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A HYBRID SIMULATION APPROACH FOR MODELING CRITICAL CARE DELIVERY IN ICU

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ABSTRACT

Critical care delivery entails a complex human-centric system. Patients and a multidisciplinary care team are the major autonomous agents in the system. Their actions and interactions with each other and the environment drive the dynamic evolution of the system and determine the system outcomes (e.g., patient outcome, provider burnout, care quality, system efficiency). The objective of this study was to model critical care delivery in an ICU to provide decision support to ICU resource management. A hybrid simulation approach combining agent-based simulation for modeling patients and care providers, and discrete event simulation for modeling care pathways was developed. This approach leverages clinical knowledge for modeling individual patient trajectories and care services endogenized from patient needs. It allows us to understand how the arrival flow of patients, the patient disease condition, and the care protocols jointly affect ICU census and provider workload, and build a pathway towards digital twinning of ICUs.

1 INTRODUCTION

An intensive care unit (ICU) is defined as an organized system that provides care to critically ill patients by provision of specialized medical and nursing care, enhanced capacity for patient monitoring, and different modes of physiologic organ support for sustaining life during a period of life-threatening organ system dysfunction (Marshall et al. 2017). An ICU is considered one of the most critical units in a hospital since its operations often extend beyond the walls of ICUs to impact upstream units like emergency departments, surgical units, and downstream units like hospital ward operations (Marshall et al. 2017). The uncertain patient care pathways hamper our capability to accurately predict care demands and thus provide matching resources to ensure quality patient care. Recent progress in systems engineering research has provided us with qualitative frameworks to approach complex social-technical systems, e.g., SEIPS 3.0 (Carayon et al. 2020), and Safe Dx (Singh and Sittig 2015). However, a quantitative method is also desired, allowing us to model the interaction of care providers and patients in the ICU, and measure the output of the ICU "production" process, such as patient length of stay, mortality rate, and well-being of ICU operations, such as patient diversion due to full capacity, delays in service provision, and service interruptions.

Our work is motivated by a parallel effort to advance our understanding of critical care patient trajectories indicated by levels of organ system dysfunction (Hou et al. 2024). To incorporate patient's uncertain trajectories in ICU modeling, we propose a hybrid simulation approach. The patient arrival and the stay and departure are modeled using discrete event simulation (DES), whereas patient clinical states (different levels of organ dysfunction, and discharge and death states), and care provider tasks/services are modeled via agent-based simulation (ABS). There are several unique features distinguishing our model from existing ICU simulation efforts (Dong et al. 2012). First, we use a novel data-driven approach to learn patient trajectories and develop a multi-state model that encodes clinical knowledge as a foundation to predict patient state changes. This model directly maps patient clinical states to different levels of care support needs, which allows us to understand how the disease progression impacts providers' workload. Second, unlike many hybrid simulation models of ICU where one modeling paradigm (e.g., systems dynamics or a machine learning prediction model) serves as an input to another modeling paradigm (e.g., a DES model), our model directly incorporates bi-directional interactions between patients and care providers and the care delivery processes. The configuration of team-based care protocols such as service priorities and care provider roles are accurately modeled to gauge their impact on patient state dynamics. Changes in one patient's clinical state as a service request will trigger provider services and possibly induce service interruptions (of another patient). Meanwhile, provider capacity constraints might delay patients from receiving care timely. This allows us to understand how the capacity constraints potentially impact the promptness and quality of care. Differentiated from many existing works, patientâĂŹs length of stay and mortality risk are no longer modeled as a fixed distributional input but are endogenized by patient-provider interactions and their interactions with the ICU operating environment. Lastly, because of the careful delineation of different aspects in the ICU operations, this hybrid simulation approach provides us with more granular information about the system's performance. Compared to many other studies, which focus exclusively on patient outcomes, or ICU census prediction, we are able to measure the presence of patients in different clinical states in the ICU, and the distribution of providerâĂŹs time and effort on different care tasks; these outputs together can be analyzed as a proxy of provider workload and cognitive load to assess the risk of provider burnout.

The organization of the paper is as follows. In Section 2, we provide a brief review of hybrid simulation approaches and ICU simulation models. In Section 3, we introduce how we model patients, care providers, and their interactions using ABS and DES. In Section 4, we present a case study of a medical ICU in an academic hospital to illustrate our modeling approach. Finally, discussions and a concluding remark can be found in Sections 5 and 6.

2 LITERATURE REVIEW

Hybrid simulation is defined as the combination of two or more simulation methods or continuous and discrete systems (Kar, Eldabi, and Fakhimi 2022). Several commercial software packages, e.g., AnyLogic, FlexSim, Simio, among others (Paape et al. 2023), provide the capability to integrate or combine the traditional simulation methods of DES, system dynamics (SD), and ABS.

When it comes to the ABS or SD technique, the hospital capacities are generally considered at an aggregated level (Anagnostou et al. 2022). However, a hybrid approach where the hospital operations are also specifically modeled along with patient behaviors and population interactions can help track performance metrics, and provide insight into resilient operations, the preventive measures required, and the impact on the community and the healthcare system (Anagnostou et al. 2022). On the other hand, when it comes to the entities of DES, they typically have a predefined movement throughout the system, but the human-type movement such as disease trajectories might not be fully dictated by simple constraints (Dubiel and Tsimhoni 2005). DES cannot model human movement and decision-making like ABS to allow for autonomous and intelligent entity interactions for achieving a specific goal in the environment (Dubiel and Tsimhoni 2005).

As a complex human-centric system, healthcare systems have broadly embraced hybrid simulation techniques. Some sample studies that combine DES with ABS techniques in healthcare include managing an orthopedic department to reduce waiting times (Kar, Eldabi, and Fakhimi 2022), planning health and social care services for dementia with telecare (Penny, Bayer, and Brailsford 2023), and addressing the complex problem arising from Emergency Medical Services (Olave-Rojas and Nickel 2021). Some studies also combine DES with SD such as the model for Chlamydia infection, which used DES for patient outflow and SD for the infection process in the community (Viana et al. 2014). A hybrid model for age-related macular degradation health was developed with DES and SD components sitting inside an overarching agent-based model. The patients as agents having age-related macular degradation were combined with DES of the eye unit patient clinic. Embedded SD models in each eye characterize progressive sight loss from age-related macular degradation and other conditions (Viana et al. 2012). Reflections on these two approaches to hybrid simulation in healthcare can be found in Viana (2014). In the context of modeling ICU operations, most of the studies used DES along with ABS or SD and machine learning (Williams et al. 2020; Lu et al. 2021; Possik et al. 2023; Zhang et al. 2023; Ortiz-Barrios et al. 2023). Additionally, our preliminary work attempted to develop a framework for digital twinning an ICU at the system level, with the vision of enabling bi-directional communication between the physical system and the simulated system for real-time decision support (Zhong et al. 2022). In this work, we primarily focus on simulation method development, which is an important step towards future digital twin development. More works related to hybrid simulation in healthcare can be found in reviews and visionary papers (Brailsford 2015; dos Santos et al. 2020; Kar et al. 2022).

3 METHODS

3.1 Patient Modeling

Analyzing the natural history, responses to treatment, and outcomes of critical illness syndromes is challenged by the dynamic and longitudinal nature of the organ systems evolvement and clinical interventions (Klein Klouwenberg et al. 2019). The multistate model conceptualizes a stochastic process in terms of a set of comprehensive, mutually exclusive states, and the transitions among them, accounting for competing events at each transition. Multistate models yield high-fidelity analyses of the dynamic state transition and temporal dimensions of a clinical conditionâĂŹs progression and are chosen to model patient clinical trajectories in our study.

To ensure generalizability and driven by the need to calibrate these states using electronic medical record data, we introduce the following states, capturing the major clinical states of patients during their clinical course in the ICU.

The initial state represents patient entry into the model (i.e., admission to ICU), and immediately following admission, patients are in one of the transient states, denoted as no organ dysfunction, single organ dysfunction, and multiple organ dysfunction. Another transient state is "discharged from ICU," indicating stabilization of patient conditions. Finally, two absorptive states, death and "discharged from hospital," denote the end state of a patientâĂŹs care episode for this ICU stay. Figure 1 illustrates the states and all possible transitions, with the darker color lines indicating transitions between transient states and lighter (pink) color lines indicating transitions to absorptive states. Note that we introduce the intermediate state/transient state "discharged from ICU" to capture "readmission" due to a sudden deterioration or escalation of a patient transferred from the ICU to a step-down unit or a general care ward but not yet to be discharged from the hospital. Also, different levels of organ dysfunction imply different levels of care needs/interventions and provider workload, and correspond to different levels of mortality risk.

In the case study, focusing on sepsis patients, we narrow it down to two types of organ dysfunction, respiratory and cardiovascular organ systems failure. Pulmonary infection is the commonest cause of sepsis identified in our preliminary work (Lal et al. 2020). The most common organ dysfunction is respiratory failure, occurring in 82.6% of patients at some point during their ICU stay, followed by cardiovascular failure (45.5%) (Lone and Walsh 2012). As a proof-of-concept, we define "no organ dysfunction" as patients without respiratory and cardiovascular support, "single organ dysfunction" as patients receiving either respiratory or cardiovascular support, and "multiple organ dysfunction" as patients receiving both types of organ system support. Note that adopting this definition is due to limited data and low resolution of temporal data to accurately identify other organ failures (e.g., renal, liver, gastrointestinal, etc.). However, the multistate modeling method is generalizable to any patient cohort and user-defined states.

3.2 Provider Modeling

We mainly model three classes of providers, namely, "Consultants" (also known as attending physicians or intensivists), "Residents," a class of clinicians including residents, fellows, nurse practitioners, and physician assistants as they share similar roles, and "Nurses." There are other providers (e.g., pharmacists,

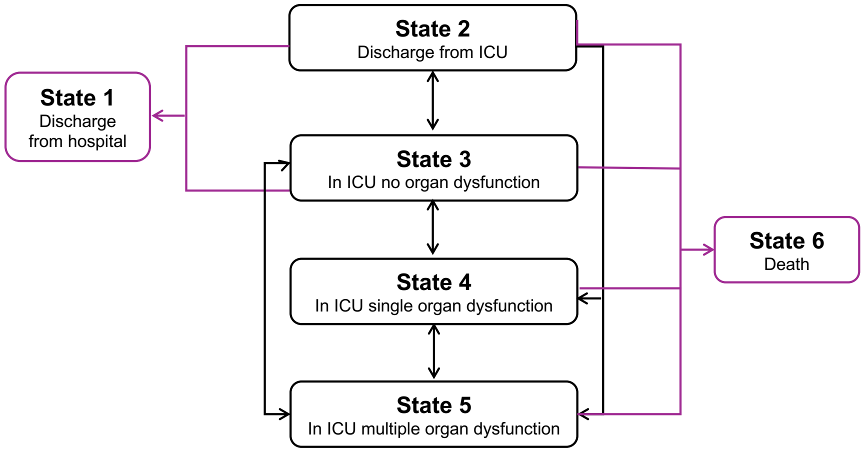

Figure 1: Patient multistate transitions. States 2-5 are transient states and states 1 and 6 are absorptive states. The darker color lines indicate transitions between transient states and lighter (pink) color lines indicate transitions to absorptive states.

respiratory therapists, physical and occupational therapists, and allied health staff). Their tasks might be part of the team-based tasks to be delineated below and are implicitly modeled. We first introduce the set of tasks providers perform and then discuss how we model providers as agents in the simulation.

Patient care is provided by an interdisciplinary care team. A consultant is the "captain of the ship." Consultants' *tasks* are broadly categorized as (1) diagnostic; (2) interventional; and (3) documentation/team communication. The first two classes of tasks will involve patients and the last class can be performed without the presence of patients. To make a diagnosis, the physician will review patient medical history, perform physical examination, communicate with patients, their family members, and other care team members (e.g., nurses), and to gain additional diagnostic certainty, additional diagnostic testing is usually pursued, including lab tests, imaging, ultrasound, among others. These diagnostic test results will be reviewed for decision-making. Once a reasonable diagnostic certainty is achieved, interventions/treatments are appropriately provided. Interventions include medications and procedures, as some form of organ support in our modeling context. The information/data generated during the diagnostic and interventional processes will be documented in the patientâĂŹs medical records (Ball, Miller, and Balogh 2015). See Figure 2 for the typical workflow of consultants.

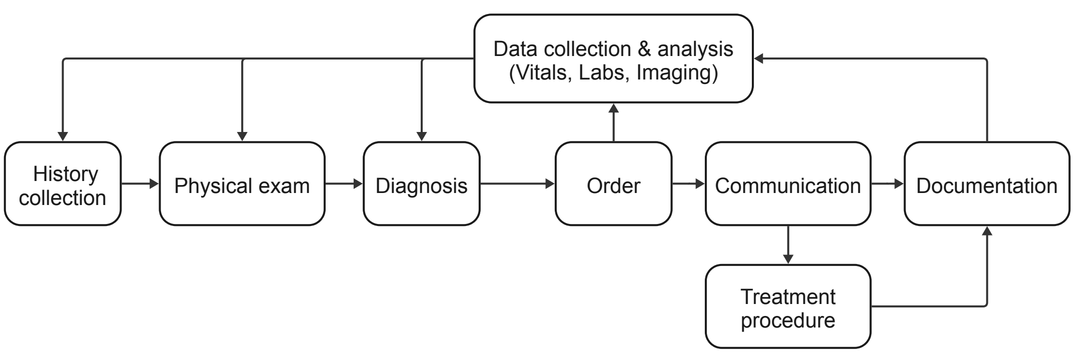

Figure 2: ICU consultant workflow.

In team-based care, residents, nurse practitioners/physician assistants, and nurses will be involved in these tasks with different roles and participate at different levels. For instance, once physicians order lab tests or prescribe medications, nurses will be responsible for performing the blood draw, or instructing the patient to take oral medications, or administering intravenous fluids (see Figure 3 for nurse workflow). As another example, a consultant supervises a procedure done by a resident but might not be able to stay during the entire procedure, whereas a nurse or a resident will need to. The diagnosis-intervention-documentation cycle will be (1) performed routinely and repeatedly during each patient encounter; (2) triggered by special events, like an admission of a patient, a clinical state change of the patient (e.g., from single organ dysfunction to multiple organ dysfunction), and discharge. Also, note that some tasks might be skipped or might be performed multiple times depending on the triggering events.

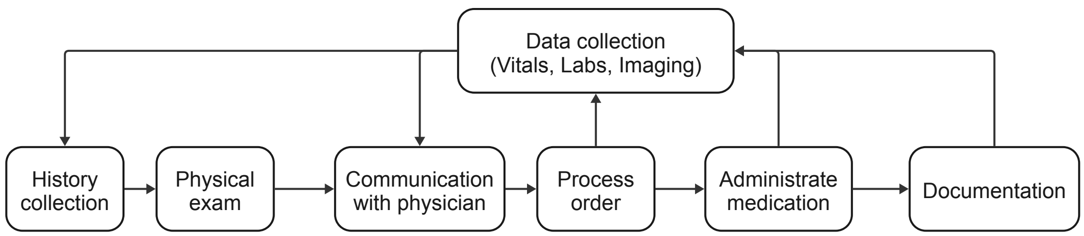

Figure 3: ICU nurse workflow.

Due to a lack of data to fully calibrate the time spent on each task, which is highly variable across patients and providers, in this study, we model these tasks at a high level, i.e., as a diagnosis-intervention-documentation cycle, differentiated by the mechanism that triggers it. Subsequently, care providers will have the following *states*.

First, “Idle/Documentation,” indicating the provider is not currently assigned to any patients. This also includes a state of “Precharting," when the care team is informed about a potential patient that will be admitted to the ICU either from the same facility or as a transfer. The team gathers preliminary information on the patient based on their past medical history along with other information to prepare for admission. Although documentation and precharting are different from being “idle,” they both have the lowest priority in the task list, i.e., once a provider is called, they can immediately attend to the patient (an instant state transfer). This contrasts with the other states, where the provider needs to finish their current tasks (non-preempt) or at least part of the task to be able to attend to another patient.

Second, “Rounding” – the provider is performing the daily rounding. Rounding is scheduled in the morning (e.g., between 8am-10am, and the total time varies by patient census, disease complexity, and provider team) and in the afternoon (e.g., from 3pm-5pm). For the rounding state, providers are not “seized” by a particular patient, since they will round the ICU to visit each patient, have a team-based discussion to assess patients’ health status, and make treatment/discharge/transfer decisions. When the rounding process is finished, if there is no other request from patients, the provider will return to the “Idle/Documentation” state.

For nurses and residents, they will have another state, “Patient Check,” to represent the routine check-ups of patients regardless of patient clinical state. We model it as an hourly operation, i.e., nurses and residents will visit their designated patients hourly if were not preempted by other more urgent tasks.

The remaining states, “Admission,” “Resuscitation,” and “Discharge” are triggered by patients’state changes. When a new patient is admitted to the ICU, the provider will be “seized” by this patient and in the “admission” state, until the admission procedure is done. When a patientâĂŹs health state deteriorates, e.g., from “no organ dysfunction” to “single organ dysfunction,” the provider will be “seized” by this patient and will be in the “Resuscitation” state until the diagnosis-intervention-documentation cycle is finished, if no other high priority task interrupts the current care service.

Because the providers are also considered resources (seized and released by patients in the context of DES), we need to handle competition among services and patients (see Figure 4 for illustration, where three patients are present in the ICU simultaneously requesting services (rounding, admission, and resuscitation). The priority among these seize actions is assumed to be "Resuscitation> Admission> Rounding> Patient Check> Discharge." The same order applies to all providers. As an illustrative example, if there are two pending patient requests, one is calling for admission and the other is calling for discharge at the same time, the provider will attend to the admission request first. We allow services to be interrupted under certain conditions, e.g., if there is a call for resuscitation from patient B while the only consultant is currently working on admitting patient A, then, the consultant can leave if there is at least a resident staying with patient A to finish the admission process. The *condition* is specified based on the state the provider is in (i.e., the current service type), the type of the new service being requested, and the type of provider.

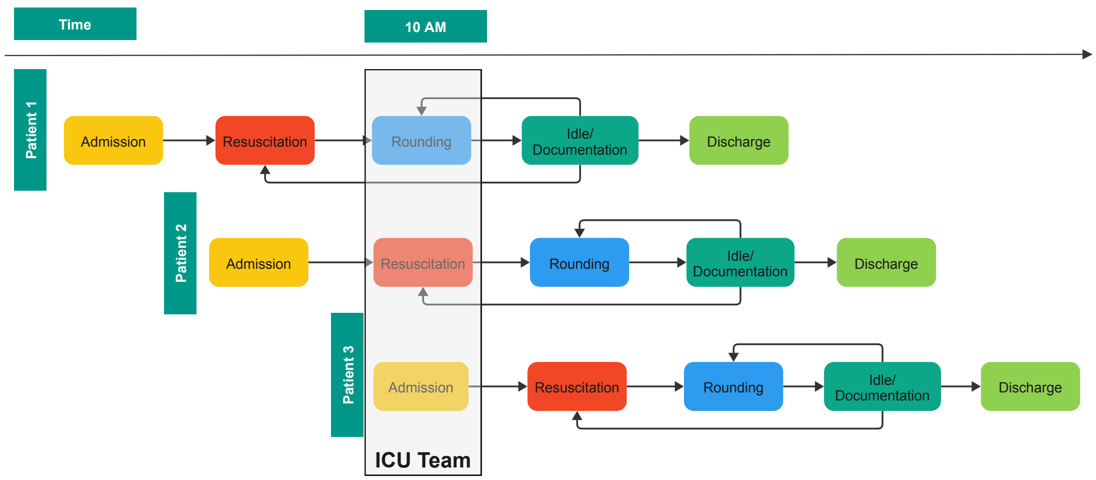

Figure 4: Service requests originating from multiple ICU patients.

Since the care services are provided by the care team, we additionally model the sufficient conditions for a service to start and the necessary conditions for a service to finish. For instance, the admission process can start as long as we have a nurse in idle state. However, for the admission process to be completed, we still need the presence of the consultant for a certain amount of time to finish the necessary examination and diagnosis. Note that, to start a service, we might not need all team members to present at the same time, and the time they spend on the service can be different; for instance, the service time for nurses spent on the admission process is typically longer than that of a physician (a nurse normally stays until services rendered by all other team members are done).

3.3 Patient-Provider Interaction

Patients and providers are both autonomous agents, and they interact with each other dynamically. Patients'state transitions are mainly driven by the pre-determined transition rates learned from actual data (Hou et al. 2024), but the actual transition can be delayed due to resource constraints. In our study, patient state transitions are initiated based on the pre-defined transition rates (organ dysfunction dynamics), but the successful transition to another state would need service completion. For instance, the transition rate between no organ dysfunction and discharge would determine the sojourn time for a patient to stay in "no organ dysfunction" state before the transition to discharge starts, but we also need the discharge service process to be done to get the patient care transitioned out of the ICU. As another example, if a patient needs to be admitted, but all the providers are attending to other patients who are deteriorating, then, the admission process will be delayed. This means a state transition from "admit to ICU" to one of the organ dysfunction states is initiated but cannot finish until the admission process is completed. In the simulation, we are able to track the delay (for patients) and service interruptions (for providers) due to resource competition.

Providers'state transitions are triggered by both patients'state changes and scheduled routine tasks, making it impossible to decouple provider state transition from patient state transition. Therefore, we can quantify the impact of resource constraints on patient care pathways and also the impact of volume and mix of patients (different organ dysfunction levels) on providers'workload.

3.4 DES and ICU Environment

Patients are the entities in the DES. Patients arrive at the ICU following a predefined schedule (subject to randomness). This can be modeled as a non-stationary Poisson process, if the exact arrival time is not known, or can be imported from a database/excel file, if the time of arrival can be predicted or estimated (e.g., based on operating room schedules, hospital transfer schedules, emergency room triage data). Patients will then go through the state transitions as described in the previous section. The initial state transition will also be given as a patient attribute (e.g., some patients are admitted with one organ dysfunction, some with multiple, and some with none). This can be generated following a distribution based on real data, or imported if known during the arrival.

Once a patient finishes the transition to "discharge," i.e., completing the discharge process, the patient will be removed from the simulation. For the ICU, we also model patient beds as an important resource. Without an available bed, patients will be "rejected." In real practice, patients might be transferred to another hospital unit/another hospital. Since our main focus is on patient-provider interaction, we do not include other resources (e.g., equipment like mechanical ventilators, medical supplies, medications). These resources are not autonomous agents and can be modeled in a similar fashion as patient beds.

4 CASE STUDY

4.1 AnyLogic Model Development

We developed the hybrid simulation model using AnyLogic Personal Version 8.8.6 and a demonstration version of the model can be accessed through the AnyLogic Cloud https://rb.gy/1h42qh. The model begins with the user interface where we have user input variables – number of consultants, number of residents, number of nurses, and number of beds in the ICU. In addition, users can opt to provide an Excel file with patient arrival information, including estimated arrival time and clinical state during admission. Patients might have no organ dysfunction or multiple organ dysfunction, as they might be admitted from different sources. Currently, the data related to agent behaviors are set by model developers based on user input in the development stage. These include time-varying patient state transition rates, provider service time by service (and patient state) type, service priority, and other team-based care coordination protocols. Following this, the ICU model then has the following tabs. "Model" – overview of the ICU simulation, visible to the user after they run the model. "Logic" – the DES part of the model. "Inputs" – where we show the values of the inputs, and ask the user to input the values of some model parameters. "Unit output" presents the major metrics, such as length of stay, mortality rate, and number of patients discharged and died per day. The final tab is "Resources," which shows the utilization of consultants, residents, and nurses, as well as ICU beds. The tabs are defined as view areas in AnyLogic.

4.2 Input Analysis

For patient modeling, the time-varying transition rates of the multistate model were learned from real-world data approved by the Mayo Clinic Institutional Review Board (IRB). The data included hospitalization characteristics such as arrival time and reason, ICU length of stay, hospital length of stay, and discharge status, as well as temporal variables such as vital signs, lab orders and results, procedures, and medications, among others. Following expert opinions, we labeled patient states based on the organ support they received during their ICU stay, such as mechanical ventilator use (e.g., for respiratory system support), vasopressor (e.g., for cardiovascular system support), mainly based on patient hospitalization characteristics and temporal variables (Klein Klouwenberg et al. 2019). The states were tagged on an hourly basis for up to seven days (less than 10% of patients stayed longer than seven days (Hou et al. 2024)) and this labeling approach provides a high-resolution record to capture the dynamics of patient trajectories. The statistical analysis of ICU patient state transitions is developed based on a continuous-time multistate Markov model using the *msm* package in R (R Core Team 2021). The time-varying transition rates reflect the distinct state evolution patterns during the immediate post-admission phase and the subsequent recovery or deterioration phase. As a remark, we do not differentiate "organ support" and "organ dysfunction" as the time organ failure starts was not accurately recorded or was not available due to data reporting standards. Therefore, "organ support" is deemed as a proxy for "organ dysfunction."

In the simulation implementation, we used functional transition rates, i.e., the transition rates between different organ system dysfunction states and absorptive states are a function of time. This respects the non-stationary clinical trajectories in the initial stage of ICU stay but also represents a modeling challenge as the built-in software feature for modeling state transitions assumes constant transition rates. In particular, AnyLogic has five main types of transitions from different states – time, rate, condition, message, and arrival of agent; none is directly applicable. We addressed this issue by creating a time variable and a statechart to update the transition rate hourly closely following the multistate model parameters estimated using real patient data.

For provider modeling, there is a lack of real records to parameterize provider behaviors. The quantitative data including the service times per service type (and patient state) per provider type are modeled using triangular distributions in minutes based on expert opinion and literature. The qualitative data include the service priority, the scheduling disciplines (preemptive vs. non-preemptive), and the team-care protocols, e.g., what is the minimum requirement for the service to start, how interruptions are handled for each provider by roles, and what conditions are needed for a service to complete. These are obtained based on expert opinion.

4.3 Model Verification and Validation

We separately verify the performance of the patient model, provider model, and hybrid model. We created a separate patient ABS to replicate the multistate Markov model with time-dependent transition rates exclusively. The number of patients in each state, discharge from hospital, discharge from ICU (but still in the hospital), no organ dysfunction, single organ dysfunction, multiple organ dysfunction, and death, up to 48 hours, were obtained using the ABS and were compared with the real observation of a patient cohort. Note that the process becomes stationary (i.e., the transition rates become constant) after several hours of stay so we did not simulate for an extended period. The net number of patients in the first three states was compared to the real observations and the average relative error was 3.88% (with the maximum being 7.81%). The provider behaviors are examined individually and as a team to ensure the task priorities and the team coordination logic are correctly implemented. The simulation outputs including mean and 95% confidence interval (C.I.) of several major performance metrics are listed in Table 1. We also provide estimates of these performance metrics either from historical data used to parameterize the input parameters, or from expert opinion and literature (e.g., OECD Library (2024), Premier (2017)) if not directly available, and these values are listed under the "Estimate" column with the corresponding data sources. It can be seen the model outputs match our expectations. For provider utilization, note that we combine the idle state with documentation that does not involve direct patient contact, and the utilization reported below only considers the time for direct patient care. The documentation time might be estimated based on patient census and this can be used to adjust the utilization obtained from simulation outputs. In addition, it can be seen that nurse utilization is significantly below the estimate. This is because, in the current model, we set the number of nurses as a constant matching the number of beds, assuming a one-to-one nurse-to-patient ratio. In actual practice, the number of nurses on duty might change over shifts and might not always guarantee the one-to-one ratio. Considering the bed occupancy being around 75% and the two-to-one ratio observed in real practice, the nurse utilization reported by the simulation model is in a reasonable range. Note that we reported daily rejection and daily service interruption but no actual data can be found. Rejection represents a missed opportunity and is not typically recorded, but it is known that the hospital does have patient diversion due to full capacity. Our simulation suggests that there are over 1,000 tasks performed daily by providers (we count each hourly patient checkup as a separate task and that contributes to the majority of the tasks). Therefore, the average interruption of 30 tasks represents a 2% interruption rate.

Table 1: Comparison of AnyLogic simulation outputs and statistics from data or expert opinion ("n.a." stands for not available).

	Simulation		Comparison	
Measurement	Mean	C.I. (95%)	Estimate	Source
Length of stay (days)	2.96	(2.54, 3.27)	2.98	Historical data
Average daily admission (patients)	5.80	(5.46, 6.32)	6 - 7	Historical data
Average daily rejection (patients)	0.84	(0.11, 1.82)	n.a.	
Average daily discharge (patients)	4.58	(4.21, 4.96)	6 - 7	Historical data
Average daily service interruption (tasks)	29.49	(26.36, 31.65)	n.a.	
Mortality rate (%)	7.2	(4.1 , 11.9)	7 - 8	Historical data
Bed utilization (%)	75.2	(67.7, 79.5)	60 - 80	Expert opinion
Consultant utilization (%)	73.9	(71.6, 77.4)	70 - 75	Expert opinion
Resident utilization (%)	74.9	(71.7, 78.2)	75 - 85	Expert opinion
Nurse utilization (%)	51.1	(47.5, 55.0)	85 - 90	Expert opinion

4.4 Model Generalization

For the development overhead, the initial model conceptualization is the most critical step that needs intense collaborative efforts between engineers and clinicians. Additionally, data collection (including getting the IRB approval for patient data), preprocessing, and analysis, can be time-consuming. The model is expected to represent common ICU practices in general US hospitals. To apply it to a different setting, the model can be easily adjusted to reflect changes in demand and supply. We quantify patient demand based on patient arrivals and patient disease burden. The change of the former can be achieved by changing the (time-varying) patient arrival rates, and the latter can be done by changing the initial organ dysfunction level immediately after admission, or by learning a different set of multistate transition rates based on the patient cohort of interest. To reflect changes in supply, a different number of patient beds, and a different number of providers per type of provider can be directly changed through the user input interface. Different service protocols such as priority of tasks, task durations, and protocols for patient admission and discharge can also be adjusted using a similar modeling technique as introduced in Sections 3.2 and 3.3. For the application of the model, it can be used both for long-term planning (steady-state simulation) and to present real-time ICU status on an hourly basis as the statistics are updated hourly for most of the model outputs.

5 DISCUSSION

Operating an ICU and providing care for critically ill patients necessitates a high investment in personnel, technology, and medical resources within a short time, and is naturally associated with high costs. The complexity of the care processes involved, and the fluctuation in the number of and the clinical state of patients at a specific time, make managing ICU resources very challenging. Many principles of organization, team-based care structure, leadership, and training have been institutionalized. However, ICU operations in the post-pandemic era suffer elevated personnel shortages, an ever-growing aging patient population, and more complex care needs (Arabi et al. 2021). We hope to strengthen our analytical capability to support ICU operations. Although the complex patient-provider interaction and the supply-demand dynamic have been qualitatively investigated, the exact quantitative assessment would provide operationalizable insights for managing ICU in day-to-day practice. To the best of our knowledge, our work is unique in the ICU modeling literature, bolstered by its detailed and high-fidelity representation of patient-provider interactions, offering more dimensions of the performance metrics to support decision-making. As our understanding of critical care medicine, and the physiological and clinical patient pathways advances, we expect to provide more robust prediction and evaluation of the patient demands and the ICU resource arrangement.

5.1 Limitations

As a proof-of-concept, we focus on the feasibility of characterizing patient pathways based on clinical knowledge and modeling a multidisciplinary care team and their interactions with patients. We thoroughly investigated different providerâĂŹs tasks and workflows. However, due to a lack of data, we were not able to quantitatively model each providerâĂŹs exact operations. Electronic medical record data are organized around patients, but many operational data are not easy to record, visualize, or provide insights to improve ICU operation efficiency. Therefore, we also have limited information about performance metrics at the system level for validation and only focused on the outputs related to patient outcomes, ICU admission and discharge, and ICU census. We anticipate the growing adoption of RFID technology, automated data entry, and enhanced documentation protocols can help provide data revolving around providers for researchers to characterize provider workload and processes accurately. In addition, for ease of exposition, we did not include many resources that are not autonomous agents, e.g., medical equipment, medication, and other clinical supplies. These components can be modeled using a similar approach to modeling patient beds. We also did not include provider schedules by assuming the same number of providers for each day under investigation. This can be addressed by obtaining an accurate roster of providers on duty. By doing so, we can create agents for each provider to accommodate their specific service-related model parameters. Schedule change disciplines and the handoff process will also need to be modeled.

The model was developed using AnyLogic, which is known for its multi-method simulation feature necessary for hybridizing ABS and DES. Although AnyLogic is closed-source software, we believe our modeling approach, e.g., how to model the overall patient flow as discrete events and hybridize it with the agent-based models of patients and providers, and how to define different states of patients and their transitions, various states of providers, and the mechanisms for provider-patient interactions, are generalizable to other simulation software.

5.2 Future Work

Our vision is to develop a digital twin of the ICU system by enabling bi-directional data communication between the physical ICU system and the simulation model. To that end, we plan to advance patient modeling by developing trajectory prediction at the individual level, based on the real patient data obtained from admission and data generated during ICU stay synchronized at major time points like 6-hour, 12-hour, 24-hour since admission, etc. The team has already developed a patient digital twin prototype (Rovati et al. 2024), which can be integrated into the ICU system simulation. To ensure high-fidelity simulation, we will also advance provider modeling and incorporate other clinical staff and medical resources.

The real-time prediction of ICU patient census and organ system support needs will help us determine clinical resource allocation in real-time (e.g., nurse staffing and triage policies). This can be done by developing an AI surrogate of the hybrid simulation model to perform optimization with affordable computational costs. The decision will be implemented in the physical system and synchronized in the simulation model to reflect the most up-to-date operational conditions.

6 CONCLUSION

In this study, we develop a hybrid simulation approach to modeling ICU operations taking into consideration of the intense interaction between care providers and patients. DES is used to model patient flow whereas

ABS is used to model patient behaviors and provider behaviors. We incorporate clinical knowledge to model patient trajectories during their ICU stay to allow for a better account of the associated care needs and provider workload. We expect this model can be used to support ICU operations and has the potential to be extended into a digital twin of the ICU system.

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