Emergency Care Journal

Official Journal of the Academy of Emergency Medicine and Care **(AcEMC)**

eISSN 2282-2054

https://www.pagepressjournals.org/index.php/ecj/index

Emerg Care J 2024 [Online ahead of print]

To cite this Article:

Angler Y, Lossin A, Goetz O. **The importance of discrete event simulation as a methodology for performance evaluation in the emergency department.** *Emerg Care J* doi: 10.4081/ecj.2024.12562

The importance of discrete event simulation as a methodology for performance evaluation in the emergency department

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Key words: emergency department, computer simulation, discrete event simulation, performance measurement, artificial intelligence.

Contributions: YA, conception and design of the work, data collection, project management; AL, critical review of the work for important intellectual content and suggestions for improvements, critical review of the collected data and its interpretability; OG, critical review of the work for important intellectual content and suggestions for improvements, critical review of the

collected data and its interpretability. All the authors have read and approved the final version of the manuscript and agreed to be held accountable for all aspects of the work.

Conflict of interest: the authors declare no potential conflict of interest.

Funding: none.

Ethics statements: as part of the study, only the throughput times (time data) of the patients through the emergency department were recorded. This was preceded by coordination meetings with the clinic management of the hospital and the head physician of the emergency department in order to obtain their acceptance and written consent for the inspection and process analysis in the form of a time measurement study. The consent was given in compliance with strict anonymization, which does not allow any conclusions to be drawn about the project hospital. At no time was personal data or data that would allow conclusions to be drawn about the type of illness or the state of health of a patient recorded. The interviews conducted with the medical staff were carried out with written permission and in compliance with anonymization. Based on this procedure, authorization by the local ethics committee was waived.

Availability of data and materials: all data generated or analyzed in this study are included in the manuscript.

Acknowledgments: the authors would like to thank the project hospital for their comprehensive support during the process recordings in the emergency department and for the valuable information from the practical work.

Abstract

Emergency Departments (ED) face the challenge of providing high-quality patient care under difficult conditions due to staff shortages or overcrowding. These challenges mean that more than ever, ED need to find ways to provide high-quality patient care despite limited resources and bottlenecks. Process analysis using Discrete Event Simulation (DES), taking into account performance-related assessment indicators, can help to improve patient care and resource utilization of staff and infrastructure. Based on process observations, interviews and time studies, a process model was developed in a general hospital ED to realistically simulate workflows. The results allow the assumption that digital technologies and an increase in staff capacity can reduce length of stay and waiting times for patients while improving staff distribution and infrastructure utilization. The study suggests that DES has great potential for use as a performance evaluation tool in the ED. In times of increasing digitalization, the potential of artificial intelligence in the context of process improvements, but also the challenges of this technology, must be given greater consideration.

Introduction

Emergency Departments (ED) will face several challenges in the coming years, such as dealing with demographic change, staff shortages, the increasing demands of digitalization and managing overcrowding. Well-designed process structures with defined performance evaluation parameters have the potential to ensure efficient and high-quality patient care despite limited resources. One method that provides valuable potential for process analysis and performance evaluation is Discrete Event Simulation (DES). DES is a computer-based methodology used to simulate the dynamic processes of a real system.[1] DES is often used in hospital planning to model the patient pathway, optimize resource utilization and increase efficiency in the healthcare system.[2,3] Due to the explosive impact of ED as described above, the aim of this study is to analyze the workflow in an ED using the example of a general hospital by means of a DES. With the help of the application functions of a DES, it is possible to simulate the processes in the ED in an evidence-based model and to analyze their effectiveness on the performance indicators of Length of Stay (LOS), waiting time and staff/ infrastructure utilization. Our research study provides an important contribution by demonstrating the extent to which a DES can serve as a valuable tool for performance evaluation. In addition, the work provides suggestions for the use of new technologies in the course of increasing digitalization in the ED.

Materials and Methods

The DES study was conducted in an ED of a German general hospital with 300 beds. The ED focuses on internal medicine, general vascular and visceral surgery, orthopedics, urology, anesthesia and intensive care. The ED provides general medical care in the rural region 24 hours a day, seven days a week and treats an average of 14,000 emergency patients per year. Due to the medical orientation of the department, it is an interdisciplinary Spoke-ED that brings together various specialist areas, staff and equipment in a single organizational unit. The rural nature of the region leads to a lack of medical care, which is why the ED of the project hospital is the central point of contact for the local population. As a result of this limited care structure in the region, the ED often struggles with overcrowding.

For the study, the authors obtained the written consent of the hospital management and the head physician of the ED for the process analysis and data collection in the ED. The consent specified that only patient throughput times through the ED would be recorded and that anonymization would be guaranteed. This ensured that no information could be drawn about the patients or their state of health.

In a first step, observations and interviews were conducted with medical staff to gain a deeper understanding of the processes, activities and patient flows in the ED. The information from the observations and interviews is an important element for the correct representation of patient flows in the simulation model (Table 1). As the health status of patients in an ED can vary greatly, it was important to understand the patient prioritization scheme to create a realistic simulation. The general hospital uses the Manchester Triage System (MTS) which uses the colored categories red, orange, yellow, green, and blue to define the urgency of patient's care. Based on the MTS system, the blue, green and yellow patients are cared for by general nurses. The orange and red patients, due to their higher severity, are cared for by nurses with training in critical care medicine. There are always two physicians with the identical qualification level in the ED who treat all patients regardless of their MTS level. The medical staff, the examination rooms, the shock rooms, the triage room, the care rooms and the waiting area for patients were included in the modelling. According to the medical staff, the triage room is used for the initial assessment of the patient and for classification into an MTS level. The two shock rooms are reserved for orange and red patients, as special medical equipment for emergency treatment (*e.g.* resuscitation equipment) is available in this room. For blue, green and yellow patients, there are two identical examination rooms for minor interventions of various kinds and the care rooms (*e.g.* wound care).

The data collection on patient flow in the ED (Table 1) was based on a time study over a three-week survey period.[4] In the time study, a distinction was made between waiting time and activity time. Waiting time is defined as the time the patient spends between the end of an activity and the start of a new activity. In contrast to the waiting time, the activity time refers to the entire duration of a single activity that a patient completes.[5] They both together defined patients LOS (Table 1). Waiting times and activity times differ depending on the color of the priority class. Red and orange patients generally receive faster treatment than the other patients because it is more urgent. The MTS level "red" was not recorded in the simulation study for ethical reasons. The green and blue patients were put together in one group because of their quite similar need of resources.[4] Once the time data had been collected, the data was analyzed in the form of an input analysis. The data analysis was carried out using the advanced functions of Microsoft Excel 2019. For each time category and data series, the authors of the research study determined the mean value and standard deviation from the total time values, segmented according to urgency (Table 2). As part of the simulation study, the authors used the triangular distribution method to determine suitable probability distributions. The main advantage of this method is the plausibility of obtaining the minimum, most probable and maximum value for a sub-process (T1-T7) via estimates from experts. The triangular distribution was based on estimates from medical staff and experienced emergency physicians to derive the times for T1-T7 and for the regular patient arrival volume for each MTS stage (Table 3). The collected time data from the time study formed the basis for the experts' estimates. For the design of the model, the authors made several hypotheses to limit the complexity of the modelling and to identify possible limitations (Table 4).

Based on the three-week survey phase, the authors determined a runtime of 120 hours to represent the survey period from Monday to Friday over eight hours each day in the simulation model. The number of replications was set at 30 replications. After completing the 30 replications, the authors compared the data from the time study and the baseline model using the mean to test the validity of the model and its degree of approximation to reality (Figure 1). For verification, MedModel provides automated debugging, which was used to detect conceptual errors.[4]

Based on the results of the base model, five what-if scenarios were created to run hypothetical scenarios to analyze the impact of changes in the performance parameters of LOS, waiting times and resource utilization in the ED. These what-if scenarios were created in consultation with the medical staff of the ED and other experts from the healthcare sector.[4] LOS and waiting times were measured in minutes, while the utilization rate was measured as a percentage based on the time a particular staff or infrastructure resource was unavailable.

Scenario 1 was Treatment of yellow patients in a shock room; Scenario 2, the use of a physician assistant; Scenario 3, the use of a further physician; Scenario 4 the use of digital technologies by electronic triage systems, Clinical Decision Support System (CDSS) or emergency assistance system, and Scenario 5, the use of an additional nurse for the MTS level blue/green/yellow.[4]

Results

Results from the basic model

Basic model: Length of Stay and waiting time

Analysis of the model showed that blue/green patients had an average LOS of 267.37 minutes, which is equivalent to 4.45 hours. Yellow patients left the ED after 129.16 minutes (2.15 hours), while orange patients spent an average time in the system of 73.44 minutes (1.22 hours) (Table 5).

Basic model: utilization of personnel capacities

The results of the basic model showed that the degree of utilization of physician one (79.77%), physician two (71.17%) and the blue/green/yellow nurses (69.51%; 65.40%) can be considered relatively high (Figure 2).[4]

Basic model: utilization of infrastructure capacities

The results of the simulation of the basic model showed that the utilization of the infrastructure capacities diverge intensively. While the examination room one (81.85%), examination room two (66.59%) and the waiting area (84.22%) are highly utilized, rooms such as the shock room one (21.94%), shock room two (25.04%), care rooms for aseptic treatment (39.91%; 37.75%) or the triage room (40.63%) are only used to a low or moderate extent (Figure 3).[4]

Scenario results

Scenario: Length of Stay and waiting time

Table 2 shows that Scenario 3 and Scenario 4 led to a reduction in waiting times and lengths of stay for all patient categories (Table 5). Compared to the base model, the LOS in Scenario 3 decreased by 8% for blue/green patients, 6% for yellow patients, and 4% for orange patients. Scenario 4 can be used to achieve even greater improvements to reduce LOS. For example, compared to the basic model, the LOS can be reduced by 10% for the blue/green patients, 12% for the yellow patients and 15% for the orange patients.[4]

Scenario: utilization of personnel capacities

The findings highlight that in all scenarios, there was an improvement in the distribution of medical staff utilization (Figure 2). Furthermore, an enhanced dispersion of utilization was shown to reduce the LOS, as evidenced by Scenarios 2, 3, and 4. Additionally, it was observed that digitalization (Scenario 4) can streamline processes, increase efficiency, and ultimately lead to faster outcomes. In Scenario 5, it was demonstrated that adding another nurse for high patient volumes in MTS categories blue/green and yellow results in reduced workload per nurse. [4]

Scenario: utilization of infrastructure capacities

As a result of an improved distribution of infrastructure utilization, an increase in utilization to 48% was achieved for shock room 2 in Scenario 1, compared to 25% in the basic model. The utilization of the care rooms was also increased slightly, while the utilization in the highly frequented examination rooms decreased (Figure 3).[4]

Discussion

By comparing the scenarios with the basic model, initial ideas for action could be derived for the ED of the project hospital.

Idea 1

Use of digital technologies to reduce LOS, waiting times and staff workload. The increasing digitalization of the ED offers a range of value-adding potential to relieve the burden on medical staff and improve patient care. Digital applications are already very effective at the beginning of the rescue chain. Data-based and telemedical networking with the ambulance service via an emergency assistance system enables early preparation for the arrival of emergency patients at the hospital. Medical and administrative data can be transferred completely, digitally and seamlessly from the ambulance to the ED. In addition, the targeted use of CDSS enables faster decisions to be made and diagnoses to be made more quickly. Various research studies also point to the benefits of CDSS in the ED. Çetin *et al*. (2023) integrated a decision support system for emergency triage into a hospital's information management system. Based on their results, the authors were able to show that the CDSS increased the accuracy of the triage decision and reduced the triage time.[6] Fernandes *et al.* (2020) also found in their systematic review of the effects of CDSS for triage in the ED that there was an improvement in decision making by healthcare professionals, leading to better clinical management and patient outcomes.[7] In their randomized controlled clinical trial, Fitzgerald *et al*. (2011) were able to indicate that the use of a CDSS based on Artificial Intelligence (AI) was able to reduce the error rate within the first 30 minutes of shock room care.[8] Tedesco *et al.* (2022) identified in their narrative review an increasing effectiveness of innovative tools in reducing waiting time and improving performance and patient experience in ED.[9] Based on the results of the simulation study in comparison to the research literature, it can be assumed that digitalization offers value-adding potential for process improvement in the ED.

Idea 2

Increasing the number of staff in the ED to reduce LOS and waiting times and reduce the workload for staff. The scenarios support the idea that increasing the number of medical and nursing staff by one person each has a major impact on shortening throughput and waiting times while at the same time reducing the workload of staff. However, this idea must always be seen in relation to the shortage of specialist staff in many ED. Several studies see waiting for the doctor and the lack of nursing staff as central problems in the ED.[10-12] Scenario 3 is therefore a very theoretical approach, which assumes that a sufficient number of physicians and nurses are available. The establishment of a physician assistant could represent a concrete alternative. This would create an additional resource in the ED system that could relieve the burden on physicians, especially when treating non-urgent patients. De la Roche *et al.* (2021) indicate in their study that a Physician Assistant has a statistically significant positive effect (*e.g.* reduction in initial assessment time) on the overall performance of an ED.[13] King *et al.* (2023) show in their review study that, given the increasing demand for healthcare services and the weakening British National Health Service (NHS), physicians assistance has a potentially positive impact on improving throughput in the ED.[14]

Idea 3

Expansion of the use of a shock room for the yellow patient category to achieve better capacity utilization. Stringent room allocation per MTS category may seem sensible to promote standardized procedures and thus practice well-established processes in the ED. A series of simulation studies show that spatial reorganization can deliver far-reaching efficiency potential.[15-17] Based on Scenario 1, the idea can be derived that one of the two shock rooms should also be used for the yellow patient clientele to achieve better utilization of the shock rooms. Despite this idea, red and orange-colored patients always have the highest priority for treatment in the shock room.

When formulating ideas, it should be considered that the simulation can only ever represent an approximation of reality with the use of assumptions. For example, it should be noted that the study does not take into account seasonal and daily fluctuations. However, these fluctuations can influence output parameters such as LOS or resource utilization, as additional bottlenecks can occur at weekends or at night, for example, due to fewer staff and more patients. It should also be noted that red patients are also treated in the real system. Even if red patients do not suffer from a lack of resources, the treatment of this patient level has an impact on the availability of resources, as doctors and nursing staff prioritize red patients. Nevertheless, the ideas are based on a well-structured DES model that efficiently maps the entire process of the complex system and its resources. As such, the DES study offers optimization potential for practical implementation.

Due to the challenges described in the introduction performance measurement and evaluation in the healthcare sector, especially in EDs, is becoming increasingly important to ensure high-quality patient care under economically viable conditions. The importance of this is also emphasized in other scientific studies. Soldatenkova *et al*. (2023) developed a performance measurement framework based on available administrative data to assess the performance of an ED in terms of time efficiency, throughput or quality.[18] Taleb *et al.* (2023) developed an integrated approach of a DES model and data envelopment analysis to measure the performance of an ED and evaluate the efficiency of potential resource allocation configurations for future performance improvements. The authors conclude that the performance evaluation approach can support decision makers in improving the management of the ED by identifying inefficiencies and improving efficiency through appropriate interventions.[19] In the context of performance measurement and evaluation, the selection of suitable parameters is an important success factor. Parameters that are tailored to a process can provide valuable insights, while the selection of unsuitable parameters can lead to incorrect or distorted views. A performance measurement system must therefore fulfil high requirements. In their review of existing performance measurement frameworks in healthcare, Purbey *et al.* (2007) point out that a performance measurement system must always respond to changes in an organization's external and internal environment. The authors propose a system that focuses on measurement in terms of efficiency, effectiveness and flexibility.[20] Zadooud *et al*. (2020) derive from the results of their systematic literature review that in more than 50% of the identified frameworks for evaluating the performance of a healthcare facility, the eight dimensions of effectiveness, safety, accessibility, equity, efficiency, acceptability, patient centeredness and timeliness were considered.[21]

In comparison with the scientific literature, it can be shown that the present DES model can serve as an effective tool for measuring and evaluating the performance of EDs. Based on selected performance parameters such as LOS, waiting times and utilization rates, the DES model provides decision makers in the project hospital with practical ideas to make informed decisions for the ED and drive continuous improvement. Taking into account the eight dimensions of Zadooud *et al.* (2020), this makes it possible to evaluate the effectiveness of care, patient safety, accessibility to the ED, equity of care, efficiency of processes, patient acceptance and patient-centred and timely care. In addition to the added value for efficient and effective performance evaluation, the DES model provides assumptions on how changes in processes affect the performance of the ED, which ensures a high degree of adaptability and flexibility to a changing environment and thus also covers the requirements for a performance measurement system mentioned by Purbey *et al.* (2007).

Another key focus of the simulation study was to investigate the future development of the ED under the influence of digitalization. The importance of digitalization for the ED will steadily increase in the future. The use of AI provides great potential for improved emergency care. As a result, AI is increasingly becoming the focus of research studies in ED. Uoda *et al.* (2023) highlight the benefits of Machine Learning (ML) due to increasing technology and data collection. ML integrated into a DES has the potential to predict patient flows and resource utilization via simulation models to better target processes at an early stage.[22] Duma and Aringhierie (2023) used an online algorithm based on a process mining model to perform real-time resource allocation in the ED. The results from the study indicate that the online allocation algorithm combined with a prediction tool can improve ED performance and thus reduce overcrowding.[23] The potential of ML for the simulation of patient flows also arises from the high variability in EDs due to strong fluctuations in patient volume and patient LOS. Piljuk and Tomforde (2023) derive from their systematic literature review that most studies focus on diagnosis prediction, decision support, admission prediction, severity of illness estimation and prediction of emergency care.[24] Abuhay *et al.* (2023) developed an ML-based patient flow model to improve the prediction of patient flow and their LOS. The researchers were able to show that an ML-based prediction model has a high accuracy in realistically predicting patient arrivals, LOS and other parameters. This enables EDs to allocate capacities and required resources in a timely and patient-centered manner. [25]

In addition to all the potential, the challenges of using AI in the ED must also be considered. A large number of studies identify the main challenges to the application of AI as patient harm due to AI errors caused by biased data, misuse of medical AI tools, bias due to unequal representation of a particular minority group, lack of transparency, privacy and security issues, gaps in accountability and barriers to implementation in terms of increasing demands on medical staff (high computer skills required) and the financial investment hospitals need to make.[26-29]

Conclusions

The results of the research study assume that DES is a suitable tool for obtaining practical conclusions about the level of performance in the ED. In particular, the performance parameters of LOS, waiting times and resource utilization are suitable for evaluating the level of performance for patient care. Because a DES study can also be used to evaluate the target state via what-if scenarios in addition to the performance evaluation of the actual state, this analysis option offers decision-makers in the ED the opportunity to derive ideas for improvement. Regarding potential for improvement, DES studies in the healthcare sector will increasingly have to include the potential of digitalization in the future. Increasing digitalization means that more real-time data will be available to EDs more quickly in the future. This makes it possible to use AI-supported tools to make predictions about patient arrival rates or suitable treatment paths. For this reason, future simulation projects should therefore increasingly consider the potential of AI-supported applications and their impact on process improvements in the ED.

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Table 1. Standard process: activity and waiting times for patients in the Emergency Department. Source: Angler *et al.* (2024).

Arrival at the Emergency Department	
T1 Time between arrival and triage	Waiting time
T2 Triage & registration	Activity time
T3 Time from registration to transfer by nursing staff	Waiting time
T4 Transfer of patients to the examination room by nursing staff	Activity time
T5 Checking the patient and their vital signs	Activity time
T6 Time until arrival of the doctor	Waiting time
T7 Treatment & diagnosis	Activity time
Leaving the emergency department or hospitalization	

Table 2. Process times in the Emergency Department (time unit: minutes).

	Blue/Green		Yellow		Orange	
	M	**SD**	**M**	**SD**	**M**	**SD**
T1 Time between arrival and triage	3.34	1.51	5.27	3.28	0.0	0.0
T2 Triage & Registration	9.27	1.59	9.51	1.17	8.43	1.45
T3 Time from registration to collection by nursing staff	188.34	70.58	45.54	31.20	0.0	0.0
T4 Collection/reception and transfer of patients to the examination room	4.11	1.43	4.16	1.59	2.51	0.33
T5 Examination of the patient and their vital signs	7.13	2.28	7.59	4.00	0.0	0.0
T6 Time from the nursing examination to the	16.29	8.35	9.07	2.33	11.18	3.33

	Blue/Green		Yellow		Orange	
	M	**SD**	**M**	**SD**	**M**	**SD**
arrival of the doctor						
T7 Treatment & diagnosis	34.27	24.50	46.21	27.22	49.34	1.32
Leaving the emergency department or hospitalization	263.55	77.09	128.56	48.34	72.27	0.17

M, Mean; SD, Standard Deviation

Table 3. Triangular distribution T1-T7 (time unit: minutes).

	Blue/Green	**Yellow**	**Orange**
Arriving patients	**TRIA (15, 20, 25)**	**TRIA (5, 10, 15)**	**TRIA (1, 3, 5)**
T1 Time between arrival and triage	TRIA (1, 2, 6)	TRIA (1, 2, 6)	TRIA (1, 4, 6)
T2 Triage & Registration	TRIA (6, 8, 12)	TRIA (6, 8, 12)	TRIA (6, 8, 10)
T3 Time from registration to collection by nursing staff	TRIA (50, 150, 240)	TRIA (5, 30, 60)	/
T4 Collection/reception and transfer of patients to the examination room	TRIA (2, 4, 8)	TRIA (2, 4, 8)	/
T5 Examination of the patient and their vital signs	TRIA (5, 8, 12)	TRIA (5, 8, 12)	Activity of the physician
T6 Time from the nursing examination to the arrival of the doctor	TRIA (2, 10, 30)	TRIA (2, 8, 12)	TRIA (2, 4, 6)
T7 Treatment & diagnosis	TRIA (10, 20, 50)	TRIA (15, 25, 45)	TRIA (25, 45, 60)

Table 4. Hypotheses for the model design.

Model hypotheses
a) Time recording took place exclusively from Monday to Friday.
b) Time recording only took place between 08:00 and 18:00.
c) Due to a small sample, the time registrations were distributed over a triangular distribution.
d) Seasonal, day-dependent or temporal fluctuations in capacity utilization in emergency admissions were not taken into account.
e) Laboratory requirements, imaging examinations or diagnoses were not recorded as separate activities, but were integrated into the treatment time.
f) Fluctuations in treatment times due to different qualification levels (e.g. specialist to assistant doctor) were not taken into account.
g) The MTS level "red" was not included due to a lack of resources and for ethical reasons.
h) Due to the same medical resource requirements, the MTS levels blue and green were merged.
i) The care of an orange patient always takes priority over blue, green or yellow patients. For all other patients, "first come, first served" applies.
j) Based on the external observations made in the emergency department, it is assumed that all blue, green and yellow patients are discharged from the emergency department after treatment.

Table 5. Comparison between basic model and scenarios according to mean value (in minutes). Source: Angler *et al.* (2024).

	MTS-level	Entities	LOS	Waiting time
Basic model	Blue/Green	20	267.37	52.94
	Yellow	10	129.16	36.57
	Orange	5	73.44	16.56
Scenario 1	Blue/Green	20	267.86	53.36
	Yellow	10	129.02	37.23
	Orange	5	74.14	17.43
Scenario 2	Blue/Green	20	248.80	33.54
	Yellow	10	129.22	36.43
	Orange	5	74.47	17.68
Scenario 3	Blue/Green	20	246.35	32.15
	Yellow	10	121.21	29.53
	Orange	5	70.84	14.38
Scenario 4	Blue/Green	20	239.91	33.66
	Yellow	10	113.97	29.45
	Orange	5	62.51	14.00
Scenario 5	Blue/Green	20	254.83	41.06

	MTS-level	Entities	LOS	Waiting time
	Yellow	10	124.88	30.57
	Orange	5	73.51	16.72

MTS, Manchester Triage System; LOS, Length of Stay

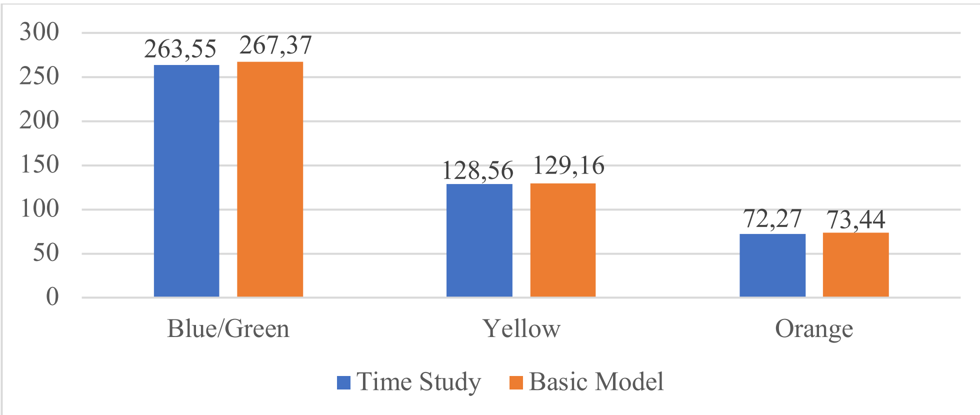
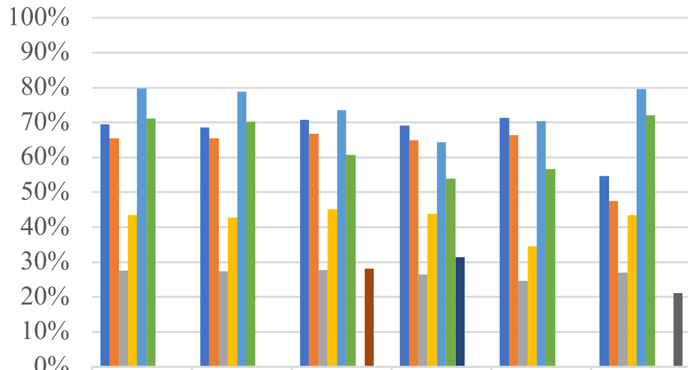
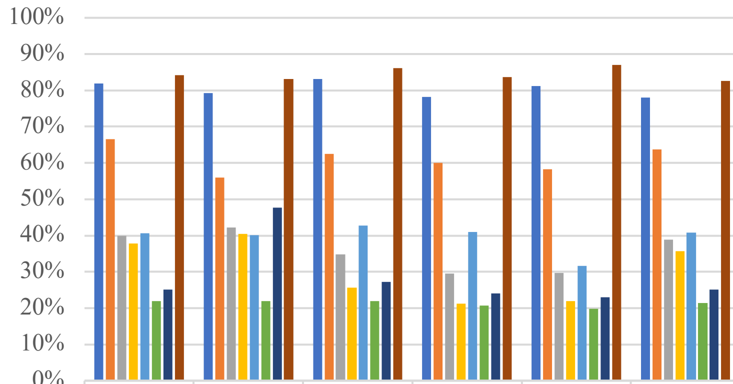


Figure 1. Time comparison between time study and basic model by total mean value in minutes. Source: *Angler et al.* (2024).



	Basic Model	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Nurse Blue/Green/Yellow 1	69,51%	68,54%	70,70%	69,18%	71,30%	54,74%
Nurse Blue/Green/Yellow 2	65,40%	65,41%	66,81%	64,98%	66,41%	47,45%
Nurse Orange	27,57%	27,39%	27,83%	26,40%	24,60%	27,02%
Triage Nurse	43,43%	42,79%	45,07%	43,77%	34,56%	43,41%
Physician 1	79,77%	78,74%	73,59%	64,40%	70,34%	79,52%
Physician 2	71,17%	70,21%	60,68%	54,02%	56,72%	72,14%
Physician 3	0	0	0	31,48%	0	0
Physician Assistant	0	0	28,19%	0	0	0
Nurse Blue/Green/Yellow 3	0	0	0	0	0	21,20%

Figure 2. Comparison of staff utilization between the basic model and the scenarios. Source: *Angler et al.* (2024).



	Basic Model	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Examination room 1	81,85%	79,27%	83,07%	78,28%	81,20%	77,96%
Examination room 2	66,59%	55,92%	62,57%	59,98%	58,28%	63,77%
Care room 1	39,91%	42,25%	34,73%	29,43%	29,61%	38,81%
Care room 2	37,75%	40,38%	25,66%	21,23%	21,95%	35,75%
Triage room	40,63%	40,16%	42,71%	40,92%	31,62%	40,86%
Shock room 1	21,94%	21,85%	21,97%	20,75%	19,77%	21,42%
Shock room 2	25,04%	47,74%	27,29%	24,07%	22,92%	25,13%
Waiting room	84,22%	83,22%	86,21%	83,58%	86,93%	82,56%

Figure 3. Comparison of infrastructure utilization between the basic model and the scenarios. Source: Angler *et al.* (2024).

Submitted: 12 April 2024

Accepted: 1 Agosto 2024

Early access: 9 August 2024