counseling, assessment, and treatment for behavioral, emotional, and mental disorders. Collectively, counselors represent the majority of the employee-base at CAPS and are the key operators of the facility. Consequently, appropriately managing their time and effort (which is the responsibility of the director) is key to achieving a good-performing system that effectively meets student demand. The duties and time commitment of counselors can be broadly categorized into four service types. The first three service types correspond to serving three different types of patients: (1) first-time, (2) ongoing, and (3) crisis. As the name implies, first-time patients are new patients who will be seen for the first time. Ongoing patients represent patients who have been previously seen by a counselor and who are now part of an ongoing treatment plan. Crisis patients are patients who are going through an emergency and who need immediate attention. The fourth and final service type is referred to as “other” which includes a host of activities (e.g., organizing workshops) that counselors are responsible for. The allocation of the counselors’ time across these four service types plays a key factor in characterizing the overall performance of the system.

In an effort to have a well-planned semester cycle, it is typical for CAPS directors to construct and commit to a master schedule plan at the beginning of each semester. This plan outlines, for each counselor, a distribution of time commitment for each of the aforementioned four service types that spans the entire semester. Such a plan is referred to as a scheduling policy. Counselors at CAPS are required to construct their specific work schedules in a manner that satisfies this master plan laid out by the directors. Such a work schedule is referred to as a schedule topology and consists of a detailed allocation of each
working hour to one of the four services for all counselors. Figure 1 provides an example of a schedule topology for two counselors across 2 days. In this example, a day is made up of eight slots each of which is allocated to one of the four service types. For example, counselor 1 has a higher emphasis on serving ongoing patients with slots 1, 4, 7, and 8 of day 1 and slots 3 and 7 of day 2 allocated to serving ongoing patients. Establishing a scheduling policy at the beginning of each semester cycle is of great importance to CAPS directors because it provides three distinct advantages. First, doing so leads to a structured, and transparent mechanism that greatly facilitates the effective management of a large number of counselors. Second, it allows directors to craft schedules that take advantage of the specific strengths of counselors. For example, if a specific counselor has been trained to effectively handle crisis patients, then the director may lean toward a scheduling policy that allocates more “crisis” service types to that counselor. Third, a scheduling policy provides directors with a high-level picture of all operations which allows them to devise schedules with sought-after specifications. For example, a scheduling policy can be used to ensure a fair and equitable distribution of workload among counselors.

Once a scheduling policy is committed to, counselors use it to construct a schedule topology, and arriving patients throughout the semester are scheduled in a manner that follows the topology. For example, if a first-time patient enters the system, then they can only be scheduled to “first-time” slots. Clearly, the scheduling policy will play a major role in determining the overall performance of the system (measured through the two KPIs discussed in section 1). For example, a schedule topology which is based on policy that does not commit enough time to vulnerable crisis patients will inevitably lead to a high average crisis time. This is undesirable as it can potentially lead to detrimental consequences such as the patient being unsafe to themselves or to people around them. As such, determining an appropriate scheduling policy that provides favorable system performance is of utmost importance. However, identifying such a policy is challenging as the decision needs to be made under high levels of uncertainty. This is the case because the scheduling policy is set up at the beginning of the semester prior to realizing any of the patient arrivals. Part of the objective of this paper is to provide a simulation-based mechanism to quantify the performance of a given policy, especially ones that take advantage of certain demand trends specific to CAPS. Such a tool is valuable to CAPS directors as it can assist them in identifying good-performing policies that are specifically tailored to their needs.

4. Overview of CAPS operational flow

This section aims to provide a high-level overview of the operational flow at CAPS and the sequence of processes (referred to as paths) that patients go through when entering the system. A patient’s path is heavily governed by their type (i.e., first-time, ongoing, crisis). In general, there are two ways by which patients can enter the system: First, if the arrival is a first-time patient, then students must book a first-time appointment by either using an online portal or by visiting CAPS in person. While there are some operational differences between these two types of booking approaches (e.g., an in-person first-time appointment booking requires students to complete a survey-based assessment report), the differences do not involve counselors’ time and hence do not impact the two considered KPIs. Consequently, we do not differentiate between these two first-time appointment booking methods. Note that the time between a patient’s request for a first-time appointment and the actual appointment time is the access time. Second, if the arrival is a crisis patient, then the process is simpler as no appointments are required and the patient can simply walk in during service hours and request a crisis meeting. Given the urgency of the situation, it is key for CAPS to provide the service as soon as possible. Of course, to be able to achieve such a service level, the scheduling policy must allocate sufficient slots for crisis patients. This, however, comes at a cost of having fewer first-time and ongoing slots which negatively impact access time. Such trade-offs highlight the difficulty in identifying good-performing policies. For both entry types, counselors are selected in a probabilistic manner based on their availability; however, preferences are given to counselors that are available earlier.

Upon completing the first session (whether as a first-time or crisis patient), counselors determine the best course
of action for their patients. Consequently, the subsequent path that students end up going through heavily depends on their specific characteristics. In fact, the set of all possible patient paths is quite diverse. While it is not possible to concisely go over all possible paths due to space limitations, numerous discussions with TAMU CAPS enabled us to comprehensively identify and factor in all possible paths that students can take. For example, one of the most common paths is based on a traditional one-on-one treatment cycle. In such a path, the patient is assigned to a specific counselor that they see on a periodic basis. The frequency of the meetings depends on several factors including, but not limited to, patient needs and counselor and schedule availability. The student continues attending one-on-one sessions until the counselor determines that the patient no longer needs treatment. The number of sessions that students end up attending can thus vary greatly. If additional sessions are deemed necessary, the patient type will transition to “ongoing.” This transition is not always guaranteed to occur for all paths (e.g., patient paths that involve referring the student to off-campus mental health providers). In this study, we aim to replicate the current treatment behavior since our focus is on the resource-level challenges facing CAPS. That is, the aim is to analyze the system in a manner that does not impact the current strategy for deciding on treatment plans.

Figure 2 provides a high-level schematic summary of the operational flow at CAPS. Starting from the left, patients enter the system. If the arriving patient type is “first-time,” then an appointment for the first-time visit is booked and, when the appointment time is attained, the patient proceeds to CAPS. The difference between the request and appointment times is the access time. If the arriving patient type is “crisis,” then the patient directly proceeds to CAPS, and the time needed to start attending to the patient is the crisis time. Once the patient arrives at CAPS, they will be seen by a counselor, and at the end of the session, it will be decided whether the treatment for the patient needs to be continued. If yes, the patient is sent to the “scheduler” where new appointments are booked based on the patient type “ongoing.” The patient will then wait until the selected appointment time is attained, after which they will head back to CAPS. Alternatively, if it is deemed by the counselor at the end of the session that no further treatment is required (or if the student is referred to off-campus mental health providers), the patient proceeds to exit the system.

The operational flow at CAPS is subject to high levels of uncertainties and variations that arise from numerous sources. For instance, as previously discussed, the paths that students end up going through vary substantially by a number of random and uncontrollable factors. These include patient types, specific characteristics and needs of patients, and counselors’ decisions for determining an appropriate treatment plan. In addition to the variations in the patients’ paths, several other sources of randomness exist. For example, students might cancel their appointments. In such a case, the time slot that was previously booked needs to be freed up. It is also possible for students not to show up to an appointment (referred to as no-shows). In this case, it is difficult to make the time slot available for immediate booking. Therefore, in case of no-shows, time slots are often reallocated to serve crisis patients. Other examples of uncertainty include time-varying arrival rates, counselor downtime, and random service times. These uncertainties, when compounded, result in a highly stochastic system that is challenging to analyze and understand.

5. The simulation model

The DES model was implemented in Simio® which is a popular commercial simulation software that has a set of expansive features that allow for modeling complex simulation processes.66 Our software choice is motivated in part by the availability of a full license that is also accessible to
Table 1. Example of the tabular format for the schedule topology presented in Figure 1.

| Day | Slot | Counselor 1 | Counselor 2 |
|-----|------|-------------|-------------|
|     |      | Service type | Booked | Service type | Booked |
| 1   | 1    | 1           | 0 | 3 | 0 |
| 2   | 0    | 0           | 2 | 0 |
| 3   | 2    | 0           | 3 |
| 4   | 1    | 0           | 2 | 0 |
| 5   | 0    | 0           | 3 | 0 |
| 6   | 2    | 0           | 3 | 0 |
| 7   | 1    | 0           | 2 | 0 |
| 8   | 1    | 0           | 1 | 0 |
| 2   | 9    | 0           | 2 | 0 |
| 10  | 2    | 0           | 3 | 0 |
| 11  | 1    | 0           | 2 | 0 |
| 12  | 0    | 0           | 3 |
| 13  | 2    | 0           | 1 | 0 |
| 14  | 0    | 0           | 3 | 0 |
| 15  | 1    | 0           | 2 | 0 |
| 16  | 2    | 0           | 3 | 0 |

a"First-time" = 0, "Ongoing" = 1, "Crisis" = 2, and "Other" = 3.
b"No" = 0 and "Yes" = 1.

In addition to the schedule topology, the file also embeds critical information regarding the current scheduling status of the system. As the simulation progresses, this external file is dynamically updated to reflect recent bookings and modifications. For example, if a crisis patient arrives at time 0, then (based on the schedule provided in Table 1) the nearest available crisis slot is given by slot 2 of counselor 2. In such a case, a reservation will be made for the student to attend that session and the value of the corresponding “Booked?” column must be updated from 0 to 1. Another example is when a student cancels an appointment. Here, the value in the column “Booked?” must be updated from 1 to 0 to make the slot available for future patients. Since topology information is embedded within the tabular form, all resulting scheduling processes are guaranteed to adhere to the selected schedule topology. It is worth highlighting that in certain circumstances, the column “Service type” may be dynamically updated as well. For example, if a no-show occurs, then the service type of the corresponding slot is modified to 2 to make the slot available to crisis patients. While this inherently modifies the selected topology, these modifications may be set into place by CAPS directors. Such specific complexities are extremely difficult to consider using other modeling approaches, which further motivates the use of a simulation-based model.

The simulation model has two main elements: counselors and patients. Counselors are modeled as servers while patients are represented as discrete entities. The general sequence of events is as follows. Patients enter the system according to a non-stationary process and are categorized into two types: regular and crisis. Regular patients are the patients who do not encounter any crisis attacks throughout their treatment cycle. In contrast, crisis patients are the patients who will encounter at least one crisis attack during their course at CAPS. The crisis attacks can either occur at the beginning of their treatment cycle (i.e., they enter the system via a crisis session) or they can occur in between one-on-one sessions. Depending on availability, whenever a patient experiences a crisis attack, the counselor assigned may be different from any previous crisis counselor they have visited, or their regular counselor with which they have periodic one-on-one sessions. The patients’ type will heavily impact the path that they will end up going through, which is why these two categories of patients were considered in the first place. The proportion of regular and crisis patients is determined from historical data and can potentially vary with time. Each entity is then assigned certain features depending on its type. Examples of features for regular patients include the total number of sessions, and no-show and cancelation probabilities. Crisis patients are assigned additional features such as crisis attack probabilities. Differentiating patients allows us to customize the features based on their type.
Once the initial features have been assigned, patients enter a scheduler in which they will be assigned the time and counselor for their first-time session. This assignment process heavily depends on the schedule topology and the current availability of the counselors, which are recorded in the external file discussed at the beginning of this section. To achieve the assignment, we first note that the service type of a triage session can either be “first-time” or “crisis,” and the scheduling process is different between the two. In particular, since a crisis is an emergency that needs urgent attention, patients who require a crisis session are allotted the earliest available crisis time slot among all the counselors. In contrast, patients seeking non-crisis sessions might be inclined to meet a specific counselor for their triage session, who might not necessarily have the earliest available slot among all counselors. In order to incorporate this aspect into the simulation, we use a triage counselor assignment procedure for patients seeking non-crisis triage sessions, as shown in Figure 3. Suppose a patient arrives in the system at time $t$ and is looking for a regular triage session. To find an appropriate counselor, we first find the earliest compatible slot for each counselor which we denote by $E_i$ for counselor $i$. This represents the first slot in counselor $i$’s schedule after time $t$ that is of service type 1 and is not booked. The earliest compatible slots are then used to establish a probability distribution given by:

$$P(i) = \frac{E_i^{-1}}{\sum_{j=1}^{C} E_j^{-1}}$$

where $P(i)$ denotes the probability of being assigned to counselor $i$, $\forall i \in \{1, \ldots, C\}$. Our aim is to construct a probability distribution where counselors with closer available times have a higher probability of being assigned. Observe that the numerator is the inverse of the earliest time. Thus, the lower the earliest time, the higher the value of the numerator. This simple procedure allows patients to be assigned to counselors having earlier available times while factoring in the variability that emulates the other factors that might influence their decision.

Once the first-time session is booked, the patient waits until the assigned session time and then visits their assigned counselor. At the end of the session, a number of checks are performed which are based on the features that have been assigned to the patient. For example, if additional sessions are not required, then the patient will exit the system. If additional sessions are required, then the patient is sent back to the scheduler to determine an appropriate time slot for their next session. The appointment time of the next session depends on several factors such as counselor preferences, patient needs, and schedule availability. An analysis of the number of days between sessions performed on the patient-level record data set reveals some interesting features (see Figure 4 which provides the empirical distribution of the time between sessions). Observe that the figure clearly depicts three distinct spikes corresponding to 7, 14, and 21 days, which highlights the fact that counselors conventionally prefer meeting on a weekly, bi-weekly, or tri-weekly basis. This choice is based on the counselor’s expert opinion on when the next session should ideally occur. Another key observation is that the proportion of cases of 7 days is much more common than cases for 14 or 21 days. This indicates that counselors often see the need to schedule weekly appointments. Finally, note that the lower proportions around the peaks can be explained by the second factor, that is, the inability (due to slot availability) to find a time on exactly 7, 14, or 21 days after their session. As a result, based on schedule availability, the two parties might agree on a day in and around the initially estimated preferred
date. This is an important feature of the operations at CAPS that needs to be intricately modeled into the simulation.

The empirical distribution illustrated in Figure 4 cannot be directly used in our simulation to model the time between sessions. This is because, as discussed previously, after a session is completed, the next session’s time is dependent on the availability in the counselor’s schedule at that point in time. Thus, to accurately emulate this behavior, we adopt a two-phase procedure described in Figure 5. First, using the empirical distribution in Figure 4, we establish a distribution to determine the base frequency of the meetings. These base probabilities are determined by obtaining the frequencies of cases where the gap between sessions is 7, 14, and 21 days which are then normalized to obtain a probability distribution. This pre-processing step is performed only once and is represented in Figure 5 by the components above the dashed horizontal line.

Suppose, at time $t$, a patient completed a session and a new future session needs to be scheduled (node 1 in Figure 5). The first step in achieving this is to generate the ideal day for the session based on the aforementioned distribution (node 2). Once generated, we search the counselor’s schedule for this ideal day to find the earliest compatible session. If such a session is found, we schedule the patient’s next session during this slot. If an available session is not found, we search “around” the ideal day to find a compatible slot. This is done using the iterative procedure described in node 3 of Figure 5. The procedure starts by searching the counselor’s schedule for a day after the ideal day. If no compatible slot is found, the procedure will look at a day before the ideal day. If a compatible slot is still not found, the procedure continues searching around the ideal day based on the following sequence: $+2$ days, $-2$ days, $+3$ days, $-3$ days, and so on. Once an appropriate session is identified, then the patient is scheduled for that session (node 4).

As any simulation model, certain assumptions were made in this study based on discussions with TAMU CAPS. First, we impose some assumptions on patient behavior. Specifically, we assume a non-stationary Poisson arrival process for new patients, although our model has the flexibility to utilize any other distribution of patient arrivals. We further assume that no patients are carried over from the previous semester to the semester considered in the simulation. That said, certain modifications can be made to our simulation model to account for the continuity of treatment across semesters. For instance, at the start of the simulation, using patient-appointment records of the previous semester, we can identify the patients who are being carried over and block off a certain part of the counselors’ schedules to account for sessions that need to be dedicated to these patients. Other than that, since CAPS usually provides services to patients for approximately one academic year, after which they are referred to external counselors, extending the run length of the simulation to one academic year can allow us to capture treatment continuity to a greater extent. Regarding the arrivals of each client type, we assume a uniform Poisson split for regular and crisis patient arrivals across the semester. In fact, we also investigated an alternate modeling choice where we considered a weekly change in the proportions of this Poisson split. However, based on the results of numerical experiments, we concluded that varying these proportions does not substantially impact the performance of the model (discussed in section 6.2). Second, we impose some assumptions on counselor behavior. Particularly, we assume that all 36 counselors have identical responsibilities. It must be noted here that our model can easily be improved in order to allow consideration of more nuanced
scheduling policies which vary for each counselor. We also assume that counselors do not have any days off and always stick to their schedules. This aspect of the simulation can be improved by incorporating additional logic which blocks the schedule of counselors on certain days based on certain conditions. Of course, we also need to reschedule the appointments that were scheduled on these days.

6. Case study: TAMU CAPS

In this section, we use the established DES model to conduct a case study on the specific operations of Texas A&M’s Counseling Center (TAMU CAPS). In Fall 2021, TAMU reported a total student enrollment of 72,982 (92% of which enrolled in the main campus in College Station) making it one of the largest universities (by enrollment) in the entire nation. Owing to the large student population, TAMU CAPS has been particularly affected by the surge in demand. This makes TAMU CAPS an ideal candidate for such an analysis as it is in need of identifying strategies that increase access to mental health services. The main objective of this study is to utilize the DES model to quantify the impact of certain key parameters on the overall operations of CAPS. In particular, we perform a series of experiments to investigate the impact, on the KPIs defined in section 1, of: (1) varying the proportion of external referrals, (2) imposing a maximum session limit, and (3) the scheduling policy. In what follows, we first provide a detailed description of the data sources used in this study (section 6.1). Next, we discuss the main input parameters used in the DES model and describe the methods used to obtain these parameters from the data sources (section 6.2). We then verify and validate our DES model by running an experiment with the current operating parameters and comparing its performance to the reported performance of TAMU CAPS (section 6.3). Finally, we run the aforementioned series of simulation experiments with varying operating parameters and perform sensitivity analyses for each of our KPIs (section 6.4).

6.1. Time horizon and data description

We run the numerical experiment for the Fall 2019 semester which spans across 18 weeks starting from 2 September 2019 up until 30 December 2019. The Fall
2019 semester was chosen in order to avoid any anomalies in the data during the onset of COVID-19. In terms of data, the analysis in this section utilizes two main data sets both of which were provided by TAMU CAPS. The first data set provides detailed patient-level record data while the second provides information regarding counselor scheduling. All the data were anonymized to protect the identity of patients and counselors. We provide a detailed description of the structure of each of these data sets below.

The patient-level record data set contains anonymized information about each session that has been scheduled at CAPS across the entire semester. Each row corresponds to a unique session for a patient and contains information such as the patient ID, the session type (e.g., crisis, ongoing, or other), whether a cancelation or no-show occurred, the ID of the assigned counselor, and the session date and time. This data set is an integral component of this study, and most of the input parameters for the simulation are obtained by analyzing this data set. Before performing any analysis, however, the data were carefully reviewed in order to remove any potential anomalies such as technical issues related to data collection. The details of obtaining these parameters and their usage in the model are discussed in section 6.2.

The counselor schedule data set contains information about the number of sessions allocated to each service type by each of CAPS’ counselors. This data set contains a total of 36 rows, one for each unique counselor at TAMU CAPS. Each column of this data set provides information on the total time per week that the counselors are expected to allot for each unique service. Recall that other than direct counseling of patients via first-time, ongoing, or crisis sessions, counselors also need to allocate time for other services such as organizing workshops, intern supervision, and student documentation. For the purpose of this study, these time slots are allotted to the “other” service type as discussed in section 3. These session types involve several added nuances of operations that are beyond the scope of this study. Moreover, the administrative responsibilities are not associated with any sort of patient waiting time. As a result, we do not conduct any analysis for the “other” service category.

It is important to note that the information provided in the counselor schedule data set does not characterize a unique schedule topology. However, it provides an idea of the proportion of time that each counselor spends for each service category across the entire semester (the scheduling policy). In order to get a realistic representation of the schedule topology based on this data set, we use the proportions of each service category in the schedule to generate random realizations of schedule topologies. In our experiment, in sections 6.3 and 6.4, we perform several replications of the simulation, each with a different random topology realization, and calculate the average estimates of the KPIs across the replications for a specific proportion distribution. This choice was motivated by the fact that CAPS directors choose to specify scheduling policies to counselors (instead of schedule topologies) because it is difficult to impose a specific topology on counselors. Consequently, in practice, different counselors have different schedules all of which are based on a given policy. Since our objective is to replicate the current behavior of TAMU CAPS, we decided to investigate the performance of various schedule policies by generating random topologies and observing their average performance across a set of replications. This analysis will thus shed light on the performance of a schedule policy rather than a schedule topology, which is what CAPS directors are interested in. This can be used as a master plan by CAPS and can potentially act as a guideline for the counselors to plan their schedules for the semester.

### 6.2 Input analysis

A fundamental component of the simulation is the arrival rate of patients as it will play a vital role in describing the dynamics of the simulation model. To estimate the arrival rate, we use data on the total number of new patient arrivals on a per week basis. These data are summarized in Figure 6 which plots the number of new patient arrivals as a function of time. The data clearly reveal an interesting pattern: as the semester starts, a rush of requests is observed. This demand gradually reduces with a sudden drop right before Thanksgiving break (shaded blue region). The demand then picks up right before final exams (shaded green region). This pattern is consistently observed across semesters (e.g., for the spring semester a similar trend is observed, where the drop in demand is observed right before Spring Break). Recall that part of the objective of this analysis is to take advantage of such predictable cyclical demand patterns. To obtain the per-
hour arrival rates from these data, we divide the total number of arrivals for each week by the total number of work hours per week (set to 40). As common in the literature, we assume that arrivals follow a non-stationary Poisson process with arrival rates obtained from Figure 6.

It is important to note that the above arrival rate takes into account the arrival of both regular and crisis patients. Consequently, determining whether the arriving patient is a crisis or a regular patient is a core element in modeling the arrival process and the simulation. This is because, upon arrival, the subsequent processes that patients undergo are dependent on whether they are a regular or a crisis patient. In order to model the differences in arrival rates for regular and crisis patients, we adopt a Poisson split. Specifically, we obtain the proportion of crisis patients and regular patients from the data and use these proportions for the Poisson split.

In this context, we investigate two different modeling choices—one where the proportions of regular and crisis patients are set to a constant for the entire time horizon, and another where these proportions change on a weekly basis. To this end, we obtain the proportion of regular and crisis arrivals for each week of the Fall 2019 semester and perform a simulation experiment that incorporates a weekly non-stationary proportion of arrivals. The mean expected access time for the varying ratio case (9.33 days) is almost identical to that of the constant ratio case (9.47 days), and the mean expected crisis time (1.08 h) is also very close to that of the constant ratio case (1.02 h). Next, we perform a paired t-test to investigate whether the results are statistically different. For the expected access time, the p-value obtained by performing a two-tailed test with a significance level (α) of 0.05 is 0.49, and for the expected crisis time, the p-value is 0.32. Note that the p-values for both tests are much higher than the significance level of 0.05, and thus, we do not have enough evidence to conclude that the mean difference between the paired simulated outputs is statistically significant. As a result, it can be concluded that adding this level of system variability does not substantially impact the results of the experiment, and therefore, these proportions are considered constant across the semester. The proportions of regular and crisis patients are 90.4% and 9.6%, respectively.

Upon arrival, several important initial features are allotted to each patient. One of the most important features is the number of sessions that the patient has to attend. Patients can require a different total number of sessions, which is determined by their counselor. In order to allow for this variability, we use a probability distribution based on information obtained from the patient-level record data set. The distributions of the total number of sessions for regular and crisis patients are shown in Figure 7(a) and (b), respectively. Although somewhat similar, the two distributions have some unique characteristics which highlight the difference in treatment patterns between regular and crisis patients. For instance, it can be observed that crisis patients are more likely to utilize a higher number of sessions, which emphasizes their need for CAPS’s services for a relatively longer period. Another important distinction is that regular patients have a higher probability of requiring just one session, while crisis patients have a higher tendency of requiring more sessions. This can be attributed to the fact that crisis patients arriving at the system during a crisis typically schedule a follow-up session with the counselor. Using these distributions, and depending on the arriving patient type, a random number of total sessions are generated for each arrival.

At this point, it is worth highlighting that throughout this study, we have chosen to use the empirical distributions obtained directly from the data provided by TAMU CAPS. This choice is primarily motivated by the fact that our objective is to accurately replicate the current behavior of TAMU CAPS. This is because the focus of this paper is on the resource-level challenges facing CAPS with the aim of analyzing the system in a manner that does not impact the current strategy. In general, a drawback of
using empirical distributions is that they might not capture rare tail events. In our case, however, all distributions are discrete with bounded support, and hence, this issue does not appear in our problem. There are certain situations where the empirical distribution was not directly utilized such as the time between sessions. In this case, a custom procedure was constructed as discussed in section 5.

Another important initial feature that is specific to crisis patients is the crisis attack probability. Recall that crisis patients may arrive in the CAPS system during an emergency crisis attack. However, the patient-level record data also reveal that crisis attacks can occur at any point in between sessions. This aspect is modeled into the simulation using the crisis attack probability. At the end of a session, and once the next appointment has been decided upon by the counselor and the patient, crisis patients have a probability (characterized by the crisis attack probability) of experiencing a crisis attack before the next scheduled session. This probability is estimated from the patient-level record data set and is found to be 14.6%.

Once the initial features have been allotted, patients can book their first-time session and then continue their treatment cycle with the assigned counselor until they meet the total number of sessions that was assigned to them. However, during their course of sessions at CAPS, patients may cancel or not show up for their scheduled session. As mentioned in section 5, these two probabilities are two key features assigned to each patient entity upon their arrival. In the same context, there are two other probabilities assigned to each patient: the no-show exit and the cancelation exit probabilities. Our discussions with TAMU CAPS, as well as an analysis of the data, revealed that in the event of a no-show or a cancelation, there are instances where patients do not reschedule their appointment and simply discontinue their visits to CAPS. These four probabilities can vary depending on the patient type and the time of the simulation. Table 2 provides these probabilities during Fall 2019 for each week and for each patient type. The no-show (cancelation) probability is obtained from the data by computing the ratio of the number of no-show (cancelation) sessions to the total number of sessions scheduled by patients. However, the no-show (cancelation) exit probability is the ratio of the number of no-show (cancelation) sessions that were followed by a patient’s exit to the total number of no-show (cancelation) sessions. These probabilities are computed separately for regular and crisis patients for every week of the semester. Note that from the description of the four probabilities, it is clear that the values across the rows need not sum to 100% since many students end up attending their scheduled sessions. The mean value across the semester is reported in the last row.

Observe that, on average, the no-show and cancelation probabilities are lower for crisis patients in comparison to regular patients, which highlights that crisis patients have a higher inclination to attend their counseling sessions. It is also observed that the exit probabilities are notably lower for crisis patients, which alludes to the fact that crisis patients have a higher tendency to complete their full course of sessions. In addition, the no-show probability for regular patients attains its highest values during the 13th

| Week | Regular patients | Crisis patients |
|------|------------------|----------------|
|      | NS (%) | NSE (%) | C (%) | CE (%) | NS (%) | NSE (%) | C (%) | CE (%) |
| 1    | 7     | 50      | 21    | 22    | 3      | 0      | 13    | 0      |
| 2    | 10    | 55      | 23    | 23    | 6      | 0      | 21    | 16     |
| 3    | 8     | 44      | 16    | 30    | 6      | 0      | 10    | 22     |
| 4    | 9     | 57      | 20    | 32    | 14     | 57     | 24    | 7      |
| 5    | 9     | 57      | 22    | 35    | 12     | 31     | 17    | 20     |
| 6    | 11    | 66      | 25    | 33    | 8      | 23     | 23    | 11     |
| 7    | 11    | 72      | 20    | 40    | 10     | 67     | 23    | 29     |
| 8    | 11    | 69      | 21    | 38    | 12     | 35     | 16    | 46     |
| 9    | 10    | 64      | 25    | 37    | 4      | 46     | 17    | 32     |
| 10   | 11    | 66      | 24    | 39    | 16     | 43     | 25    | 18     |
| 11   | 10    | 72      | 24    | 43    | 9      | 34     | 17    | 51     |
| 12   | 11    | 74      | 22    | 47    | 13     | 49     | 15    | 28     |
| 13   | 15    | 75      | 22    | 58    | 10     | 46     | 24    | 32     |
| 14   | 18    | 95      | 20    | 75    | 9      | 86     | 32    | 66     |
| 15   | 11    | 83      | 26    | 50    | 17     | 77     | 4     | 100    |
| 16   | 10    | 55      | 6     | 99    | 11     | 100    | 0     | 0      |
| 17   | 0     | 0       | 0     | 0     | 0      | 0      | 0     | 0      |
| 18   | 0     | 0       | 0     | 0     | 0      | 0      | 0     | 0      |
| Mean | 10    | 59      | 12    | 38    | 9      | 40     | 16    | 27     |

NS: no-show probability; NSE: no-show exit probability; C: cancelation probability; CE: cancelation exit probability.
and 14th weeks of the semester (i.e., during Thanksgiving break). In order to investigate whether the weekly changes in the no-show and cancelation–related probabilities have an impact on the KPIs, we perform simulation experiments based on two different modeling choices. In the first model, we consider the probabilities to be constant across the semester (based on the mean values presented in the last row of Table 2), and in the second model, we consider them to vary weekly, based on the row-wise values of Table 2. The results of the simulations reveal significant differences in the KPIs, and performing two-tailed paired $t$-tests between the two pairs of simulated results reveals that the difference is statistically significant—considering a significance level ($\alpha$) of 0.05, the $p$-values are extremely low ($\approx 10^{-8}$ for the expected access time and $\approx 10^{-10}$ for the expected crisis time). Given this, we incorporate the weekly no-show and cancelation–related probabilities into the model to make the simulation a more accurate representation of reality.

### 6.3. Model verification and validation

Before verifying and validating the simulation model, two important aspects of the experimental setup need to be discussed: the warm-up period and the number of replications. For simulation models that focus on steady-state analysis, the warm-up period is an important parameter as it allows the simulation model to reach steady-state conditions and helps eliminate any initialization bias. However, in the case of CAPS, where the center shuts down at the end of each semester, the initial dynamics at the beginning of each semester play a vital role in the simulation and hence cannot be ignored. In addition, the varying arrival rate in each semester play a vital role in the simulation and hence need to be considered. This entire procedure is repeated a number of times to generate topology realizations. This is done in the following manner: we enumerate each time slot across the semester for all counselors and allocate it to one of the four services, based on a discrete probability distribution. The probability of selecting any one of the four services is uniformly allocates these services based on the identified proportions.

Initially, we focused on verifying the routing logic of the simulation, i.e., whether students visit the appropriate counselor, whether students who require more sessions rebook an appointment at the end of each session, and also whether students who are done with their course of sessions exit the system. This was done by running the model for one student at a time and following them along their course. For instance, we verified whether crisis patients have random crisis attacks during their course and whether they immediately book a crisis session with the earliest available counselor. We also made sure that the various custom algorithms implemented in the model, such as the triage counselor assignment and the next session slot allocation procedures, are working as intended. For instance, when a student is booking a slot, we generated detailed outputs of the earliest compatible session for all counselors to make sure that the model works as intended.

Another important step before conducting the simulation experiments is to validate the model. That is, to determine whether the simulation accurately describes the real world for the purpose of this study. To achieve this, we run the simulation model using the Fall 2019 data sets and compare its output to the reported Fall 2019 metrics of the system. We do this for three metrics: the access time, the total number of students served, and the overall utilization of first-time sessions. To run this experiment, we first need to define the current schedule topology being implemented in TAMU CAPS. As discussed in section 6.1, the counselor schedule data set characterizes a schedule policy and not a topology. In this study, we utilize the scheduling policy to generate topology realizations. This is done in the following manner: we enumerate each time slot across the semester for all counselors and allocate it to one of the four services, based on a discrete probability distribution. The probability of selecting any one of the four services is set to the proportion of that service according to the schedule policy considered. For each of the realized topologies, the simulation is executed, and the metrics of interest are stored. The data reveal that, on average, counselors spend 8% of their time on first-time sessions, 4% on crisis sessions, 25% on ongoing sessions, and the remaining 63% of the time is dedicated for “other” services. To generate a topology realization that adheres to these proportions, we execute a pre-processing procedure at the very beginning of the simulation on the external excel file that uniformly allocates these services based on the identified proportions. This entire procedure is repeated a number of times to generate a distribution of outputs.

We run the experiment and obtain detailed outputs for the aforementioned three metrics. Figure 8 shows the box and whisker plot for the simulated expected access time across the 32 replications of our experiment. The average
expected access time is obtained to be 9.47 days, with a half-width (HW) of 0.4 days. The figure also displays the reported average expected access time during Fall 2019 (red dot) equal to 9.5 days. Observe that the simulation output closely aligns with the reported access time. To further demonstrate this, we perform a one-sample t-test (two-tailed) and obtain a p-value of 0.44. Therefore, considering a significance level (α) of 0.05, we do not have enough evidence to indicate the two are statistically different. This observation is important as it indicates that the simulation accurately describes the real world for the purpose of this study. Next, let us consider the total number of students served. Figure 9(a) provides the box and whisker plot of the simulated total number of students served, with the red dot representing the reported value by TAMU CAPS for Fall 2019. The mean simulated total number of students served is 1431, which closely aligns with the reported number of students served by TAMU CAPS in Fall 2019 (equal to 1463). The results of a one-sample t-test (two-tailed) further reveal that there is no statistical difference between the two (p-value = 1). Finally, we consider the average utilization of first-time sessions for counselors. The percentage is based on the total number of first-time slots utilized by clients, obtained from the simulation, among the total number of first-time slots in the counselors’ schedule topologies. The same average counselor utilization is calculated based on the data provided by TAMU CAPS. The box and whisker plot in Figure 9(b) demonstrates the simulated overall utilization for first-time sessions, with the red dot representing the reported value by TAMU CAPS for the Fall 2019 semester. The simulated mean utilization is 64.3%, which is similar to the reported value of 63.8%. Performing a one-sample t-test (two-tailed) confirms that there is no statistical difference between the two results (p-value = 0.09). In summary, comparing the simulated results for all three metrics with the actual reported numbers, we conclude that the DES model emulates the operations at TAMU CAPS to a high degree of accuracy.

6.4. Simulation experiments and sensitivity analysis

As discussed at the beginning of section 6, we conduct three experiments to investigate the impact of: (1) varying the proportion of external referrals, (2) imposing a maximum session limit, and (3) the scheduling policy. The results from these experiments are outlined below.

To meet the rise in demand, various CAPS centers, including TAMU CAPS, refer students to external off-campus mental health providers. Typically, it is only after a few sessions that the counselor is in a position to judge whether the patient needs to be referred. Once that decision has been made, the students can still attend a few more sessions with their regular counselor to ensure a smooth transition to their new provider. For TAMU CAPS, the proportion of external referrals was identified to be 5.6%. Other relevant information, such as the average number of sessions attended prior to a referral as well as the average number of transition sessions after a
performance of the system. The results demonstrate how solely changing the proportion of external referrals to the crisis time, as illustrated in Figure 10(b). Such a policy is introduced in various CAPS systems to increase access to newer patients. In our model, this policy is implemented in the following manner: we generate a random number of total sessions from the distribution described in section 6.2, and then select the minimum value among the generated number and the maximum session limit as the number of sessions to be allotted to the patient. For our experimental setup, we considered a range of values for the maximum session limit (2–12) and run a total of 32 replications for each case to observe its impact. All the other parameters are set to the current operating values. The results for this experiment are shown in Table 4, which reports the mean values of our two KPIs and the HW of a 95% confidence interval, as well as the range of the simulated values in parenthesis. Observe that changing the maximum limit does not lead to any notable changes in the expected access time. This is more clearly demonstrated in Figure 11(a). Although this can seem anomalous, some insight into the operating scheme of TAMU CAPS makes the observation quite intuitive. This is because the access time is the time taken from the patient’s request for a first-time session to the appointment time. The primary factor that impacts this

determination of the expected access and crisis times for varying proportion of external referrals. The results are shown in Table 3, and they reveal that neither the expected access time nor the expected crisis time is impacted by changes in the proportion of external referrals. This is counter-intuitive since one would expect that external referrals would improve access to new patients. However, note that students are only referred to external providers once they are done with a certain number of sessions. Thus, they still exhaust valuable first-time slots. As a consequence, it does not impact the access time since it still ends up utilizing the same number of first-time slots. A similar observation can be made with regard to the crisis time, as illustrated in Figure 10(b). Such results demonstrate how solely changing the proportion of external referrals will not have the desired impact on the performance of the system.

![Graph](image-url)

Figure 10. Expected access time (a) and expected crisis time (b) as a function of the proportion of external referrals. The red dots represent the current operating parameters at TAMU CAPS.

| Proportion of external referrals | Expected access time in days\( ^a \) | Expected crisis time in hours\( ^a \) |
|---------------------------------|--------------------------------------|--------------------------------------|
| 2.8%                            | 9.23 ± 0.45 (7.26 – 11.56)           | 1.08 ± 0.08 (0.61 – 1.68)           |
| 4.2%                            | 9.36 ± 0.44 (7.00 – 12.30)           | 1.11 ± 0.15 (0.46 – 2.97)           |
| 5.6%\(^b\)                     | 9.47 ± 0.37 (7.81 – 12.00)           | 1.02 ± 0.07 (0.74 – 1.50)           |
| 7.0%                            | 9.27 ± 0.42 (7.11 – 12.02)           | 1.08 ± 0.09 (0.71 – 1.74)           |
| 8.4%                            | 9.22 ± 0.45 (7.21 – 12.50)           | 1.12 ± 0.11 (0.61 – 2.01)           |
| 9.8%                            | 9.15 ± 0.37 (7.34 – 11.24)           | 1.06 ± 0.11 (0.54 – 1.96)           |
| 11.2%                           | 9.00 ± 0.39 (6.54 – 11.69)           | 1.04 ± 0.09 (0.71 – 1.75)           |

\(^a\) Each cell has the format: average ± HW (min–max).
\(^b\) Current operating parameter at TAMU CAPS.

Table 3. Expected access and crisis times for varying proportion of external referrals.
time is the proportion of first-time slots available in the schedule topology. Since the schedule topology remains the same across the cases on average, merely changing the maximum session limit does not influence the access time for patients. Similarly, for the expected crisis time, there is no significant impact with changes in the maximum session limit, as illustrated in Figure 11(b).

Another important metric is the waiting time for “ongoing” sessions, referred to as the ongoing wait time. Longer ongoing wait times are not desirable, and therefore, it is important to investigate the impact of changing the proportion of external referrals and the maximum session limit on the ongoing wait time. In Figure 12, we plot the expected ongoing wait time as a function of the maximum session limit as well as the proportion of external referrals. The results reveal two important observations. First, from Figure 12(a), it can be seen that as the maximum session limit increase from 2 to 10, the ongoing wait time increases slightly from 10.1 to 10.6 days. The reason for this trend is that as the maximum session limit decreases, patients are allowed a lower number of ongoing sessions, and as a result, a larger number of ongoing sessions in the schedule are made available for patients. Consequently, patients do not have to wait a long time to find a compatible session.

### Table 4. Expected access and crisis times for varying maximum session limits.

| Maximum session limit | Expected access time in days | Expected crisis time in hours |
|-----------------------|-------------------------------|-------------------------------|
| 2                     | 9.18 ± 0.42 (7.38 – 12.29)   | 0.92 ± 0.06 (0.63 – 1.27)     |
| 4                     | 9.14 ± 0.36 (7.38 – 11.30)   | 0.81 ± 0.07 (0.52 – 1.19)     |
| 6                     | 9.41 ± 0.41 (7.56 – 12.75)   | 0.90 ± 0.06 (0.65 – 1.35)     |
| 8                     | 9.16 ± 0.38 (7.38 – 12.05)   | 0.99 ± 0.08 (0.68 – 1.64)     |
| 10b                   | 9.47 ± 0.37 (7.81 – 12.00)   | 1.02 ± 0.07 (0.74 – 1.50)     |

*aEach cell has the format: average ± HW (min–max). bCurrent operating parameter at TAMU CAPS.*

**Figure 11.** Expected access time (a) and expected crisis time (b) as a function of the maximum session limit. The red dots represent the current operating parameters at TAMU CAPS.

**Figure 12.** Expected ongoing wait time as a function of the maximum session limit (a) and the proportion of external referrals (b). The red dots represent the current operating parameters at TAMU CAPS.
for their ongoing sessions. However, the decrease in ongoing wait time from a maximum session limit of 10 to 2 is about half a day, which is not significant from a business perspective for TAMU CAPS. Second, from Figure 12(b), it can be seen that changes in the proportion of external referrals do not seem to have any impact on the ongoing wait time. This can also be concluded from the results shown in Table 5, which presents the ongoing wait time in days for varying proportions of referrals. Note that for different values of the proportion of referrals, the confidence intervals of the ongoing wait time are overlapping. Thus, although having a higher proportion of external referrals can potentially lead to a higher number of available ongoing slots in the counselors’ schedule, it does not have a significant effect on the expected ongoing session wait time. This can be explained by noting that external referrals do not necessarily occur right after the first session. This will ultimately lead to a lower impact on the number of ongoing patients.

The first two experiments revealed that, for a fixed proportion distribution, neither the expected access time nor the expected crisis time is significantly impacted when varying the proportion of external referrals and the maximum session limit. To identify potential bottlenecks in the system, as well as to gain some insight into the dynamic behavior of the scheduling process at CAPS across the semester, we conduct an additional set of experiments in which we investigate the weekly utilization rates of counselors corresponding to first-time and crisis sessions across the semester. More precisely, the utilization rate of first-time (crisis) sessions in a given period is equal to the number of scheduled first-time (crisis) sessions divided by the total number of first-time (crisis) sessions. Figure 13 plots the simulated weekly expected average counselor utilization rates. Looking at the first-time utilization, it initially starts relatively low at around 60%, but by the second week, it rapidly increases to around 90% which is maintained up until week 11. After this, the utilization rate gradually decreases until it attains a value of zero. This decrease is primarily due to the overall low demand for first-time sessions toward the end of the semester. The high utilization rate for a significant portion of the semester explains why CAPS centers report a high access time. In contrast, the crisis utilization rate is much lower and attains a peak value of around 60%. This is expected as crisis sessions need to be readily available at all times to be able to quickly address emergency situations.

The results in Figure 13 reveal that the first-time sessions have exceedingly high utilization rates which are leading to long access time for students. Therefore, having a higher proportion of first-time sessions in the counselors’ schedule can potentially improve the system’s performance. To investigate this further and observe the impact of the proportion distribution on the two KPIs, we run a two-dimensional sensitivity analysis on the proportions of first-time slots \( pf \) and crisis slots \( pc \). We vary these values while fixing the proportion of slots dedicated to the “other” category. Consequently, the change in \( pf \) and \( pc \) will ultimately impact the proportion of ongoing slots (to preserve a total proportion of 1). Following the approach discussed in section 6.3, we generate a random topology for a given pair \((pf, pc)\) and run the simulation for the entire semester. This process is repeated for a total of 32 replications. We conduct this analysis for a range of \( pf \) values in \{5%, 7%, 9%, 11%, 13%, 15%, 17%\} and \( pc \)

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Table 5. Ongoing wait time\(^a\) for varying proportion of referrals.

| Proportion of referrals | Ongoing wait time (days) |
|-------------------------|--------------------------|
| 2.8%                    | 10.61 ± 0.04             |
| 4.2%                    | 10.60 ± 0.04             |
| 5.6%\(^b\)              | 10.61 ± 0.04             |
| 7.0%                    | 10.56 ± 0.05             |
| 8.4%                    | 10.57 ± 0.04             |
| 9.8%                    | 10.54 ± 0.04             |
| 11.2%                   | 10.57 ± 0.04             |

\(^a\)Each cell has the format: average ± HW.

\(^b\)Current operating parameter at TAMU CAPS.

Figure 13. Simulated average utilization of first-time slots (a) and crisis slots (b).
| $p_c$ | 1%   | 3%   | 5%   | 7%   | 9%   |
|-------|------|------|------|------|------|
| 5%    | EAT  | 27.1 ± 0.4 | 26.9 ± 0.6 | 27.3 ± 0.6 | 27.2 ± 0.6 | 27.2 ± 0.6 |
|       | (24.7 – 29.6) | (23.4 – 31.7) | (24.2 – 31.5) | (24.2 – 31.2) | (22.2 – 31.4) |
|       | ECT  | 45.4 ± 2.4 | 2.2 ± 0.3 | 0.7 ± 0.1 | 0.4 ± 0.0 | 0.2 ± 0.0 |
|       | (32.3 – 60.2) | (1.3 – 3.8) | (0.5 – 1.1) | (0.2 – 0.6) | (0.2 – 0.4) |
| 7%    | EAT  | 13.3 ± 0.6 | 13.5 ± 0.5 | 13.8 ± 0.6 | 13.5 ± 0.6 | 13.6 ± 0.6 |
|       | (10.0 – 16.1) | (10.6 – 16.5) | (10.9 – 19.8) | (10.3 – 16.7) | (10.3 – 16.8) |
|       | ECT  | 46.3 ± 3.0 | 2.0 ± 0.2 | 0.7 ± 0.1 | 0.4 ± 0.0 | 0.2 ± 0.0 |
|       | (30.4 – 63.7) | (1.1 – 3.0) | (0.4 – 1.1) | (0.2 – 0.5) | (0.1 – 0.4) |
| 9%    | EAT  | 6.6 ± 0.4 | 6.5 ± 0.2 | 6.7 ± 0.4 | 6.6 ± 0.3 | 6.6 ± 0.2 |
|       | (5.4 – 9.6) | (5.3 – 7.9) | (5.2 – 9.3) | (5.2 – 8.5) | (5.7 – 8.0) |
|       | ECT  | 48.1 ± 3.3 | 2.3 ± 0.2 | 0.7 ± 0.1 | 0.3 ± 0.0 | 0.2 ± 0.0 |
|       | (26.1 – 69.7) | (1.4 – 4.6) | (0.5 – 1.2) | (0.2 – 0.6) | (0.1 – 0.3) |
| 11%   | EAT  | 3.9 ± 0.1 | 4.0 ± 0.2 | 4.1 ± 0.2 | 3.9 ± 0.1 | 4.0 ± 0.2 |
|       | (3.1 – 4.5) | (3.2 – 5.1) | (3.3 – 4.8) | (3.3 – 4.7) | (3.1 – 5.6) |
|       | ECT  | 47.8 ± 2.7 | 2.2 ± 0.3 | 0.7 ± 0.0 | 0.3 ± 0.0 | 0.2 ± 0.0 |
|       | (32.9 – 60.2) | (1.4 – 5.9) | (0.5 – 1.1) | (0.2 – 0.7) | (0.2 – 0.3) |
| 13%   | EAT  | 2.7 ± 0.1 | 2.6 ± 0.1 | 2.7 ± 0.1 | 2.6 ± 0.1 | 2.7 ± 0.1 |
|       | (2.3 – 3.2) | (2.2 – 3.4) | (2.3 – 3.1) | (2.2 – 3.4) | (2.0 – 3.1) |
|       | ECT  | 51.0 ± 2.6 | 2.2 ± 0.2 | 0.7 ± 0.1 | 0.3 ± 0.0 | 0.2 ± 0.0 |
|       | (36.0 – 66.6) | (1.1 – 4.7) | (0.4 – 1.3) | (0.2 – 0.5) | (0.1 – 0.3) |
| 15%   | EAT  | 2.0 ± 0.1 | 2.0 ± 0.0 | 2.0 ± 0.1 | 2.0 ± 0.1 | 2.0 ± 0.1 |
|       | (1.8 – 2.3) | (1.7 – 2.3) | (1.8 – 2.4) | (1.8 – 2.3) | (1.7 – 2.6) |
|       | ECT  | 53.0 ± 2.2 | 2.2 ± 0.2 | 0.7 ± 0.1 | 0.3 ± 0.0 | 0.2 ± 0.0 |
|       | (40.5 – 63.0) | (1.1 – 4.3) | (0.4 – 1.0) | (0.2 – 0.6) | (0.1 – 0.3) |
| 17%   | EAT  | 1.6 ± 0.0 | 1.6 ± 0.0 | 1.6 ± 0.0 | 1.6 ± 0.0 | 1.6 ± 0.0 |
|       | (1.4 – 1.8) | (1.3 – 2.0) | (1.4 – 1.8) | (1.4 – 1.8) | (1.4 – 1.9) |
|       | ECT  | 54.1 ± 3.2 | 2.0 ± 0.2 | 0.6 ± 0.0 | 0.4 ± 0.0 | 0.2 ± 0.0 |
|       | (40.7 – 76.1) | (1.2 – 3.0) | (0.4 – 0.9) | (0.2 – 0.6) | (0.2 – 0.4) |

Each cell is composed of two rows. The first row reports the mean KPI value (in days for EAT and hours for ECT) ± the half-width for the 95% confidence interval. The second row reports the range of the simulated values in parenthesis (min–max).

The results are shown in Table 6 which reports the expected access and crisis times, the HW of the 95% confidence interval, as well as the range of simulated values for all scenarios. The results reveal several interesting behaviors, discussed below.

Looking at the expected access time, the results show that it is heavily dependent on $p_f$ with higher proportions leading to lower expected access times. Even small variations can lead to large differences. For example, reducing $p_f$ from 8% to 7% increases the expected access time by a substantial 43% (on average). Increasing $p_f$ to 9%, however, reduces the expected access time by an average of 30%. The sensitivity of the expected access time to $p_f$, however, exhibits diminishing returns. To better see this, Figure 14(a) plots the expected access time when $p_c = 4\%$ (currently used at TAMU CAPS) as a function of $p_f$. Such an observation is important because increasing the value of $p_f$ beyond a certain point may not be worthwhile since it will only lead to marginal improvements. The results also reveal that the expected access time is not impacted by $p_c$. This is somewhat expected since varying the proportion of the topology dedicated to crisis should not impact the access time. Such results can help CAPS directors determine scheduling policies that meet their ideal performance. For example, if CAPS aims to have an expected access time of just 3 days, then our results can be used to determine a $p_f$ value that will attain this performance ($p_f \approx 12.5\%$). Shifting the focus to the expected crisis time, Table 6 reveals similar trends. In particular, the expected crisis time is decreasing with $p_c$ with the greatest reduction observed for lower $p_c$ values. This diminishing returns feature is more clearly depicted in Figure 14(b). For example, reducing $p_c$ from 4% (current implementation) to 3% increases the expected crisis time by an average of 110% while increasing $p_c$ to 5% improves the expected crisis time by an average of 32%. Also, the results in Table 6 reveal that the expected crisis time does not seem to be heavily correlated with $p_f$, since the confidence intervals of the expected crisis time across varying $p_f$ values are overlapping.

Again, these results can be used to identify values of $p_c$ that result in desirable performance. For example, if the
we repeat the two-dimensional sensitivity analysis for two

target expected waiting time is 15 min, then, based on our
analysis, a $p_c$ value of approximately 8.9% would be
needed to attain this performance.

Finally, to observe the combined effect of varying the
external referral proportion, the maximum session limit,
and the scheduling policy on the access and crisis times, we
repeat the two-dimensional sensitivity analysis for two
additional scenarios. For the first, the external referral pro-
portion and maximum session limit are set to the highest
values (i.e., 11.2% and 10, respectively) and for the sec-
ond scenario, they are set to the lowest values (i.e., 2.8%
and 2, respectively). The results of the first and second
scenarios are shown in Tables 7 and 8, respectively. The
results follow the same trend as that of Table 6, i.e., the

Table 7. Comparison of expected access time (EAT) and expected crisis time (ECT) with varying proportions of first-time ($p_f$) and crisis ($p_c$) sessions for a maximum session limit of 10 and an external referral proportion of 11.2%.

| $p_f$ | $p_c$ | EAT 1% (min) | EAT 3% (min) | EAT 5% (min) | EAT 7% (min) | EAT 9% (min) |
|------|------|-------------|-------------|-------------|-------------|-------------|
| 5%   |      | 27.0 ± 0.7  | 27.4 ± 0.7  | 27.4 ± 0.7  | 27.6 ± 0.7  | 27.3 ± 0.7  |
|      |      | (22.4 – 30.9 | (24.1 – 32.0 | (22.6 – 31.5 | (24.9 – 32.7 | (22.7 – 31.3 |
|      |      | (25.8 – 57.7 | (1.2 – 3.4  | (0.4 – 0.9  | (0.3 – 0.5  | (0.2 – 0.5  |
| 7%   |      | 13.6 ± 0.6  | 13.4 ± 0.6  | 13.3 ± 0.5  | 13.5 ± 0.7  | 13.7 ± 0.6  |
|      |      | (10.9 – 17.7 | (10.7 – 18.0 | (10.5 – 16.3 | (10.6 – 19.2 | (10.7 – 16.6 |
|      |      | (4.0 – 1.4  | (0.2 – 0.5  | (0.1 – 0.3  |
| 9%   |      | 6.6 ± 0.3   | 6.5 ± 0.4   | 6.6 ± 0.3   | 6.7 ± 0.3   | 6.6 ± 0.3   |
|      |      | (5.3 – 8.8  | (5.0 – 9.3  | (5.2 – 8.1  | (5.5 – 8.8  | (5.2 – 7.9  |
|      |      | (24.0 – 68.2 | (1.0 – 3.2  | (0.4 – 1.4  | (0.2 – 0.5  | (0.1 – 0.3  |
| 11%  |      | 3.9 ± 0.1   | 3.9 ± 0.1   | 3.9 ± 0.1   | 3.9 ± 0.1   | 3.9 ± 0.1   |
|      |      | (3.2 – 4.9  | (3.3 – 5.1  | (3.3 – 5.0  | (3.3 – 4.6  | (3.0 – 4.5  |
|      |      | (35.0 – 64.7 | (1.0 – 3.4  | (0.5 – 1.0  | (0.2 – 0.6  | (0.2 – 0.3  |
| 13%  |      | 2.7 ± 0.1   | 2.7 ± 0.1   | 2.7 ± 0.1   | 2.7 ± 0.1   | 2.7 ± 0.1   |
|      |      | (2.2 – 3.2  | (2.2 – 3.2  | (2.3 – 3.3  | (2.3 – 3.0  | (2.4 – 3.3  |
|      |      | (33.9 – 65.5 | (1.3 – 3.7  | (0.4 – 1.0  | (0.2 – 0.6  | (0.2 – 0.4  |
| 15%  |      | 2.0 ± 0.0   | 2.0 ± 0.0   | 2.0 ± 0.0   | 2.0 ± 0.0   | 2.0 ± 0.0   |
|      |      | (1.8 – 2.3  | (1.7 – 2.2  | (1.7 – 2.2  | (1.8 – 2.3  | (1.8 – 2.2  |
|      |      | (31.9 – 69.9 | (1.3 – 3.4  | (0.4 – 0.9  | (0.2 – 0.7  | (0.2 – 0.4  |
| 17%  |      | 1.6 ± 0.0   | 1.6 ± 0.0   | 1.6 ± 0.0   | 1.6 ± 0.0   | 1.6 ± 0.0   |
|      |      | (1.4 – 1.8  | (1.4 – 1.8  | (1.4 – 1.8  | (1.4 – 1.9  | (1.4 – 1.8  |
|      |      | (35.0 – 68.2 | (1.3 – 3.3  | (0.4 – 0.9  | (0.2 – 0.6  | (0.2 – 0.4  |

Each cell is composed of two rows. The first row reports the mean KPI value (in days for EAT and hours for ECT) ± the half-width for the 95% confidence interval. The second row reports the range of the simulated values in parenthesis (min–max).
Table 8. Comparison of expected access time (EAT) and expected crisis time (ECT) with varying proportions of first-time (pf) and crisis (pc) sessions for a maximum session limit of 2 and an external referral proportion of 2.8%.

| pf | pc   | 1%    | 3%    | 5%    | 7%    | 9%    |
|----|------|-------|-------|-------|-------|-------|
|    | EAT  | 27.0 ± 0.6 | 27.3 ± 0.6 | 27.5 ± 0.7 | 27.2 ± 0.8 | 26.9 ± 0.6 |
| 5% |     | (22.0 - 30.2) | (23.6 - 31.4) | (22.4 - 32.1) | (23.5 - 31.9) | (22.5 - 30.6) |
|    | ECT  | 19.9 ± 4.3 | 1.5 ± 0.1 | 0.6 ± 0.1 | 0.4 ± 0.0 | 0.3 ± 0.0 |
|    |     | (7.7 - 55.1) | (1.0 - 2.1) | (0.5 - 1.3) | (0.3 - 0.7) | (0.3 - 0.5) |
| 7% | EAT  | 13.5 ± 0.5 | 13.4 ± 0.5 | 13.8 ± 0.7 | 13.5 ± 0.6 | 13.2 ± 0.7 |
|    |     | (11.4 - 16.9) | (10.0 - 16.2) | (10.9 - 17.4) | (10.7 - 17.4) | (10.5 - 18.3) |
|    | ECT  | 19.3 ± 3.6 | 1.5 ± 0.1 | 0.7 ± 0.0 | 0.4 ± 0.0 | 0.3 ± 0.0 |
|    |     | (7.4 - 49.5) | (0.7 - 2.0) | (0.5 - 0.9) | (0.3 - 0.7) | (0.3 - 0.7) |
| 9% | EAT  | 6.4 ± 0.2 | 6.5 ± 0.3 | 6.5 ± 0.3 | 6.7 ± 0.3 | 6.6 ± 0.3 |
|    |     | (5.2 - 7.3) | (5.2 - 8.1) | (5.0 - 8.1) | (5.5 - 8.4) | (5.2 - 8.3) |
|    | ECT  | 19.5 ± 3.5 | 1.4 ± 0.1 | 0.6 ± 0.1 | 0.4 ± 0.0 | 0.3 ± 0.0 |
|    |     | (6.8 - 46.1) | (0.9 - 1.9) | (0.4 - 1.0) | (0.3 - 0.7) | (0.2 - 0.4) |
| 11%| EAT  | 4.0 ± 0.1 | 4.0 ± 0.2 | 3.9 ± 0.1 | 3.9 ± 0.1 | 3.9 ± 0.1 |
|    |     | (3.3 - 4.8) | (3.1 - 5.1) | (3.1 - 5.1) | (3.4 - 4.5) | (3.3 - 4.7) |
|    | ECT  | 21.1 ± 3.6 | 1.5 ± 0.1 | 0.7 ± 0.0 | 0.4 ± 0.0 | 0.3 ± 0.0 |
|    |     | (8.8 - 43.4) | (1.0 - 2.2) | (0.4 - 0.9) | (0.3 - 0.7) | (0.2 - 0.4) |
| 13%| EAT  | 2.6 ± 0.1 | 2.6 ± 0.1 | 2.7 ± 0.1 | 2.7 ± 0.1 | 2.6 ± 0.1 |
|    |     | (2.2 - 3.1) | (2.4 - 3.1) | (2.4 - 3.3) | (2.3 - 3.2) | (2.3 - 3.1) |
|    | ECT  | 23.2 ± 5.5 | 1.5 ± 0.1 | 0.7 ± 0.0 | 0.4 ± 0.0 | 0.3 ± 0.0 |
|    |     | (5.0 - 60.9) | (1.0 - 2.1) | (0.4 - 1.0) | (0.3 - 0.6) | (0.2 - 0.5) |
| 15%| EAT  | 2.0 ± 0.1 | 2.0 ± 0.0 | 2.0 ± 0.0 | 2.0 ± 0.1 | 2.0 ± 0.1 |
|    |     | (1.7 - 2.4) | (1.8 - 2.3) | (1.7 - 2.3) | (1.7 - 2.3) | (1.7 - 2.3) |
|    | ECT  | 19.0 ± 2.7 | 1.4 ± 0.1 | 0.6 ± 0.0 | 0.4 ± 0.0 | 0.3 ± 0.0 |
|    |     | (5.1 - 34.5) | (0.9 - 2.2) | (0.4 - 1.0) | (0.3 - 0.7) | (0.2 - 0.5) |
| 17%| EAT  | 1.6 ± 0.0 | 1.6 ± 0.0 | 1.6 ± 0.0 | 1.6 ± 0.0 | 1.6 ± 0.0 |
|    |     | (1.4 - 1.8) | (1.4 - 1.8) | (1.4 - 1.8) | (1.4 - 1.8) | (1.4 - 1.8) |
|    | ECT  | 24.0 ± 4.5 | 1.4 ± 0.1 | 0.7 ± 0.1 | 0.4 ± 0.0 | 0.3 ± 0.0 |
|    |     | (6.5 - 56.2) | (1.0 - 2.1) | (0.4 - 0.9) | (0.3 - 0.7) | (0.2 - 0.4) |

Each cell is composed of two rows. The first row reports the mean KPI value (in days for EAT and hours for ECT) ± the half-width for the 95% confidence interval. The second row reports the range of the simulated values in parenthesis (min–max).

7. Conclusions, limitations, and future research directions

In this paper, we construct a simulation model that mimics the operational flow of college counseling centers. The considered model is general and incorporates a number of realistic factors that are often ignored in the literature. To demonstrate the benefits of the simulation model, we use data from TAMU CAPS and perform a series of numerical experiments to investigate the impact of certain factors on the system’s performance. Our experiments lead to key observations on the effect of different policy changes on the system-level resources at counseling centers. First,
increasing the proportion of external referrals or imposing maximum session limits does not result in the desired impact if the structure of the schedule topology is not considered. This is an important observation as many CAPS facilities have implemented such policies with the hope of improving the performance of the system. Second, our experiments on the schedule topology reveal that the proportions dedicated to each of the service types have a significant impact on the system performance. Our results can be used by CAPS directors to identify the proportions for each of the service types that lead to the desired system performance. For the specific case of TAMU CAPS, it was identified that a first-time proportion of 12.5% and a crisis proportion of 8.9% would result in a system that meets their desired performance.

Although this paper focuses on modeling the operations of TAMU CAPS, there are some fundamental characteristics that are common to different college counseling centers across the United States. These include the provision of appointment-based sessions and walk-in crisis services, student no-shows and cancellations, maximum session limits and external student referrals, and so on. Apart from that, awareness about mental health has increased in various universities even outside the United States, and to address this several colleges across the world have established counseling centers, such as in Canada, Europe, Africa, and Asia. These counseling centers have similarities in their operations to CAPS centers in US universities. In order to utilize our framework for other institutions, certain aspects of the simulation model will need to be customized based on the specifics of their operations. However, we believe that the primary contribution of this study is to provide a foundation that will help facilitate this process of adopting a more quantitative approach to improve the operations of college counseling centers.

This work can be extended in several important directions. For example, a more rigorous investigation of the composition of optimal schedule topologies could result in even better system performance. This is valuable as our numerical experiments reveal, even for fixed proportions, the substantial impact of the topology on the performance of the system. Part of this analysis would include the investigation of time-varying schedule topologies in which the proportion dedicated to each service type can potentially change over time. This is of particular relevance to college counseling centers because of the predictable cyclical nature of the demand. In a similar context, more dynamic strategies could also be investigated where the scheduling policy is updated in real-time as the demand is realized throughout the semester. Different techniques such as machine learning, artificial neural networks, and reinforcement learning can be utilized to develop these dynamic scheduling policies. Another interesting research direction is to enrich the simulation with group-based treatment options. These have been recently introduced to handle the surge in demand. While group-based treatment options have the potential to improve system performance, their addition also results in a number of scheduling challenges. Within this context, the considered model can be used to assess and quantify the impact of such options on the system. Finally, this paper focuses on addressing the resource-level challenges facing CAPS. The process-based metrics considered in this paper are only part of the story. In practice, one needs to consider outcome-based metrics for a more complete treatment of the problem. In the future, other outcome-based metrics such as the Counseling Center Assessment of Psychological Symptoms (CCAPS) assessment reports that quantify the effectiveness of treatment plans can be incorporated into this framework. This is especially important when considering some of the policies being implemented by CAPS facilities. For example, does imposing a maximum session limit impact the effectiveness of treatments? Are group-based treatment options as effective as individual therapy? Establishing a quantitative framework to address these questions, in conjunction with the considered simulation model, can result in a counseling system with both a desirable system performance and patient outcome. We hope that this work can lead to further research in the aforementioned directions and potentially aid counseling centers in developing data-driven policies.

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