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ASSESSING THE IMPACT OF PHYSICIANS' BEHAVIOR VARIABILITY ON PERFORMANCE INDICATORS IN EMERGENCY DEPARTMENTS: AN AGENT-BASED MODEL

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ABSTRACT

In emergency departments (EDs), traditional simulation models often overlook the variability in physician practice, assuming uniform service provision. Our study introduces a hybrid agent-based discrete-event simulation (AB-DES) model to capture this variability. Through simulation scenarios based on real ED data, we assess the impact of physician behavior on key performance indicators such as patient waiting times and physician stress levels. Results show significant variability in both individual physician performance and average metrics across scenarios. By integrating physician agent modeling, informed by literature from medical and workplace psychology, our approach offers a more nuanced representation of ED dynamics. This model serves as a foundation for future developments towards digital twins, facilitating real-time ED management. Our findings emphasize the importance of considering physician behavior for accurate performance assessment and optimization.

1 INTRODUCTION

Healthcare provided to patients in a hospital emergency department (ED) constitutes a queueing system with special characteristics that differentiate it from classical queueing theory models, where some of its main results do not apply in practice. For example, it is known that a single waiting line for clients works better than individual queues when there are multiple servers, and all of them can attend to any patient. However, medical literature (Hodgson and Traub 2020; Song et al. 2015) has demonstrated that prior assignment of patients yields better results due to the direct transfer of responsibility for patient care to the physician. This patient assignment to physicians, immediately after triage, has been investigated in several studies and it is usually implemented in practice through the use of a simple rotational assignment (Hirshon et al. 1996; Levin et al. 2006; Traub et al. 2016; Traub et al. 2018b). This assignment rule, seemingly fair as it ensures that at the end of a shift, the difference in patients attended to by each physician does not exceed one, causes imbalances in the workload assigned to physicians, which increase as the shift progresses and are reflected in the different lengths of pending patients for each physician. These differences exacerbate in crowded situations, which unfortunately are very common in ED. An accepted explanation for this phenomenon lies in the varying severity of patients, which require different times for diagnosis and treatment (Cildoz et al. 2019). In Cildoz et al. (2023), a new assignment system is proposed that considers the severity level assigned during triage to assign patients using two rotational wheels, for lower and higher severity patients, respectively.

This new assignment rule ensures that the number of patients assigned at the end of the shift does not exceed one, neither in total nor for each severity level. However, the pending workload between physicians still differs, albeit to a lesser extent. One straightforward reason is that the severity level assigned during triage does not completely determine the difficulty of diagnosis and treatment. Nevertheless, there is another factor responsible of the observed variability in the pending workload among physicians: the different way in which each physician approaches each case and the whole set of pending patients. Physicians are different, act differently and make autonomous decisions that have not to be coincident in similar situations (Gowrisankaran et al. 2023; Traub et al. 2018a). We can distinguish two types of decisions: those of clinical nature and those of managerial nature. The first type accounts for the clinical diagnosis of a patient and the recommended treatment, which are out of the scope of this research. In this work, we study the influence of the physician's managerial type of decisions and behaviors, by which we mean the way in which each physician manages his/her working time, reacts to fatigue and overload, and decides the next patient that should be treated.

Our approach relies on the development of a hybrid simulation model that combines a discrete-event simulation (DES) model to represent all processes undergone by the patients in the ED with an agent-based simulation (ABS) model that represents the unique behavior of each physician and the influence of his/her characteristics on the way the treatment is provided to patients. This hybrid simulation model is used to assess the influence of variability in physician behavior in the set of the ED performance indicators. Hybrid simulation models are becoming increasingly popular in the healthcare domain, as demonstrated in recent literature reviews (Kar et al. 2022; Dos Santos et al. 2020; Brailsford et al. 2019). However, these reviews also highlight that the most common hybridization is between DES and system dynamics, while ABS remains a relatively new paradigm whose potential has not yet been fully exploited. Our proposed agent-based model is new: each physician is individually modeled, with their time spent attending each patient, as well as their need and timing for breaks, depending on their personality, experience, and accumulated fatigue up to that point.

Therefore, the modeling approach of this work extends other agent models for physicians that represent them basically considering their possible states of busy, idle, and unavailable. The research presented in this paper constitute a first attempt to link the physician modeling by agents to results of research in the field of work psychology and human behavior. Therefore, this research falls within the field of Behavioral Operational Research (BOR), which is "the study of behavioral aspects related to the use of operational research methods in modeling, problem solving, and decision support" (Hämäläinen et al. 2013). For a recent review of BOR, one can refer to Kunc et al. (2020). In addition, as conclusion of the observed results, further research should be conducted for developing new dynamic patient-physician assignment rules to account for the variability of the medical staff and the information on the past and current pending patients of all physicians.

2 PATIENT FLOW MANAGEMENT IN THE EMERGENCY DEPARTMENT

2.1 Patient flow in the Emergency Department

In the ED, patients undergo prompt assessment via a triage process to prioritize treatment based on the severity of their condition. Various triage systems, including the Canadian Triage Acuity Scale (CTAS), categorize patients into different acuity levels. Typically, EDs organize patient care into distinct circuits, with one dedicated to critical cases and another for less critical ones. The CTAS establishes arrival-to-provider time thresholds for different acuity categories, ensuring timely care delivery (see Table 1).

Table 1: CTAS Acuity Levels and Arrival-to-Provider Target Thresholds.

Category	Classification	Access time limit	Performance level (%)
1	Resuscitation	Immediate	98
2	Emergency	15 min.	95
3	Urgent	60 min.	90
4	Less urgent	120 min.	85
5	Not urgent	240 min.	80

Patient routing through the ED involves several stages (see Figure 1). Upon arrival, patients are registered and right away they go to the examination room for triage, where their acuity level is assigned. Subsequently, patients are directed to either the critical or less critical care circuits, with this paper focusing on managing the latter, which often involves separate medical teams specifically assigned to handle the less critical cases and tends to be more crowded. After triage, the patients queue for their initial consultation with a physician, during which they may be discharged or undergo further diagnostic tests. Once tests are complete and results are available, patients return for a second consultation, which may result in further test requests or, in most situations, patient discharge. Typically, patients leave the facility under their own volition, but in some cases, they may experience delays due to bed unavailability for hospital admission or ambulance unavailability for transportation to their home or another healthcare facility. These patients continue to be responsibility of the ED's physicians.

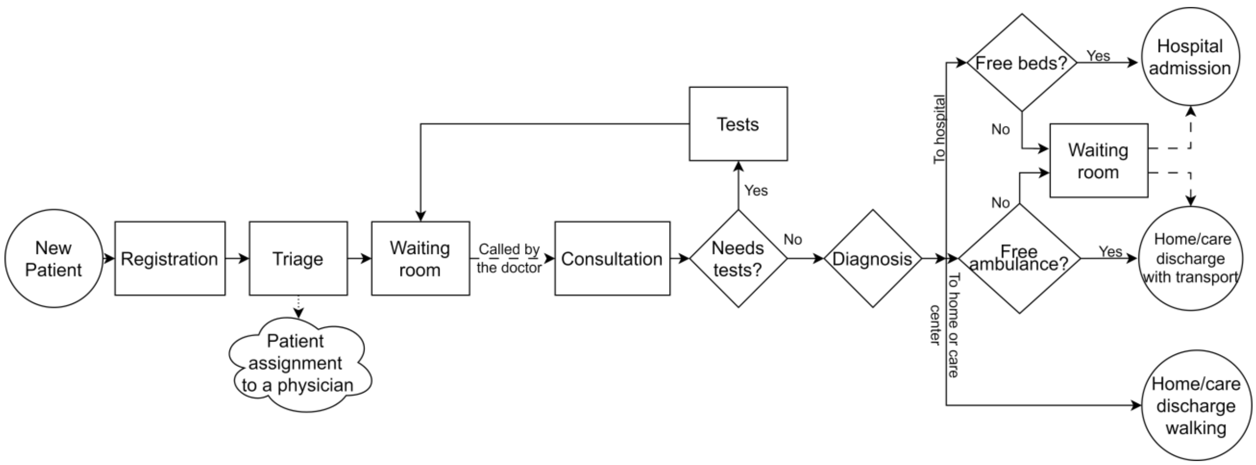

Figure 1: Patient flowchart in the ED.

2.2 Physician's stress

High workload and stress levels not only contribute to burnout but also potentially compromise patient care by increasing the likelihood of human and systemic errors, which emphasizes the need to incorporate physicians' working conditions into patient management strategies. The research in Cildoz et al. (2020) introduces a methodology enabling real-time monitoring of physician stress due to workload volume and evolving work-shift characteristics. In particular, they obtain an index that encompasses workload, time pressure, and uncertainty. Workload refers to the number and severity of patients being managed simultaneously by the physician, which varies over the length of a shift. Time pressure refers to the upper limit for the arrival-to-provider time (APT) which has been presented in Table 1 in the case of CTAS (delay in the first diagnosis could put the patient's health at risk). Uncertainty refers to lack of knowledge about the patient's illness and the tasks required to provide medical assistance to patients not yet seen or with test results pending. This index includes the following stressor factors: patient number in each priority level and healthcare treatment stage, fulfillment of waiting time targets, and physician responsibilities. A total of eleven variables are used to represent de stressor factors. The index, that keeps the stress scores in the range [0,100], is related with these variables by a logistic function:

$$\log\left(\frac{S(\boldsymbol{X})}{100 - S(\boldsymbol{X})}\right) = \beta_0 + \beta_1 X_1 + \cdots + \beta_{11} X_{11},$$

where $\boldsymbol{X} = (X_1, \dots, X_{11})$ is the vector of stressor variables describing the workload at the ED, and $S(\boldsymbol{X})$ is the stress score associated to workload scenario $\boldsymbol{X}$. This model was validated both statistically and qualitatively by physicians, who were presented with the statistical significance of each identified stressor and their relative importance. Details about the estimation of the parameters of this function can be found in Cildoz et al. (2020). As far as we know, this is the only model able to measure stress in real time.

The resulting job stress score not only serves as a key performance indicator (KPI) for assessing the ED but is used in the next section as factor affecting the behavior and decisions on the way the work is carried out by the physicians.

2.3 Patient flow management policies

Usually, each ED patient, after triage, is directly assigned to a physician, contrary to what queueing theory suggests, which favors a single queue system for efficiency. However, immediate patient assignment fosters physician accountability and efficiency. Nonetheless, creating parallel queues, one for each physician at work, may lead to workload imbalances and patient backlog for each physician. To mitigate the unbalanced work assigning several methods have been proposed, as the use of a rotational assignment rule of patients (Traub et al. 2016) or even a dual rotational method (Cildoz et al. 2023), with separate rotations for mild and severe patients, ensuring that each physician sees an equal number of patients of each severity by the end of their shift. However, these methods do not entirely eliminate disparities in pending patient counts and are still an area of active research. Both methods, single and dual rotational (acuity based rotational) policies will be considered in this paper.

2.4 Physicians' variability in ED simulation models

Patient flow management policies are typically investigated using simulation models, providing a controlled environment for experimentation. However, inaccurate representation of the real system and its management policies can yield misleading results, hindering practical implementation (Azcarate et al. 2020; Brailsford et al. 2009). Simulation models developed within the DES framework focus on modeling variability stemming from the heterogeneity of patient arrival times and acuity levels, but often overlook the potential variability arising from differences in physician behavior. In these models, all physicians are typically treated as equal servers within the ED queuing system. Some models, such as Chahal (2009) account for the evolution of physicians' productivity during the simulation. However, these models approached the problem in an aggregated manner using system dynamics, rather than considering the behavior of each physician individually. Neglecting to account for variability among physicians in simulation models may result in artificially favorable performance indicators compared to real-world observations in the ED and even may provide optimal patient flow policies which in practice they are not. In this paper, we aim to assess the impact of physician practice variability on ED KPIs. To achieve this, we have developed a hybrid agent-based-DES simulation model that incorporates physician behavior variability. We will compare the results obtained from this model with those from the traditional DES model to better understand the influence of physician practice variability on ED performance metrics.

3 HYBRID AGENT-BASED-DES SIMULATION MODEL

In this hybrid model, ABS is used to model the ED physicians, while DES is used to model the patient flow within the ED. Following Brailsford et al. (2019) classification of hybrid simulations, this model falls in the "integration" category, where it is not distinguishable where one method ends and the other begins. Physicians' internal states (such as tiredness and stress) evolve over time depending on the state of the ED. These internal states affect their consultation times and breaks, which, in turn, influence the queues and patient flow. This dynamic, in turn, modifies the agents' internal states.

3.1 Agent-Based Model for the ED Physician

Each physician is modelled as an agent, following the principles of ABS, which dictate that each physician is a single individual, whose internal state evolves over time as result of the interaction with the environment and other individuals, and capable of making autonomous decisions (see Figure 2).

Set of individual static characteristics. The model of each physician is provided with a unique *ID* (identification code); with *age* (G); with the *level of experience* (E); an attribute measuring the *Adherence to objectives* (O), which describes the importance the physician places on achieving organizational goals, that ranges in (0,100), being 0 null importance and 100 full commitment with the hospital goals; and three personality traits extracted from the OCEAN paradigm (McCrae and John 1992): *Agreeableness* (A) (measured with a parameter that ranges from 0, hostile, to 100, friendly); Conscientiousness (C) (measured with a parameter that ranges from 0, impulsive, to 100, someone who acts with preparations); and *Neurotism* (N) (ranging from 0, neurotic person, to 100, calm person. The last characteristic is the physician's *Approach to work* (W), ranging from 100, when there is a strong calling perspective, characterized by a desire to impact society, feel fulfilled, and provide quality treatment, to 0, meaning the opposite. The static parameter W depends on the personality traits A and C. These eight personal parameters are included in Table 2.

Table 2: Fixed attributes describing physician characteristics.

Notation	Attribute	Lower limit	Upper limit	Range of values
ID	Identification	-	-	-
G	Age	24	65	[24,65]
E	Experience	0	100	[0,100]
O	Adherence to objectives	Disengaged	Committed	[0,100]
A	Agreeableness	Hostile	Friendly	[0,100]
C	Conscientiousness	Impulsive	Deliberate	[0,100]
N	Neurotism	Neurotic	Calm	[0,100]
W	Approach to work	Apathetic	Altruistic	[0,100]

Environment. Each physician, through the hospital Electronic Health Record (EHR), possesses information about all the patients in the ED, such as their priority level, waiting time, their status in the system (e.g., waiting for their first consultation, second consultation, transfer, or hospital admission) and some knowledge about the patient's illness, which increases after each consultation and determines the need for additional tests and consultations. The information concerning a physician is converted into a measure of workload/stress using the expression exposed in Section 2.2.

Set of individual dynamic characteristics: stress and tiredness. Two dynamic attributes describe the state of the physician related to the current and the accumulated workload, respectively: a *Stress* attribute $S(t)$, measured by the stress score exposed in Section 2.2, which synthetizes the current workload assigned to the physician; and a mental *Tiredness* attribute $T(t)$ (in the following tiredness), that accumulates the stress experienced by the physician since the beginning of the shift and can be reduced by taking a rest. Both stress and *tiredness* are measured on a scale of 0 to 100. The tiredness, depending on the previous stress and the impact of breaks in work, is also a function of the physician's mental strength (which we associate in this work directly with the age, older physicians take longer to become tired and recover more quickly).

We consider tiredness as an adaptive response to stress (Kop and Kupper 2016) and define it as the accumulation of stress over time (integral) with an exponential decay factor, such that more recent stress has a greater impact on tiredness than stress experienced further in the past. Specifically, the tiredness of a physician increases on the working periods as follows: let t_0 be the starting time and $t > t_0$ and no breaks in the interval (t_0, t).

$$T(t) = \min\left\{T(t_0) + \frac{1}{f(G)}\int_{t_0}^{t} S(r)\alpha^{t-r}dr\,, 100\right\} = \min\left\{T(t_0) + \frac{\alpha^t}{f(G)}\sum_{t_i \in (t_0,t)} S(t_i)\frac{\alpha^{-t_i} - \alpha^{-t_{i+1}}}{\ln(\alpha)}\,, 100\right\}$$

Where t_i are the times in which events modifying the stress function $S(t_i)$ occur; α is a discount parameter, so that closer workload periods influence more the physical/mental state than distant ones, and $f(G)$ is a parameter dependent on the agent's age that accounts for differences in strength between young and senior physicians.

The tiredness of a physician decreases on the resting periods as follows:

$$T(t) = max\left\{\frac{T(t_0)}{1+f(G)\times(t-t_0)}, 0\right\},$$

where $T(t_0)$ is the tiredness at the beginning of the resting period.

Conditions for starting a rest period. After finishing seeing a patient, the physician starts a rest period in the case that the following three conditions are met:

Condition 1: the accumulated tiredness of the doctor should exceed a certain threshold δ_1.

Condition 2: the stress should be under a certain threshold δ_2, which negatively correlates with static parameter *W*.

Condition 3: depending on the static parameters *W* and *O* (Approach to work and the adherence to objectives, respectively), the physician may (depending on their personality) only take a rest if they have no assigned patients who have exceeded the maximum waiting time for their priority.

Physicians interrupt their rest when their resting conditions are violated. When the resting conditions are not satisfied the physician continues working calling the next patient.

Patient consultation time. Consultation time is usually modelled using a lognormal distribution and depend on patients' characteristics (Cildoz et al. 2019). However, ED physicians consulted for validation purposes of this model as well as medical literature (Traub et al. 2018a) also suggest that individual variability among physicians also affect the important KPIs. In particular, the level of experience correlates with shorter consultation times (Gowrisankaran et al. 2023; Jeanmonod et al. 2008), higher levels of workload (stress) correlate with shorter consultation times (Heaney et al. 1991), and higher levels of accumulated tiredness correlate with slower patient consultation (De Stefano et al. 2018). The influence of these factors is introduced in the consultation time model making the location parameter of the lognormal distribution depend on them:

$$\mu\big(E, S(t), T(t)\big) = \beta_0 + \beta_1 E + \beta_2(N)S(t) + \beta_3 T(t),$$

where $\beta_1, \beta_2, \beta_3$ represent the influence of the doctor's level of experience (attribute E), the effect of the stress (attribute $S(t)$), which depends on the *Neurotism* personality trait, and the effect of the accumulated tiredness of the agent (variable $T(t)$), respectively.

The effect on a change of value in one, or various, of the explanatory variables is a change in the scale of time:

$$t_p(E, S(t), T(t)) = exp(\beta_0 + \beta_1 E + \beta_2(N)S(t) + \beta_3 T(t) + \sigma\,\Phi^{-1}(p)).$$

Where $t_p(X_1, X_2, X_3)$ is the quantil function of the Consultation Time variable, σ is the scale parameter of the lognormal distribution and $\Phi^{-1}(p)$ is the inverse of the probability distribution function of a standard normal variable. Therefore:

$$\frac{t_p(x_1, x_2, x_3)}{t_p(y_1, y_2, y_3)} = exp(\beta_1(x_1 - y_1) + \beta_2(N)(x_2 - y_2) + \beta_3(x_3 - y_3).$$

That means, for example, that two physicians with a different level of experience, and equal value in the other two variables, provide patient consultation according to two proportional random variables, having full meaning expressions as: physician A is 5% faster than physician B.

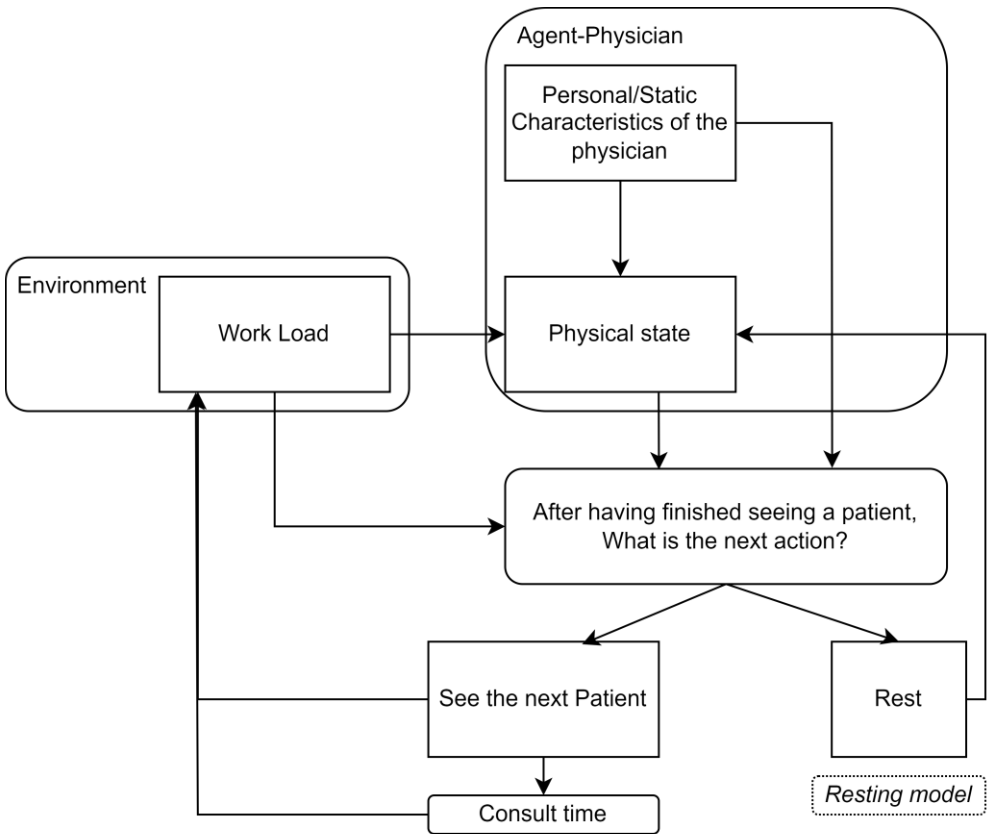

Figure 2: Agent model for a physician.

3.2 The enhanced Discrete-Event Simulation model

The dynamics of the ED are captured by a DES model, which includes the following events:

- Arrival of a new patient to the ED: For each patient, the priority level and the number of consultations needed are simulated.
- End of a physician consultation: The patient is then discharged (goes home or waits for hospital admission or transportation), or exits the ED to begin complementary diagnostic tests. Depending on its characteristics and the state of the ED, the physician either begins a new consultation (in case there are any patients waiting) or takes a break.

- Re-entry of a patient to the physicians' waiting room after medical tests are carried out, and the results are ready.
- Exit of the ED by a patient waiting for transportation or hospital admission.

The arrival of patients is simulated by sampling from the NHPP (Nonhomogeneous Poisson Process), which accounts for intraday and weekday seasonality components. The duration of the physician consultation is sampled from the lognormal distribution according to the model presented above. The selection of the next patient to be seen by a physician is simulated by following the rules of a queue discipline that prioritizes the second consultation over the first one and patients with a higher acuity index, except when the patient waiting for the first consultation exceeds the time limit (Table 1). The time to perform diagnostic tests, specialist consultations, etc., is modeled as a delay time, as they are not the responsibility of the ED staff, but depend on the overcrowding level.

The design of the simulation model is flexible enough to create many different representative scenarios of hospitals' EDs and physicians' profiles.

4 CASE STUDY AND SIMULATION RESULTS

4.1 Description of the simulated emergency department

The effect of enhancing a DES model of an ED with an agent model of the physicians to create a hybrid agent-based-DES model is assessed by modeling the ED of the University Hospital of Navarre (UHN) using both simulation frameworks, programmed in Python 3.12. This ED serves a population of half a million people with more than 140,000 annual users. It organizes patient care into two different circuits: one for more critical patients and another for less critical ones. In this study, we focus on the latter, which treats patients with priorities 3, 4, and 5 according to the CTAS scale. The patient flow follows the paths described in Figure 1. Patient arrivals exhibit intraday, weekday, and monthly seasonal components (Cildoz et al. 2019). Patient arrival data, illness description and acuity, medical test requests, probability of discharge after the first consultation, among other factors, were estimated from three-year electronic records provided by the UHN administration. The duration of physician consultations had to be recorded on-site.

4.2 Design of experiments and validation

The simulation models run scenarios describing the patient arrivals of Mondays and days after holidays, which are the busiest ones. The patient arrivals are simulated from a NHPP with the intensity of arrivals of the patient priority i, $\lambda_i(t)$, that shows a double peak period (Figure 3).

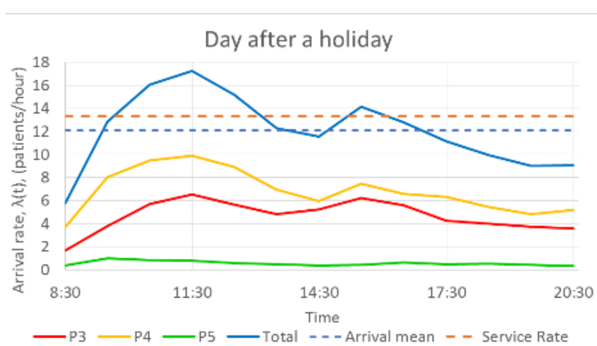

Figure 3: Intensity function of the NHPP for the patient arrival process on Mondays and days after holidays.

Each simulation run simulates the ED one-day work from 8:00 a.m. to 10:00 p.m., that coincides with the 14-hour length shift and encompasses the two arrival peaks, making it a terminating system. Six physicians are working the shift: one resident in his/her first year, three physicians with medium experience level and two physicians with high experience level, age was chosen according to the experience. The remaining static attributes are uniformly initialized at random within their respective ranges for each physician and remain constant across replications. Tiredness and stress levels are initialized at 0 for each physician at the beginning of each replication. Physicians have a break of half hour for having lunch, three of them stop in the range 13:40 to 14:30 and the other three from 14:30 to 15:15. Lunch and resting starting breaks never interrupt a consultation. The ED is simulated, on the one hand, considering all physicians with equal characteristics and, on the other hand, having different characteristics in the static parameters exposed in Section 3.1. We name these scenarios as all-equal and all-different physician scenarios. Each of these two scenarios is simulated by using two different ways to assign patients to physicians: the single rotational rule and the double rotational rule. A number of 500 replications is made for each scenario to compute averages and standard deviations of the KPIs.

The DES model was already validated with real data in previous studies (Cildoz et al. 2019), its extension to the hybrid agent-based-DES model was validated by presenting the model and results to experienced physicians of the UHN ED. In addition, to ensure model replicability, we have followed the STRESS guidelines proposed by Monks et al. (2019).

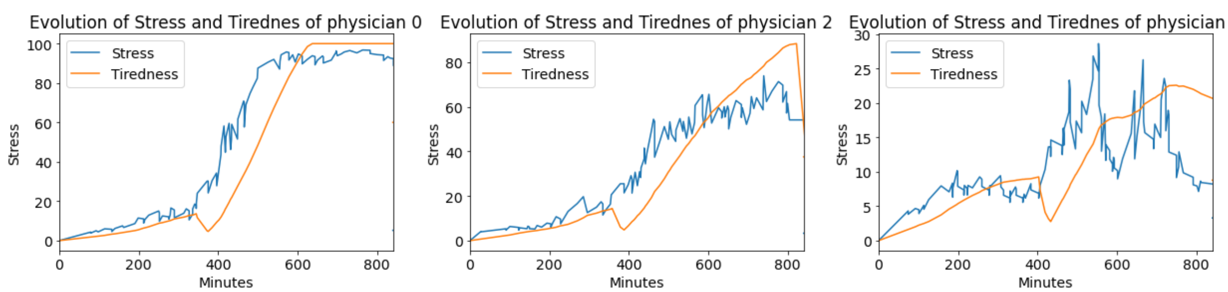

Figure 4: Evolution of the stress and tiredness parameter for three physicians (resident, on the left, medium experienced physician, on the center, high experienced physician, on the right). Simple Rotational Policy.

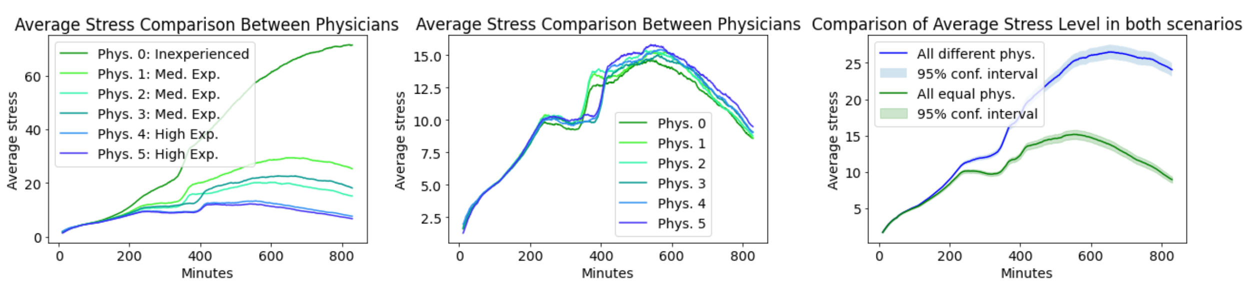

Figure 5: Average stress for the six physicians in both all-different (left), all-equal physician scenarios (center) and all physician averages (right). 500 replications. Simple Rotational Policy.

The variability in the physician behavior is reflected in the KPIs of the patients attended by those physicians, while in the all-equal physician scenarios all KPIs show homogeneous values. Tables 3 and 4 present the median and interquartile range of waiting times for the first consultation and the proportion of patients waiting beyond the CTAS upper waiting time limit. These results are provided in both models and with the two considered patient to physician assignment rules. The consultation time for the physicians in the all-equal physician scenarios has the probability distribution of the mixture of the consultation times for the all-different physician scenario. Therefore, the hypothesis test for equal consultation times in both models does not reject the null hypothesis of equal averages. Since patients are assigned to physicians and physicians select the next patient to be seen using the same set of rules in both models, the results demonstrate the significant influence of considering differences between physician on these critical KPIs.

Table 3: Proportion of patients that exceed their waiting time limit.

		All physicians are equal			All physicians are different		
Management Policy		Patient Priority 3	Patient Priority 4	Patient Priority 5	Patient Priority 3	Patient Priority 4	Patient Priority 5
Simple Rotational	Phys. 0	0,12	0,22	0,21	0,71	0,73	0,8
	Phys. 1	0,14	0,24	0,24	0,37	0,49	0,54
	Phys. 2	0,14	0,23	0,24	0,25	0,34	0,39
	Phys. 3	0,13	0,22	0,23	0,27	0,38	0,43
	Phys. 4	0,13	0,23	0,23	0,11	0,17	0,17
	Phys. 5	0,15	0,24	0,23	0,09	0,15	0,15
Acuity Based Rotational	Phys. 0	0,09	0,26	0,25	0,67	0,75	0,8
	Phys. 1	0,09	0,26	0,25	0,31	0,51	0,57
	Phys. 2	0,09	0,26	0,26	0,2	0,39	0,41
	Phys. 3	0,09	0,26	0,23	0,24	0,43	0,45
	Phys. 4	0,09	0,26	0,25	0,08	0,19	0,19
	Phys. 5	0,1	0,25	0,25	0,07	0,15	0,16

Table 4: Time until first consultation for patients of priority 3.

		All physicians are equal		All physicians are different	
Management Policy		Median	Interquartile range	Median	Interquartile range
Simple Rotational	Phys. 0	6,17	15,46	39,5	33,23
	Phys. 1	6,49	17,01	15,3	32,35
	Phys. 2	6,33	16,25	10,0	27,22
	Phys. 3	6,37	15,99	10,6	28,51
	Phys. 4	6,14	15,58	4,81	13,26
	Phys. 5	6,81	17,89	4,58	12,28
Acuity Based Rotational	Phys. 0	5,85	12,99	36,4	31,25
	Phys. 1	5,94	12,47	13,1	28,75
	Phys. 2	5,99	12,85	8,83	20,12
	Phys. 3	5,52	12,0	9,69	24,8
	Phys. 4	5,96	12,5	5,48	11,82
	Phys. 5	6,28	12,56	5,05	11,13

5 DISCUSSION OF RESULTS AND CONCLUSIONS

The results in Tables 3 and 4 indicate that the acuity-based rotational policy for assigning patients to physicians leads to improved performance indicators, such as a lower proportion of patients exceeding their waiting time and shorter waiting times until the first consultation, compared to the simple rotational policy.

However, this advantage of the assignment policy diminishes when accounting for physician variability. Incorporating different physicians introduces greater variability into the model, thereby reducing the impact of the assignment policy.

Discrete-event simulation-based analyses and queueing theory models often assume uniform service provision across physicians, which deviates from actual practice. Our study advocates for a more nuanced approach that incorporates both patient severity and physician workstyle into the analysis of ED performance metrics. In order to capture physician behavior, we have defined an agent-based model that represents the physician's mode of work in two aspects: the time required to provide diagnosis and treatment to patients, and the times at which they take breaks. This modeling is based on findings from medical and workplace psychology literature, as well as interviews conducted with ED physicians. The results support the integration of physician agent modeling to represent the variability of medical practice. The model presented in this work constitutes a first step in improving DES models to approximate digital twins that enable ED management using real-time information. To reach this medium-term objective, it is crucial to intensify research efforts and collect data at the individual level, enabling more detailed and reliable descriptions and behaviors of agents.

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