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A DATA-DRIVEN DISCRETE EVENT SIMULATION MODEL TO IMPROVE EMERGENCY DEPARTMENT LOGISTICS

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ABSTRACT

Demands for health care are becoming overwhelming for healthcare systems around the world regarding the availability of resources, particularly, in emergency departments (EDs) that are continuously open and must serve immediately any patient who comes in. Efficient management of EDs and their resources is required more than ever. This could be achieved either by optimizing resource utilization or by the improvement of hospital layout. This paper investigates, through data-driven simulation alternative designs of workflows and layouts to operate the ED of the Uppsala University Hospital in Sweden. Results are analyzed to understand the requirements across the hospital for reduced waiting times in the ED. The main observation revealed that introducing a new ward dedicated to patients having complex diagnoses with a capacity of less than 20 beds leads to lower waiting times. Furthermore, the use of data-mining was of great help in reducing the efforts of building the simulation model.

1 INTRODUCTION

The demands for healthcare and associated services will increase in the coming years concurrently with the high variability of patients in the emergency care flow. Therefore, more efficient use of resources is needed to manage hospitals, especially emergency departments (EDs) in a sustainable manner. This increase of demand makes it harder for hospitals to meet waiting times and length of stay (LoS) targets for patients at the ED. These targets could be seen as key performance indicators for (sections of) hospitals. One such target is the 4 hours LoS at EDs, implemented by healthcare organizations such as the National Health Services (NHS) in United Kingdom (UK) in order to ensure a decent level of healthcare services (Ordu et al. 2020). The level of service is also related to the triage and referral strategy applied to determine the order of priority to treat the arriving patients along with the necessary treatments to provide. Indeed, not all patients arriving at ED end up in emergency rooms for immediate admission, and many of them come for minor problems, which significantly increases the ED overcrowding, through LoS (Bouain et al. 2017). Thus, to avoid such a situation patients have to be oriented to the appropriate medical care service. In emergency rooms, patients stay under monitoring until a decision on their health is made. This decision is either to be sent home (i.e., discharged), or referred for further treatment where a bed in a specialized ward or department needs to be available first. Therefore, the overall capacity at the hospital plays an important role in determining the LoS at the ED (Yousefi et al. 2020). Conversely, from the financial point of view, the under usage of beds or any other resource is to be avoided. Consequently, determining suitable number of beds in hospital wards and departments has to be studied carefully.

This paper provides a case of the Uppsala University Hospital. For the ED of this hospital, a data-driven simulation model was designed, on the one hand, to examine the current state of the patient flow. On the other hand, to investigate potential logistics solutions for improving that flow through a novel strategy by stratifying incoming patients in several pathways. Here, the first idea is to introduce a ward dedicated (hereinafter referred to as ADA) to patients with complex diagnoses that need a longer time for evaluation to decide if they should remain in the hospital or be discharged. The second idea is to increase rationally the capacity of the emergency care's intermediate care ward, hereinafter referred to as 35C. The aims of this paper are formalized into the following key questions:

1. Assuming the current care processes and LoS targets of maximum of 2 and 4 hours (which were formulated by a clinical group of experts in the hospital), what capacity (in terms of beds, and staff to care for them) would be needed in the critical wards of ED?
2. Considering the new configuration of ED, how many places would be needed at ADA to meet all the expected admissions that do not need a specific specialist care?
3. What benefits and drawbacks the introduction of ADA bring?

The remainder of this paper is structured as follows: Section 2 gives a brief literature review of recent related works to stress the importance of resource planning, especially beds and medical staff, in ED management and to underline the effectiveness of simulation in solving such problems. Section 3 describes the design process and presents the simulation model. In Section 4, the implementation of the model is presented, followed by verification and validation. Then, the experimental study is conducted to investigate potential solutions, and the obtained results are discussed. The last section summarizes the work and highlights future improvements.

2 LITERATURE OVERVIEW

Hospitals and EDs are an enormous field of research and practice, and problems therein are discussed and solved in the literature using vast ways and methods (Günal and Pidd 2010; Yousefi et al. 2020). The undertaken review revealed that interest in EDs is more than interest in other hospital departments, and resource management is one of the most studied problems.

With respect to approaches for solutions, a great body of work has been formed over decades, but specificity and contextual approaches dominate, and generic ones are rare (Günal and Pidd 2010). Simulation-based approaches are widely used in performance evaluation and layout planning of EDs and hospitals (Fone et al. 2003; Günal and Pidd 2010; Paul et al. 2010; Gul and Guneri 2015), Operational Research (OR) and optimization mainly focus on solving scheduling and planning problems (Brailsford et al. 2009; Brailsford and Vissers 2011; Yousefi et al. 2020), while Machine Learning (ML) is the most popular in data analysis, patient flow classification, and prediction and detection of diseases (Shafaf and Malek 2019). For extracting and discovering patterns in patient flows, data-mining is the most commonly applied method (Koh et al. 2011); finally, Multi-Agent System (MAS) could be seen as a good and efficient approach for system management of ED (Chakraborty and Gupta 2014; Shakshuki and Reid 2015).

Even if computer simulation can provide beneficial decision assistance to decision-makers through realistic evaluations, it guarantees neither optimal nor best results. In other terms, simulation is rather used to evaluate solutions provided by problem-solving approaches, such as data-mining, OR, IA, heuristics, strategies, etc. Therefore, simulation has to encompass appropriate approaches in order to solve properly the problems being studied (Figueira and Almada-Lobo 2014; Yousefi et al. 2020). Two possible strategies of improving EDs capacity could be optimizing resource utilization or hospital layout extension (i.e., adding more resources). In this paper, we focused on layout extension by introducing a new ward with an adequate capacity to smoothly discharge the incoming patient flows and reduce LoS of patients in emergency rooms.

Patients arrive hospital, and EDs as well, with light to severe injuries and illnesses. Here, the issue is to discover the flow distributions, decision probabilities, and flow patterns related to the incoming patients. To this end, data-mining is used to stratify the incoming patients in several pathways and establish relationships among the identified flow patterns.

Several simulation models related to the discussed issues have been proposed. Capacity and resource planning, especially beds and medical staff, are important in ED management. Thus to manage ED capacity, resource allocation problem has to be addressed to assign resource either over priority or level of emergency (Antunes et al. 2019; Chen et al. 2020; Bahari and Asadi 2020; Ordu et al. 2020; Sasanfar et al. 2021). Of these contributions, the paper on hand followed the similar resolution steps to that of Antunes et al. (2019), i.e., process identification using data-mining, resource planning, and ED simulation with DES. ED management is also related to the overcrowding and bottleneck problems happening between ED and hospital wards (Ceglowski et al. 2007; Isfahani et al. 2020). As aforesaid, reducing LoS of patients can be achieved by improving the design of EDs or hospitals (Isfahani et al. 2020; Corsini et al. 2022), or by enhancing the process of patient triage and stratification (Bouain et al. 2017; Uriarte et al. 2017; Kovalchuk et al. 2018; Chefira and Rakrak 2019). Then, inspired by these reviewed papers, the paper on hand proposes a data-driven simulation model to investigate the impact of hospital layout extension along with an improved stratification process on both ED and system performance.

3 SIMULATION MODEL

3.1 Design Process

As the conception of simulation models for complex systems is challenging, a road-map to simplify the process is needed. In this study, we went through three steps to build the model (Abourraja et al. 2021). First, the requirements, boundaries, and objectives were defined together with the clinical experts. In parallel, the analysis step was conducted with the help of data mining to identify the different profiles of care flows and the streams of actions, see the next subsection. These outcomes are the bridge to the last step, where actors and resources are modeled in terms of agent and object concepts, while the identified streams of actions are modeled in terms of discrete event blocks with a full definition of their inputs and outputs, see subsection 3.3. The data-mining step provided a significant portion of the patient flow descriptions, as well as the distributions in every step and the clinical capacity available in every step. The last outcome of this process is the simplified representation that outlines how the care flow process was represented (Figure 1).

3.2 Data Mining Process

The simulation was based upon one year of data records of ED visits and subsequent referrals at the Uppsala University hospital for 2019. The analysis of this system was conducted with the help of data mining applied to the following data sources:

1. Patient care flows at the ED: reported patient visits to ED in 49,938 records, containing information on: route of arrival, chief complaint, main diagnosis ICD-10 (International Classification of Diseases, 10th revision, WHO), medical team treating the patient, reason for discharge. For patients admitted to wards or technical units the data also included: building where treated, LoS, co-morbidities, method of discharge and diagnosis (ICD-10) at the time of discharge.
2. Patients treated at 35C: includes 1,371 records and reported main diagnosis at discharge (ICD-10), LoS, and associated ward where the patient was admitted (including patients that were not treated in the ED).
3. Ward data: the number of available beds and patients treated at each ward over the year (343,453 records).

Table 1: Simulation settings: arrival rates.

	Arrival rate	Unit
Ambulance	$\bar{x}$=1.75 and sd=1.24	Hour
Pedestrian	$\bar{x}$=4.04 and sd=1.94	Hour
AIMA	1.62	Day

4. Imaging data: the performed sequence of scans, time of the request of the scan and time when the decision was made after the consultation of the images.

The different profiles of care flows and the treatment process that each patient underwent was extracted using data analytic tools in RStudio environment. The analysis provided the characteristics of patient flows from arrival at the ED to discharge or admission either to the wards or technical units: including logistical features (arrival method, team care assigned, discharge or inscription to a ward, technical units, length of stay, etc.) and clinical features (chief complaint, triage, ICD-10 code in ED and wards, etc.). This resulted in four patient flows: acute patient flow, not-acute patient flow, complex patient flow, and easy-go patient flow. Once the flows were identified, the distributions ad values for these characteristics (full date of visit, way of arrival, age, gender, symptoms, LoS, used resources, way of exit, etc.) were extracted, and are summarized as follows: arrival rates (Table 1), flow probability distribution (Table 2), decision values (Table 3), and stay-time in hours for each flow and location in the hospital (Table 4).

Table 2: Simulation settings: flow probability distributions.

Way of arrival	Flow	Probability	Way of arrival	Flow	Probability
Ambulance	Acute-room	0.14	Ambulance	Not-acute-room	0.0095
Ambulance	Complex	0.609	Ambulance	Easy-go	0.23
Pedestrian	Acute-room	0.02	Pedestrian	Not-acute-room	0.0039
Pedestrian	Complex	0.45	Pedestrian	Easy-go	0.52

3.3 Activity Modeling

In the simulation model Figure 1, there are four main flows of patients going through the ED at Uppsala University Hospital that arrive by ambulance or as walk-in patients: acute-room flow, not-acute-room flow, complex flow, and easy-go flow. Acute-room flow and not-acute-room flow together form the acute flow. At the triage point, the incoming patient is identified, then the adequate medical treatment is determined according to the flow probability distribution (see Tables 1 and 2). In this model, 35C is represented separately from other wards that were aggregated into a single compartment called *main ward*.

Acute-room flow concerns patients requiring immediate treatment and/or continuous monitoring in the emergency room. As soon as the patient occupies a bed, a team, composed of one doctor and two nurses

Table 3: Simulation settings: decision values (Amb. is ambulance and Ped. is pedestrian).

	Acute-room		Not-acute-room		Complex				Easy-go	
					Amb.		Ped.			
Decision	Amb.	Ped.	Amb.	Ped.	CT	NOT	CT	NOT	Amb.	Ped.
Discharge at ED/ADA	0.17	0.30	0	0	0.40	0.42	0.62	0.61	-	-
Direct to 35C	0.27	0.30	0.73	0.79	-	-	-	-	-	-
Discharge at ward 1st time	0.86	0.91	0	0	-	-	-	-	-	-
Discharge at 35C	0.43	0.5	0.15	0.23	-	-	-	-	-	-
CT scan	-	-	-	-	0.57		0.46		-	-

Table 4: Simulation settings: stay-times in hours (Amb. is ambulance and Ped. is pedestrian).

Location	Acute-room		Not-acute-room		Complex				Easy-go	
	Amb.	Ped.	Amb.	Ped.	Amb.		Ped.		Amb.	Ped.
					CT	NOT	CT	NOT		
ED	3.63	3.51	6.49	7.036	2.36	6.34	2.69	5.49	5.20	4.18
Ward 1st stay	152.83	114.29	-	-	143.13	107.08	127.89	100.43	-	-
Ward 2nd stay	139.34	107.48	185.15	171.72	-	-	-	-	-	-
35C	21.69	21.87	27.33	30.50	-	-	-	-	-	-
ADA	-	-	-	-	6.42	-	6.03	-	-	-

initiates diagnostic tests to further evaluate the patient's condition. In addition, during their stay, the patient is seen every 20 minutes by the doctor. If the patient needs to see a specialist or undergo surgery, they are moved to the corresponding ward and to 35C for intermediate care. Otherwise, the patient is monitored for approximately three hours before being discharged. At the ward, once the patient receives all examinations and/or interventions, they are either discharged or referred to 35C for further care. The diverse activities happening inside the ward are lumped and simulated with a delay block. Following treatment at 35C, the patient is discharged or sent back to the ward. As concerns the flow of acute patients not treated at the emergency room but end up at 35C is labelled as not-acute-room. It follows a similar logic as explained above with a few exceptions. Another space at ED is used instead of the emergency room, and all the patients are forwarded to the 35C either directly or after the stay at the main ward. Besides at ED, patients in this flow are seen by a nurse every 20 to 30 minutes and a doctor every 30 to 60 minutes. The complex flow is the most common in ED and contains patients with moderate to serious health problems but not life-threatening. Here, the focus is on patients requiring diagnostic scans. The patients are first moved to a dedicated room in ED to undergo the scans, where they are monitored on an hourly basis by a nurse and every two hours by a doctor. In the current routine of the hospital, the entire process of the scans, evaluation, and decision-making takes place in the ED. In our simulation, we simulated the scenario where once the scanning is completed, patients are sent to an admitting ward (ADA) for a couple of hours while waiting for results and a final decision after further evaluation. Thereafter, the patient is discharged or referred to a ward. Regarding the rest of the complex patients not doing scans, their stay in the ED is represented by a delay time. The remaining steps are similar to the above. The last flow includes patients with simple conditions, i.e., *easy-go* flow, that receive the appropriate care followed by discharge (see-and-treat). The visiting rate of nurses and doctors to these patients is once per four hours. There is an external patient flow called *AIMA* coming from outside ED that also uses 35C facilities, here all are discharged 32 hours later.

Each decision point is linked to a respective probability distribution and equipped with a statistics collector to count the traversing patients (see Table 3). The assignment of beds to patients is ruled by FIFO (i.e., First In First Out). The number of available beds in the main ward is computed using the occupancy rate because it is not only used by the ED but also by other hospital departments. If no bed is available, the patient is placed in the queue of the concerned process, and once released, the queue time is recorded. The simulation settings are exposed in Tables 1-5. In this study, resources such as beds are modeled as objects without any awareness of their environment, while doctors and nurses are implemented as simple agents having behaviors oriented toward serving patients. Resource pools are used to gather entities of the same type with the same purpose in order to make it easy the management process. For example, doctors in charge of the emergency room are in a different pool than those operating in the ED room of complex flow.

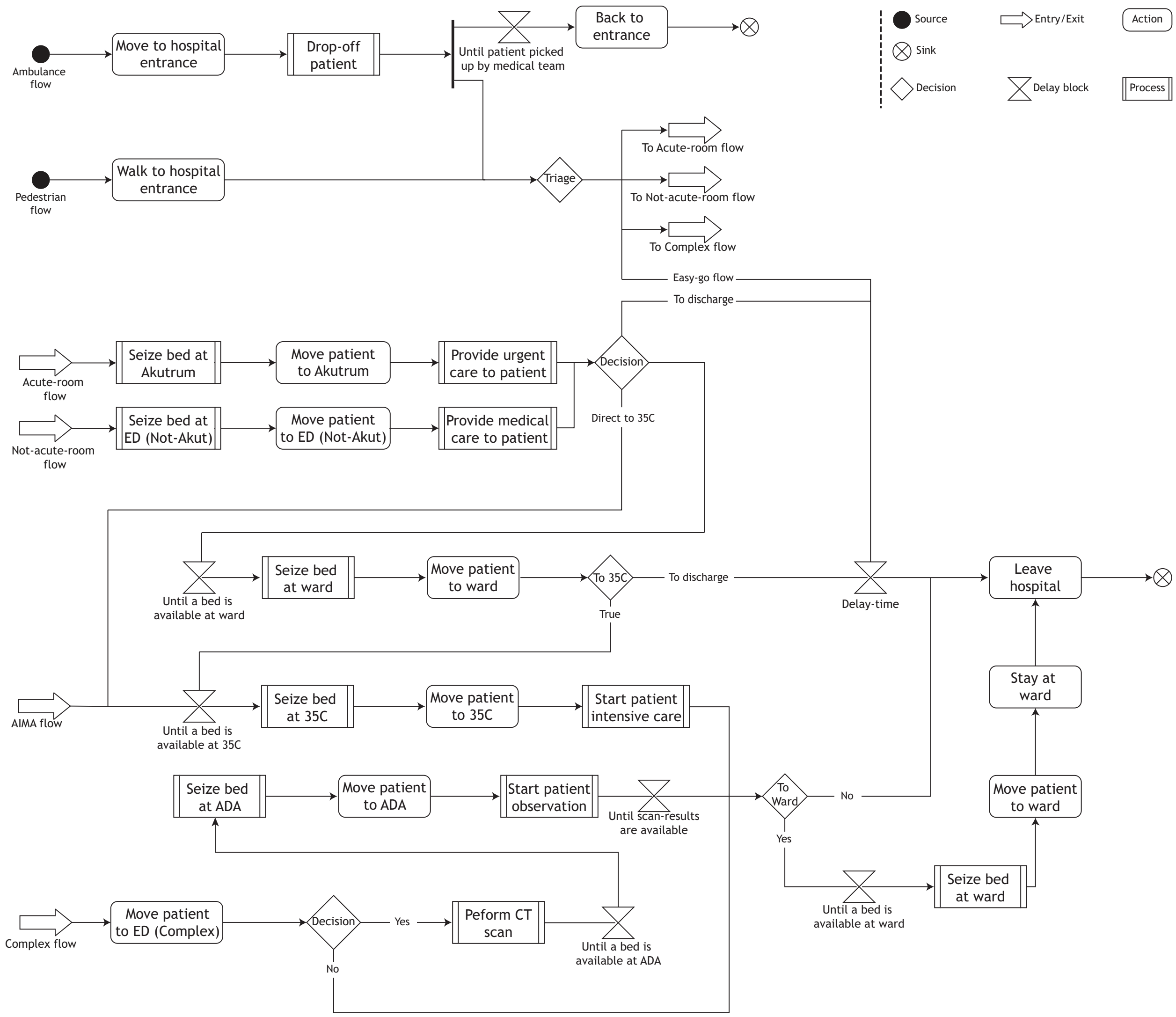

Figure 1: Simulation model.

4 RESULTS AND DISCUSSION

4.1 Implementation and Verification

In this study, AnyLogic simulation tool was chosen. The implemented model was then calibrated to the data sources and tested with respect to its ability to reflect the expected behavior. Afterward, the behavior of the model was monitored and verified through the 2D-3D window elements.

4.2 Experiment

An experimental study was conducted to analyse the proposed strategy for operating the ED and to determine the number of beds allowing a smooth turnover of incoming patients while avoiding queues and the required medical staff at ADA. In the experiment, the simulation model run for three months using two scenarios and by applying one of two constraints on the LoS at the emergency room: (1) 4-h target; (2) 2-h target, as prescribed by the Akademiska team. In the first scenario (S1), the new suggested layout was considered (i.e., with ADA), whereas in the second one (S2), the current layout was used (i.e., without ADA). This is to measure the impact of integrating ADA on ED performance and its attendant advantages. The simulation experiment was constructed around three types of inputs: fixed, variable and range, see Table 5. Fixed parameters are constant during the whole simulation experiment, while variables change value during the simulation run. Parameters are defined as a range, change value in increments between simulation runs, circling through all possible parameter combinations. Increments are chosen in a way to avoid a large number of runs and reach meaningful results. The main computed outcomes were: workload of the medical staff, resource utilization, queue length, and length of stay. To sum up, the objective of the experiment was to find out which parameter values optimize the LoS in both scenarios.

The model was fed by empirical data on the expected flow during a year, the existing resources and ED layout, see Tables 1 and 2. The daily flow is about six patients per hour, with a peak between 8:00 and 20:00. The capacity of ED rooms is shown in Table 5. Most notably, the capacity of the emergency room is four beds, and that of not-acute-room flow is seven beds. In the current layout, the main ward contains about 681 beds allocated over several rooms, and the 35C has seven beds spread over three rooms, one for observation and two for emergency. Finally, there are six gates for ambulances and one entrance for pedestrians.

Table 5: Simulation experiment's parameters.

Parameters	Type	Values	Step
Simulation period	Fixed	3 months	-
Patients per day	Variable	± 145	-
Acute-room capacity	Fixed	4 beds	-
35C capacity	Range	7 - 14 beds	1
Main ward capacity	Range	650 - 850 beds	25
Main ward occupancy	Range	0.81 - 0.92 %	1%
ED room capacity for not-acute-room	Fixed	7 beds	-
ADA capacity	Range	10 - 30 beds	10
Doctors for acute-room flow	Fixed	2	-
Nurses for acute-room flow	Range	2 - 4	2
Doctors/nurses for other flows	Range	1 - 2	1

4.3 Validation

Validation is a proof-of-concept step that takes place twice during the model development process (Law and Kelton 2000; Sargent 2013). First, when the conceptual model is ready to be presented for approval by subject matter experts to ensure that the design is correct and considered knowledge is accurate before proceeding to implementation. Second, after the implementation in order to test that the simulation model is accurate which could be achieved through two methods:

- numerical method: performing replications around a confidence level then comparing the outcomes collected from the simulation with those of the real system.
- discussion method: similarly to the conceptual model, this involves review by the subject matter experts.

Both validation steps were performed in this study. A meeting was arranged to discuss the model, and the identified inconsistencies were addressed according to expert feedback (e.g., wrong modeling of a process). AnyLogic provides a Parameter Variation Experiment that ends the execution loop after a minimum number of replications when the confidence level is reached. According to (Cumming et al. 2006) and (Petty 2012), the confidence level is fixed at 95% and the error percentage is set at 5%. Here, the confidence level was constructed around the LoS in the emergency room, and 12 replications were needed.

Table 6: Observed data vs simulation outcomes.

Parameter	Observed data	Model (S1)	Gap (S1)	Model (S2)	Gap (S2)
Beds at emergency room	4	4	0%	4	0%
Beds at 35C	7	7	0%	7	0%
Occupancy rate (%)	91	84	7%	83	8.5 %
LoS at emergency room (h)	3.57	3.78	5%	3.65	2%

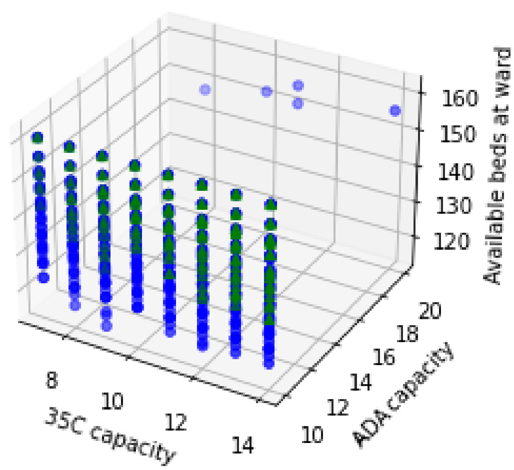

Figure 2: Needed beds at the critical wards to reach 2-h (green) and 4-h targets (blue).

Table 6 presents the main simulation outcomes versus those of the real system. According to (Cartenì and De Luca 2012), a difference less than 10% is a tolerable error in logistics models. These outcomes were discussed with the hospital authorities to assess by themselves the model's accuracy.

4.4 Findings and Discussion

The simulation model underwent a large number of runs using distinct combinations of parameters (i.e., parameters of type range). These combinations aim to evaluate the model under different circumstances and situations so to figure out which parameter values comply with the 2-h/4-h targets. The obtained simulation outputs are displayed in Figure 2 and Tables 7-8. Table 7 shows the difference between running the ED with and without an ADA ward while illustrating the needed beds at all wards to reach either 4-h target or 2-h target in both scenarios; see also Tables 6 and 8. The main observation in Table 7 is when the total capacity of the main ward increases, logically more beds are available as well as the value range of the occupancy rate becomes wider. This observation is depicted in 3D view for the first scenario in Figure 2. Table 9 summarizes the needed physicians' teams to run efficiently the different ED rooms and ADA ward in the first scenario.

The studied wards impact differently the LoS of the patient at the emergency room. Obviously, the main ward had the most significant impact on LoS, with a correlation of $R^2 = 0.69$ between LoS and its capacity. The hypothetical ADA capacity showed a stronger relationship with LoS in the emergency room than 35C, with correlations of $R^2 = 0.3$ and 0.03, respectively. ADA could be seen as an extension of the main ward, used to hold the complex flow patients waiting for CT scan results instead of occupying space at ED. Therefore, only complex of patients that need further care are sent there, thus resulting in a reduction in demand for main ward beds and LoS. This is confirmed by Tables 7 and 8 showing that

Table 7: Needed beds at the critical wards to reach 2-h and 4-h targets in the emergency room.

	35C capacity		Ward total capacity		Ward occupancy rate		ADA capacity	
Target	min	max	min	max	min	max	min	max
2-h (with ADA)	7	14	700	850	81 %	84 %	10	10
4-h (with ADA)	7	14	650	850	81 %	86 %	10	20
2-h (without ADA)	7	14	720	850	81 %	84 %	-	-
4-h (without ADA)	7	14	710	850	81 %	85 %	-	-

Table 8: 2-h target vs 4-h target (time is in hours). *ER: emergency room

	LoS ER*	Stay-Time At 35C	Stay-Time At ADA	Ward queue length	35 queue length	Ada queue length
2-h	1.78	24.90	7.42	2.33	0.83	609
4-h	2.74	25.80	8.25	4	0.88	688

Table 9: Needed doctors and nurses to run the ED units (without ADA scenario).

	Acute-room		Not-acute-room ED		ADA		Complex ED		Easy-Go ED	
	Doctors	Nurses	Doctors	Nurses	Doctors	Nurses	Doctors	Nurses	Doctors	Nurses
Team size	1	2	1	1	1	1	2	2	1	2
Avg. productivity (%)	20	26	<1	<1	16	40	89	98	40	62

the introduction of ADA in ED increases the turnover of the incoming patient flow with fewer beds than the current process requires. In the simulated scenario with ADA and the stratification of the flows, 132 beds, and 123 beds need to be available to reach 2-h and 4-h targets, respectively. While in the current scenario, the number of required beds are 136 and 135. Interestingly, the more beds in ADA, the fewer the admission of acute-room and not-acute-room patients to the main ward, see 2, which increases the LoS in the emergency room. This demonstrates the impact of ADA on LoS in the emergency room. Most patients going through ED are complex (See Table 2), and admitted patients stay for a long time (around 100 hours) in the wards (See Table 4). Consequently, the beds at the ward are occupied for a long time, meaning that the patients wait longer at the ED. Thus, the second role of ADA is controlling the rate of the complex flow admitted to the main ward, i.e., ADA can be considered as a flow faucet. Therefore, the following conclusion can be drawn: the new strategy, i.e., with ADA and better stratification of patients, is much better than the old one, i.e., without ADA.

The weak relationship between 35C and LoS in the emergency room is because of the mediating effect of the main ward, since the majority of acute-room patients are admitted and treated to a ward, rather than being treated at 35C. Also, the considerable capacity of the main ward hides the impact of 35C (sample size effect). The capacity at 35C has some impact on the occupancy in the main ward; however, the strength of this relationship is quite small ($R^2 = 0.22$) because of the fact that some patients are discharged at 35C before ward, and inversely, at ward before 35C.

As regards the medical staff, Table 9 reports that only one nurse is needed for the not-acute-room flow and two for the others. Only one doctor is necessary for each ED room, and ADA to deal with patients apart from that of the complex flow where two are needed, besides both doctors and nurses are overcharged. As aforesaid, most patients are complex, and not-acute-room are rare. In addition, the organisation of the staff in function of flow stratification and ADA could improve LoS. For example, how doctors and nurses are distributed and if ADA staff could have the possibility to operate elsewhere in ED. The simulations showed that the size of the physician teams greatly impacted the predicted LoS of complex and easy-go patients in the ED but with only a slight effect on the overall LoS in the emergency room. This is expected because the more staff, the shorter the time between visits, and as showed above, the LoS in the emergency room is strongly related to the availability of beds in the main ward.

It is clear how introducing ADA ward helps in improving the level of service provided, specially to acute patients. However, although ADA reduces the LoS in the emergency room, the outputs showed that it produces the opposite effect on the waiting time of complex patients at ED. As discussed above, the simulation model assigns admitted patients to a ward only when a bed is available; otherwise, the patients remain in ED or ADA. This could explain the observed behavior of ADA during the simulation as well as why the required available beds to reach the LoS targets are relatively high. In addition, according to the data, most of the wards reported a greater number of contacts than the number of available places, implying overcrowding, which our model does not consider. Furthermore, even if data-mining helped in establishing the different pathways of patients along with the relationships among them, the identified flow distributions provide only a high abstract representation of the incoming patient flows, see Table 2. That is, the patients are stratified based on probabilities instead of patient characteristics such as age, gender, symptoms, etc., which enable to catch more efficiently the expert knowledge. On the other hand, the designed model does not include physically the other departments of hospitals that also send some of their patients to the main ward. This has been represented by the occupancy rate of the main ward. Moreover, the geriatric flow was not considered separately in the simulation because the characterisation of these patients is still an ongoing process. In future work, this flow can be defined to investigate the impact of a ward dedicated to these patients.

To sum up, the designed simulation model not only underlined the advantages of ADA in achieving a better level of healthcare services along with revealing the necessary capacity in the critical wards of ED in terms of physicians and beds but also helped in discovering what drawbacks ADA brings. To reach the fixed LoS targets, ADA should have less than 20 beds, and the main ward should be equipped with more than 650 beds.

5 CONCLUSION

In this paper, a simulation model based on data mining and expert knowledge is developed to investigate a new strategy to manage patient flows in ED of the Uppsala University Hospital in Sweden. The main contribution of this paper to the existing literature is two-fold:

- The use of knowledge resulting from data mining process as a foundation to build the simulation model: the knowledge about ED functioning was extracted and patient flow patterns were discovered to build the foundations of the simulation model.
- Investigating the integration of a new ward in ED with an improved stratification of incoming patients on the whole system performance: the data for the experiment study were collected then fed to the simulation model to evaluate two operating scenarios (i.e., the new strategy vs the current one) under two constraints (i.e., 2-h target and 4-h target).

The study results underlined the advantages and drawbacks of the new strategy in terms of the considered aspect and reality of the studied system. However, some limitations in this study exist such as the abstract representation of the patients and the other parts of the hospitals. This will be addressed in the future works.

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