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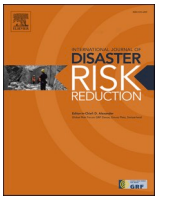

Application of behavioral simulation models to patient flows in Emergency Medical Teams (EMTs)

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ABSTRACT

The effectiveness of care provided by Emergency Medical Teams (EMTs), which often operates in resource-scarce environments with limited personnel and infrastructure, is closely linked to coordinated patient flow management. Although widely used in conventional hospital settings, structured patient flow optimization seems to be rarely promoted in these contexts. To support this quantitative analysis, this paper explores the use of a behavioural computer simulation to model patient flow through an EMT facility and evaluate main leading strategies which can potentially improve operational rapidity while solving critical interactions among patients. An agent-based behavioural simulation model, capable of representing individual movements and interactions between patients, staff members, and physical layout of the health care facility, is provided, characterizing each agent with specific attributes and constraints related to the emergency scenario. Then, behavioural key performance indicators (KPIs) are defined to analyse simulation outputs and assess the effectiveness of EMTs organization under several patient-related and operational scenarios, in terms of operational rapidity and (over-)crowding. An application to a typological field hospital under relevant working conditions demonstrates the methodology capabilities, quantitatively tracing the effective impact of consolidated strategy, dedicate facility accesses, optimization in supporting staff number and implementation of internal wayfinding systems). Behavioural simulations can be incorporated in WHO EMT decision-support frameworks in field hospitals, supporting informed re-design and adaptation of EMT management and layouts in different deployment contexts, and training and preparedness thanks to better understanding of patient flow dynamics.

1. Introduction

Patient flow refers to the movement of patients through a healthcare facility from admission to discharge, encompassing the utilization of space, staff, and resources, as well as the organizational processes that facilitate efficient transitions between stages of medical care [1]. Inefficient patient flow management is primarily associated with overcrowding and extended waiting times in hospital and emergency departments, contributing to various negative outcomes across multiple levels [2,3]. At the staff level, overcrowding increases workload and stress, reduces efficiency and morale, and raises the likelihood of medical errors and

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absenteeism [4,5]. At the system level, it leads to higher cost of care and inefficient resource allocation, reducing the overall quality of care [6–8]. These effects, translate into negative patient outcomes, ranging from increased patient dissatisfaction and prolonged waiting times [9] to more serious adverse health outcomes such as increased re-admissions [10] and higher mortality rates [11–13].

1.1. Patient flow analysis

Patient flow analysis (PFA) has been widely employed in hospital settings to enhance operational efficiency and patient satisfaction [14]. By tracking patient movements across departments, methodologies such as queueing theory [15–17], time-and-motion studies [18–20] and simulation modelling [21–23] help the identification of bottlenecks and the optimization of resource allocation.

Among these methodologies, computer simulation offers distinct advantages in evaluating and optimizing complex healthcare systems; it allows the evaluation of patient flow under varying operational conditions without [24,25] disrupting day-to-day operations and it supports the exploration of system dynamics, the identification of inefficiencies, and the assessment of potential interventions in high-demand scenarios, such as disaster conditions ([24,25]; [26]; [9,22]; [27]). In this context, microscopic simulation of pedestrian dynamics offers a valuable solution to better understand patient flows within hospital settings. These models describe behavioural rules assigned to each agent (e.g., patient or staff), depending on individual characteristics (e.g., movement speed, motion abilities, awareness levels) and objectives, often exploiting agent-based simulation [28], and then allowing to assess how these data affect outcoming dynamics at the overall population level. They are consistently used to assess emergency scenarios in healthcare facilities, including evacuation, by evaluating the performance levels of both layout and management solutions (e.g., organizing evacuation routes and support of non-autonomous patients) in respect to timings, queuing phenomena, and crowding levels [28]. Nevertheless, the same approach can be replicated for patient flow assessment in non-evacuation scenarios, and under different operational conditions, providing relevant insights especially for critical patient load levels.

1.2. Patient flow in field hospitals

Although patient flow management is critical in all healthcare settings, field hospitals present structural characteristics that fundamentally differentiate them from permanent facilities (e.g., conventional hospital) and justify a distinct modelling approach.

First, field hospitals operate under severe resource constrained environments, including limited staff, equipment, and infrastructure, which restrict their capacity to absorb variability in patient conditions, including both communicable and non-communicable diseases[29]. Second, they are designed as temporary and rapidly deployable structures, often with simplified layouts and fewer specialized units, resulting in reduced spatial flexibility and buffering mechanisms compared to conventional hospitals [29,30]. Third, the effectiveness and quality of care provided by Emergency Medical Teams (EMTs) is directly linked to the ability to ensure a controlled, necessary, and safe patient flow through the facilities, particularly during mass casualty incidents (MCIs) or disease outbreaks, where demand can exceed capacity within a short time frame[30,31], making effective organization pivotal and a tailored approach to patient flow management necessary.

In addition, field hospitals rely on streamlined organizational processes, such as simplified triage systems and rapid decision-making protocols, to ensure timely care delivery under pressure. These conditions create a system in which patient flow is more sensitive to disruptions, local congestion, and interactions between individuals and space. As a result, traditional approaches developed for stable hospital environments may not fully capture the dynamics of patient movement in these contexts.

While studies on patient flow exist in conventional hospital settings, as well as in related applications, such as process optimization in temporary COVID-19 hospitals [32], workflow analyses of field hospitals in earthquake contexts [33], and dynamic simulation–optimization approaches for mass casualty incident management [34], to the best of our knowledge, none frames the problem as a comprehensive patient flow optimization framework specifically tailored to Emergency Medical Team (EMT). According to Section 1.1, the capabilities of behavioural-based microscopic analysis of patient flow by pedestrian simulation has been limited to evacuation scenarios [35,36]. Nevertheless, it can provide data, at a finer assessment scale, to understand how behavioural interactions between individuals (i.e. patients, staff members) and between them and the layout could affect access timings, possible (over-)crowding phenomena, and possible delays in EMT fruition by patients. The same pedestrian simulation concepts in operational (non-evacuation) conditions are also widely applied to building design and operation assessment (e.g., by occupant/passenger flow analysis) remarking the advantages in supporting the definition and optimization of circulation design and crowd management strategies [35].

Such approaches, however, offer the potential to capture fine-grained interactions between patients, staff, and spatial configurations, providing insights into access delays, congestion phenomena, and system performance under stress.

1.3. Objective of the study

To address this gap, this paper applies a behavioural computer simulation to model patient flow within EMTs. The main objective is to identify two groups of indicators that can be used to create effective models to simulate patient flow in EMTs.

The first group concerns operational rapidity and aims at assessing the EMT efficiency for patient access and treatment, focusing on time- and flow-based (number of patients over the time) indicators. The second group concerns (over)crowding phenomena in the EMT areas, to evaluate if localized effects due to critical user density can appear over space and time, affecting patient comfort levels and possibility of undesirable physical contacts among individuals. In addition, this paper discusses the challenges of implementing such modelling approaches in high-stress, resource-constrained environments and proposes strategies for their adaptation to field

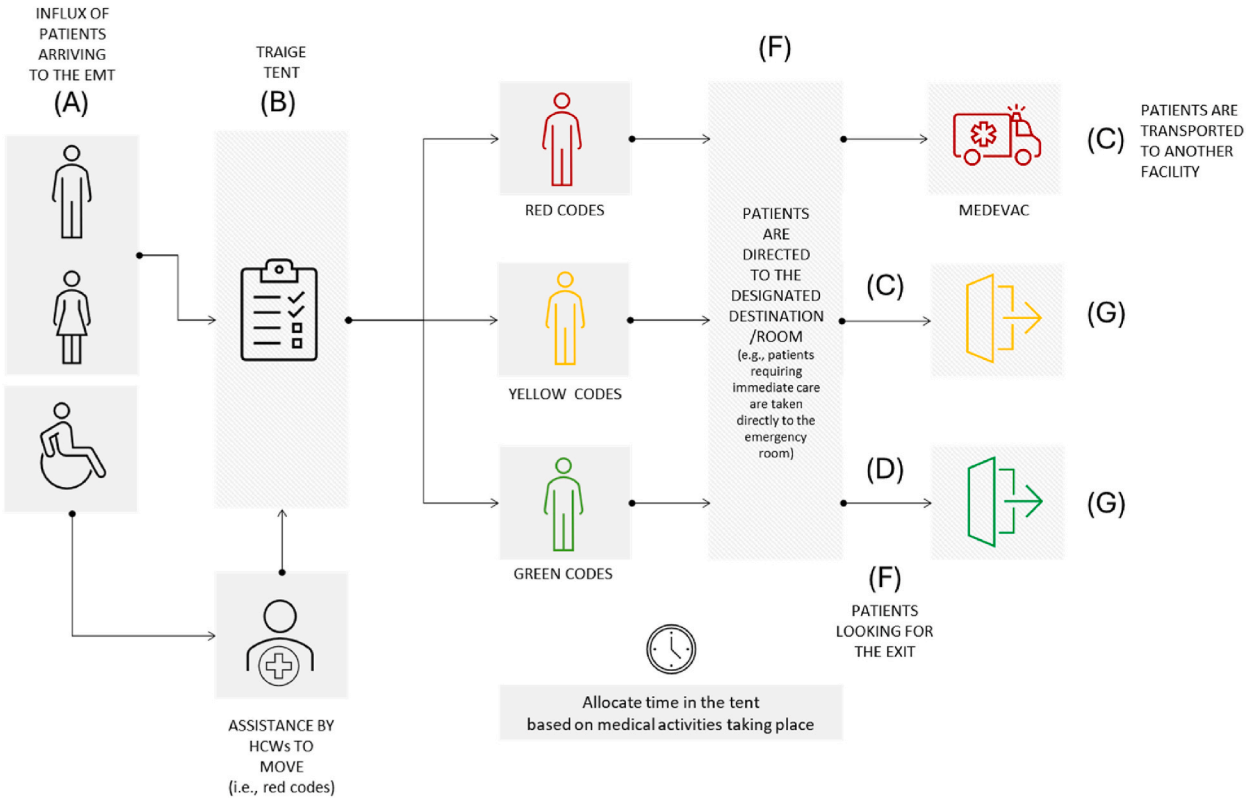

Fig. 1. Conceptual model for patient flow simulation in EMT, adopted by this work. Letters into round brackets are provided in correlation with Fig. 2.

operations. Through this analysis, it highlights the role of patient flow analysis in supporting effective disaster response and improving healthcare delivery in emergency settings.

This study presents the first behavioural simulation framework for patient flow analysis, tailored to Emergency Medical Teams, introducing a conceptual model with agent-specific rules and probabilistic parameters, and a novel set of KPIs drawn from fire safety engineering to quantify operational rapidity and overcrowding, thereby providing a replicable methodological workflow in the context of decision-support tools for EMT layout design, resource allocation, and staff preparedness.

2. Materials and methods

This work consists of three main phases. The first one concerns the definition of the patient flow simulation model, considering a selected hospital layout, and its implementation using an agent-based simulator already adopted in occupant movement assessment for healthcare facilities (Section 2.1). The model is applied to a layout derived from an existing EMT type 1 fixed [29]. The second phase concerns the definition of user-centred Key Performance Indicators (KPIs) which can describe different aspects in field hospital management and patient flow (Section 2.2). Finally, the last phase provides the definition simulation scenarios investigated in this work, which have been analysed and compared thanks to these KPIs (Section 2.3).

2.1. Definition and implementation of the patient flow simulation model

2.1.1. Conceptual model

Fig. 1 summarizes the conceptual model adopted for patient flow simulation in EMT, moving from the influx of patients arriving to the EMT, to the treatment process, up to the exit from the EMT. Different types of patients and operators have been modelled through the definition of their simulation rules according to typical behaviours in EMT, and thus of mutual interactions [37], each with specific motion abilities and speeds [38].

In Fig. 1, letters in round brackets define the main operational elements and areas which are then reported in the EMT layout reported in Fig. 2.

In view of the above, this work adopts three colour categories for patients following the Standard Operating Procedures (SOPs) of an existing EMT type 1 fixed, as outlined in Fig. 2. An EMT Type 1 is an outpatient emergency care unit designed to provide rapid

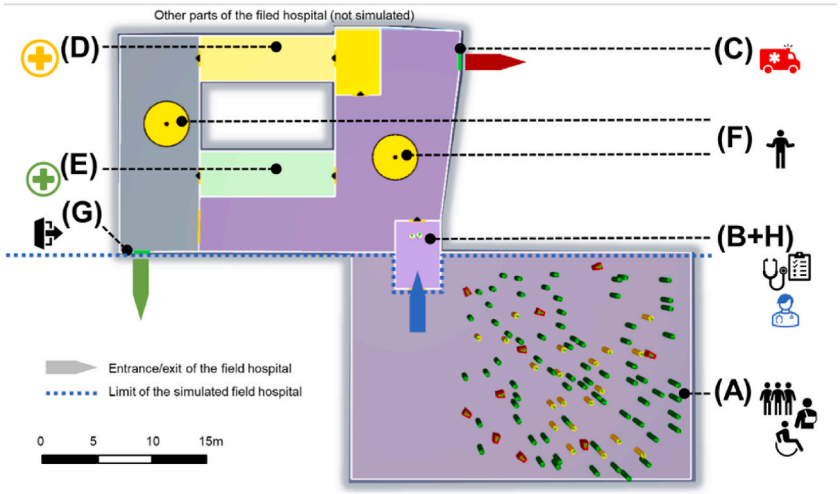

Fig. 2. Layout scheme in Pathfinder of the simulated field hospital area. Letters in round brackets refer to the blocks in Fig. 1. Small black triangles show the internal flow direction and the position of cross points and entrances between different areas and tents.

medical assistance during disasters and humanitarian crises that delivers basic emergency and primary healthcare (e.g., triage, wound care, minor procedures, stabilization) without inpatient or surgical care [29].

However, other triage systems and facility layouts can also be integrated by extending the overall concept [37]. In this regard, letters in round brackets in Figs. 1 and 2 highlight the following simulation elements.

a) Health Care Workers (HCWs) are initially positioned in the triage tent (B). In the simulation, they primarily assist non-autonomous patients, specifically those classified as red-codes patients. HCWs exit the simulation once they have collected all the red-code patients and accompanied them through the designated red-codes exits.
b) Patients generally arrive at the field hospital (A) and stop in the waiting area. They then enter the facility through the triage tent (B) and move through the facility according to the adopted triage system, in this case the Manchester Triage:
   - RED-CODE: These patients have the highest priority in accessing the facility. Once they arrive in the waiting area, an HCW moves towards them, collects them, and guides them through the facility, entering the triage tent. After the assisted red-code patients reach the red-codes exit and are evacuated to another medical facility, they are removed from the simulation. Meanwhile, the HCW becomes available again to assist other non-autonomous patients. The HCW then returns to the waiting area (A) and restarts their movement-related support activities.
   - YELLOW- AND GREEN-CODE: Yellow-code (D) and green-code (E) patients are assumed to autonomously enter the triage tent and then to move to the appropriate medical tent. After receiving medical treatment, they proceed to the field hospital exit (G). Both yellow and green patients autonomously move to the designated medical tent for treatment (F), and then to the exit (G). Once they reach the field hospital exit, they are removed from the simulation.
c) The time patients spend in the tents depends on the medical activities performed inside each tent. A maximum number of staff members and patients is defined for each tent. If a tent reaches its maximum occupancy, additional patients will wait outside and gradually enter as space becomes available.

Specifically, dwell times were modelled using uniform distributions, reflecting uncertain but constrained process durations.

- Triage: 120, 180 s
- Green (minor cases) treatment tent: 180, 360 s
- Yellow (urgent cases) treatment tent: 300, 600 s

Operators and red-codes patients receive higher priority in movement in respect to yellow- and green-code patients [37]. This means that: (1) operators can overtake other queuing patients to enter/exit the EMT; and (2) red-codes are assisted first by operators, and thus they enter the EMT as soon as possible (depending on the number and availability of operators), by also overtaking yellow- and green-code patients who are waiting to access the EMT.

Finally, the model considers that yellow- and green-code patients.

- can be aware or not of the position of (1) the specific tent they should reach in the EMT, and (2) the EMT exit. Therefore, they can perform wayfinding tasks, spending time seeking and identifying (F) the appropriate medical tent and the exit.
- Wait for availability when a medical tent reaches its maximum occupancy, by remaining in the area placed in front of the tent entrance.

Therefore, the model assumes that some "attraction areas" for these behaviours are present in the EMT layout, being placed in the area facing tents and the final EMT exit (see yellow circles in Fig. 2).

2.1.2. Implementation in the agent-based simulator

This work implements the model defined in Section 2.1.1 within the Pathfinder Thunderhead Engineering Version 2023.3 simulator.[1] This agent-based simulation model has been widely applied in studies analysing patient flows under emergency conditions in healthcare facilities [28,38,39], as it enables microscopic representation of interactions between patients and staff members including movement-related support actions. Pathfinder allows the use of "steering mode," meaning that patients and staff can dynamically select their movement directions in response to environmental conditions, thereby increasing simulation reliability compared to density-based simulation models [40]. Additionally, Pathfinder has undergone verification and validation procedures[2] in accordance with international standards [41].

A rapid setup-based application of Pathfinder has been considered to implement the general rules described in Section 2.1.1, thus avoiding source-code modifications or integrations. First, simulated agents have been mainly represented by assigning: (1) the possibility to access specific areas, tents and exits in the EMT depending on their colour code, as discussed in Section 2.1.1; (2) their individual features, associated to variability distribution and random errors, according to a probabilistic behavioural approach [28].

In particular, the individual features refer to motion speed and dimension, distinguishing operators and patients, and patients by colour code. In addition, the priority in movement is modelled through discrete priority levels, assigned to each occupant. This determines whether a patient or operator should have a higher precedence in movement relative to the others nearby, according to Section 2.1.1 general modelling rules. In this sense, red-code patients receive higher priority [37].

Finally, two triggers have been placed in the areas in front of yellow- and green-code tents, based on Pathfinder's attractor elements for managing patient flows. These triggers simulate gathering areas where patients perform wayfinding tasks or wait for the availability of the medical tent. According to Pathfinder modelling logics, each trigger is associated with an influence value that interacts with individual susceptibility of each patient to seeking or waiting actions. A higher trigger influence increases the likelihood that patients will move towards the trigger and remain there. Pathfinder evaluates the final effect by comparing the trigger influence with an individual random number associated with the patient susceptibility to the trigger. "If the random number is less than the probability value, the occupant will use the trigger.[1]"

Monte Carlo criteria have been used according to the probabilistic standpoint in simulation performing [37]. In particular, the initial position and individual features of patients were randomized, and 10 repetitions were generated for each scenario [42]. This approach allows for a rapid assessment of common issues in patient flow estimation [37]. Each repetition uses a fixed maximum simulation time of 3600 s, in line with Pathfinder's core capabilities and to enable comparison of 1-h performance across different scenarios and conditions. Simulation results are aggregated statistically using median values, which are robust to outliers, and percentile-based values, which ensure to consider less probable but representative conditions [41,43]. Moreover, the convergence of main simulation outputs is verified according to consolidated approaches. Convergence thresholds are set up to have a reasonable degree of accuracy of results for a preliminary application aimed at methodological capabilities demonstration. These thresholds are set up equal to 1% for the exit times (total and 95th percentile), and equal to 5% for metrics related to curve shape and standard deviation of exit times. These thresholds are verified for 3 consecutive runs as reference for acceptability. In view of the above, it is worth noting that this convergence assessment using Monte Carlo criteria demonstrates numerical stability rather than complete validation of the study-specific EMT model.

2.2. Key performance indicators (KPIs) definition

The simulation model defined in Section 2.1 enables the analysis of different scenarios in terms of patient input conditions and operator management strategies, thanks to the analysis of statistically aggregated results. Graphical and numerical KPIs are defined to describe the performance levels depending on the field hospital under varying management dynamics. The KPIs adopted in this work have been derived from typical pedestrian-flows analysis [44–46] and from risk-assessment procedures used in emergency contexts, such as fire safety [37,40–42].

To assess the operational rapidity of overall patient flow, the following KPIs are considered.

- Number of patients exiting the field hospital over the simulation time (graphical – represented as a curve).
- Total number of patients exiting within 1-h $P1_h$, that is the maximum simulation time (numerical – expressed in [patients]).
- Exit time for the 5% and 95% of patients, respectively T5 and T95 (numerical expressed in [s]), used to exclude behavioural outliers (i.e., early patients unaffected by queue limits, and late patients affected by tail-end queueing delays).
- Patients flow for scenario "scen" $F_{patient,\ scen}$ (numerical - expressed in [patients/s]), calculated using the interval between 5% (always fixed equal to 5 patients to have a basic comparison value) and 95% exited patients in the simulation time, as in Equation (1), to exclude behavioural outliers.

[1] https://support.thunderheadeng.com/docs/pathfinder/2023-3/(last access: 27.07.2024)
[2] https://support.thunderheadeng.com/docs/pathfinder/2023-3/verification-validation/(last access: 27.07.2024)

$$F_{patients} = \frac{0.95 \cdot P_{1h} - 5}{T95 - T5} \; [patients / s] \tag{1}$$

- Percentage differences of patients' flow, $dF_{patient}$ (numerical – expressed in %) computed using Equation (2), where $F_{patient,ref}$ is the patients' flow under baseline reference conditions. A value of $dF_{patient} > 0\%$ indicates that the investigated scenario performs well than the reference one.

$$dF_{patients} = \frac{F_{patient,scen} - F_{patient,ref}}{F_{patient,ref}} \cdot 100 \; [\%] \tag{2}$$

These KPIs captures the overall trend in patient flow outcomes for an abroad perspective. More efficient patient flow results in higher values of $P1_h$, steeper exit curves, and increased $F_{patient}$ assuming no major operational disruptions. Additionally, the average exit time per patient type T_{aver} [s] (green, yellow, and red-code patients), is calculated to evaluate differences in treatment processes across scenarios.

To assess localized effects of (over)crowding in the field hospital, the following KPIs are used.

- Boxplot of patient density in critical areas (graphical - expressed in [patients/m^2]), along with the median patient density (numerical - expressed in [patients/m^2]), which is more robust to outliers than the mean. In this study, critical areas include the triage tent entrance and the trigger zones (enter and exit of the tents) at each medical tent (Fig. 2).

Table 1
Inputs for simulation: variable/constant inputs associated with related unit of measure, assumed values per scenario and notes to the simulated conditions they represent.

INPUTS	UNITS	ASSUMED VALUES PER SCENARIO (DIVIDED BY "; ")	NOTES ON SIMULATED CONDITIONS [REFERENCES] (DIVIDED BY "; ")
VARIABLE INPUTS			
Green-/Yellow-/Red-code patients ratio	%	70/20/10; 100/0/0	Possible real-world conditions; baseline conditions [47,48]
Number of operators for assistance of patients while moving	operators	0; 2; 4	Different basic levels of assistance to the yellow- and red-code patients (0 for only green-code scenarios, see the previous line). SOP-based
Trigger effects and related waiting time to look for information	% and s	Respectively, 50% and uniform distribution from 0 to 60s (effect on patient trajectory); 0% and susceptibility 0s (no effect on patient trajectory)	No specific way of finding information shared with patients; wayfinding information shared with patients (e.g., visual signage)[a]. Author-defined.
CONSTANT INPUTS			
Number of overall patients	patients	100	Mass arrival of patients (all arriving together) on two buses. Exercise-based
Basic tent module (useable area)	m^2	24 (4.88m × 4.88m)	Standard shelter support system (based on commercial systems[b]): 1 module for triage, 2 modules for green-code tent, 1 + 2 modules for yellow-code tent (see Fig. 2). SOP-derived (see footnote 4)
Entrance, exits and walkways width	m	2	Standard width in typical field hospitals, enabling patients and operators to cross using a wheelchair or carrying a bed/stretcher. SOP-based
Basic tent module maximum capacity	occupants	4	For triage and access tents to yellow-code area, the maximum capacity is four occupants, while for tents hosting green- and yellow-code medical tasks, maximum capacity is eight occupants. Author-defined
Medical staff members remaining in tents over simulation	medical staff	2	Medical staff in triage, green and yellow codes tents according to typical operational conditions. Therefore, the maximum capacity for tent modules should be halved. SOP-based.
Green-code patient speed and operators' speed	m/s	Uniform distribution from 1.2 to 1.8 m/s	Free movement (single pedestrian) speed of autonomous people [38,42]
Yellow-code patient speed	m/s	Uniform distribution from 0.57 to 1.0 m/s	Free movement speed for disabled occupants with mobility impairments (i.e., mobility devices as wheelchairs) [38,42]
Red-code patient speed	m/s	1.06	Free movement speed for disabled occupants with mobility impairments (i.e., mobility devices as wheelchairs to beds/stretchers) [38]
Priority of patients and operators while moving	-	Ten for red-code, five for operators, two for yellow-code, one for green-code	Leading patients to accelerate the entrance of red-code patients in the field hospital, then the movement of operators, and then the entrance of yellow-code patients (in this order) in respect to green-code patients. Author-defined based on Pathfinder simulation logics.

[a] In the current work, it is considered that the trigger has a specific influence on waiting and seeking behaviours that is equal to 100% in absence of wayfinding system, and of 0% in case of wayfinding system presence. Patient susceptibility to the trigger is also considered (equal to 50%), and it is multiplied with the trigger influence to effectively calculate the final trigger influence, which is thus equal to 50% at most.

[b] E.g., see https://deployedlogix.com/product/asap-hub/.

- Time series of patient density in these critical areas (graphical – expressed as time series).
- Spatial density in critical areas of the field hospital at discrete significant simulation time (graphical - shown as a map of patient density, expressed in [patients/m^2], in the field hospital space). In this study, discrete selected simulation times are derived analysing density time series to identify significant moments that qualitatively describe typical conditions.

In general, higher KPIs values correspond to greater (over)crowding effects. Additionally, density levels should not exceed 3.6 patients/m^2, as they can lead to critical physical contacts among patients, while maintaining densities below 1.5 patients/m^2 is preferable to allow individuals to stand comfortably while waiting [45].

2.3. Simulation scenarios definition and comparison rules

Table 1 presents the simulation inputs used to create scenarios within Pathfinder, considering the layout in Fig. 2. Constant inputs are considered the same for all the simulated scenarios and based on literature works [38], while variable inputs are considered to represent different conditions for the field hospital patient flows. Considering the possible combinations between variable inputs, 12 basic scenarios have been selected as shown in Table 2.

Scenario 1 is the baseline one in terms of patients' conditions and management tasks, thus being considering the baseline for comparisons (i.e. $F_{patient,ref} = F_{patient,S1}$ for Equation (1) application).

The choice of 100 patients is based on a standardized "inject" scenario commonly used in official exercises (e.g., ModEx). These scenarios are designed to represent possible surge events in disaster settings and are intentionally constructed to stress the operational capacity of Emergency Medical Teams (EMTs). The 1-h simulation horizon was selected to represent an acute surge phase, during which patient inflow is concentrated over a short period. The referenced inject scenario can be provided as supplementary material upon request. As there is no single universal ratio for triage categories, given that distributions vary depending on disaster type, setting, and triage method, we based our assumptions on findings reported in the literature [47,48].

Except for scenarios 1 and 2, which includes only green-code patients, all remaining scenarios are duplicated to account for operator management issues related to red-code patients.

- Scenarios marked with "A" (i.e., 3A, 4A, 5A, and 6A) represent basic conditions in which red-code patients access the triage area using the same entrance as green- and yellow-code patients.
- Scenarios marked with "B" (i.e., 3B, 4B, 5B and 6B) represent basic conditions in which red-code patients access the field hospital through a separated entrance and do not access the triage.

Additionally, scenario 1, as well as the best-performing and worst-performing scenarios (based on the number of patients exiting the field hospital over the simulation time and the total number exiting within 1 h) are further examined by creating an additional sub-scenario in which the field hospital exit is closed for the first 600 s of the simulation. This sub-scenario aims to reproduce a real operational issue observed during a previous real-world drill. Once the exit re-opens, patients are assumed to be guided towards it, being fully aware of the exit location through wayfinding solutions. These additional scenarios are marked with the letter "C."

Table 2
Simulation scenario outlines according to variable input values (see Table 1). In the sub scenarios, "A" refers to no separate access for red-code, "B" refers to separate access for red-code, "c" refers to scenarios in which the exit is initially closed.

SCENARIO ID	SCENARIO DESCRIPTION (SUB SCENARIOS)	GREEN-/YELLOW-/RED-CODE PATIENT RATIO (%)		NUMBER OF OPERATORS FOR ASSISTANCE OF PATIENTS WHILE MOVING (OPERATORS)			TRIGGER EFFECTS IN TERMS OF WAITING TIME TO LOOK FOR INFORMATION (S)	
		70/20/10	100/0/0	0	2	4	UNIFORM DISTRIBUTION FROM 0 TO 60S	0S
1	Baseline health condition, no operators needed for motion assistance, no patient wayfinding support {c}		●	●			●	
2	Baseline health condition, no operators needed for motion assistance, patient wayfinding support		●	●				●
3	Standard health condition, standard operators' presence for motion assistance, no patient wayfinding support – {A, Ac, B}	●			●		●	
4	Standard health condition, standard operators' presence for motion assistance, patient wayfinding support - A, B}	●			●			●
5	Standard health condition, high operators' presence for motion assistance, no patient wayfinding support - A, B}	●				●	●	
6	Standard health condition, high operators' presence for motion assistance, patient wayfinding support - A, B, Bc}	●				●		●

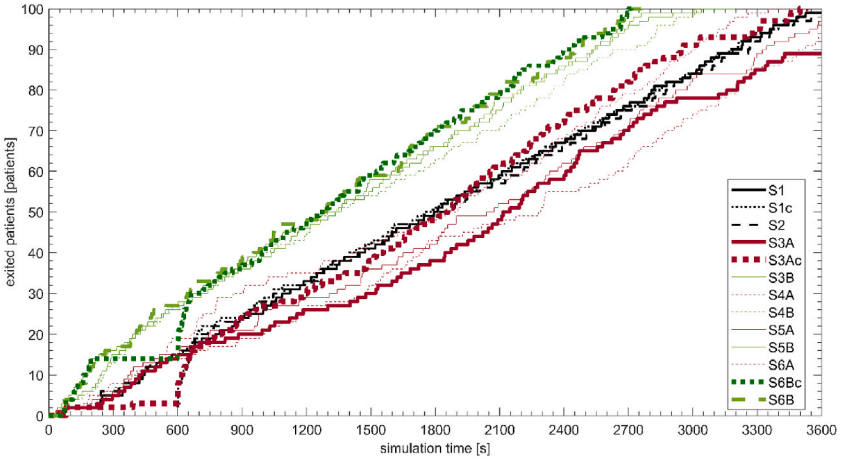

Fig. 3. Number of patients exiting the field hospital over the simulation time. Black lines refer to S1 and S2 as scenarios with only green codes simulated. For the other scenarios, different notations are used to group simulation according to Section 2.3 classification: red lines – under or equal to S1 and S2 scenarios curves, i.e. A scenario: green lines – over S1 and S2 scenarios curves, i.e. B scenarios, thus having a better performance in respect to S1 and S2 conditions; continuous lines – no wayfinding solutions; dashed lines – wayfinding solution implemented; dotted bold lines – initially closed exit (i.e. marked by "c").

Although these selected scenarios do not cover all possible effective conditions in field hospitals, they represent a broad range of situations and incorporate relevant management solutions to be implemented (e.g., varying operators' numbers, trigger effects, and different level of wayfinding support) that can influence patient flow.

3. Results

Results are presented according to the two main groups of KPIs, those related to the operational rapidity (section 3.1) and those assessing effects of (over)crowding (Section 3.2), to highlight the performances of the EMT facility under the simulation scenarios defined earlier.

3.1. Assessment based on operational rapidity

For each simulation scenario and sub scenario defined in Table 2, Fig. 3 shows the number of patients exiting the field hospital over the simulation time, while Fig. 4 visually focuses on the comparison of *T95* and T_{aver} by patient code (Fig. 4-A), and $F_{patient,\ scen}$ and related $dF_{patient,S1}$ (Fig. 4-B), as relevant performance indicators. In addition, a complete list of the KPIs is provided by Appendix A.

As expected, proving separate access to the facility for red-code patients (B-type sub scenarios) ensures not only decrease T_{aver} values for this typology of patients, but also better overall rapidity performances among the scenarios considered, since it more rapidly solves the interactions among other patients. From a general perspective, it is worth noting that the rapidity of B type sub scenarios is higher than the other scenarios, regardless of additional conditions in inputs. As shown by Fig. 3, in B type sub scenarios, the number of patients treated over time is always higher than the one of basic reference scenarios S1 and S2, where only green-code are simulated, as well as of the A-type sub scenarios, where all the patients share the same access to the facility. The impact is then demonstrated by the reduction in KPIs on treatment times during the whole simulation, as reported by Fig. 4-A, which shows how values of *T95* and T_{aver} by patient code are always lower in B type sub scenarios. In particular, the maximum variability of T_{aver} in A-type and B-type sub scenarios is associated with red-code patients, as expected. Since time-related KPIs decrease in B-type sub scenarios, patient flows shown by Fig. 4-B ($F_{patient,\ scen}$ and $dF_{patient,S1}$) increase. Nevertheless, Fig. 3 also repoint outs that most of the rapidity increase of B-type sub scenarios in respect to A-type ones can be noticed by considering simulation times up to 300s. In fact, after 300s, when all the red-code patients are treated (Fig. 4-A), curves for B-type and A-type sub scenarios have the same trend (Fig. 3).

In case of single, shared patients' access to the facility, the presence of only green-code patients or those of all the patient code seem to have a limited impact on the overall rapidity of the process. In this sense, Figs. 3 and 4 stress how similarities can be noticed considering between S1 and S2 scenarios and A-type sub scenarios, since both consider a unique access to the facility, but reasons behind such results depends on the typology of simulated patients, and on microscopic interactions among considered patients.

In S1 and S2, main crowd interactions are essentially due green-code patients, who move towards the same flow paths being affected by queuing phenomena between patients having the same priority. As a result, values of *T95* and T_{aver} by patient code (Fig. 4-A) are almost the same. In this perspective, the queuing phenomena in S1 and S2, and thus the curves in Fig. 3, are also influenced by the maximum capacity of the triage and green-code tents. Since the maximum occupant capacity of the triage tent is lower than the one of the green-code tents, "bottlenecks" essentially involve the triage tent and thus minor effects on the whole simulation curve due to

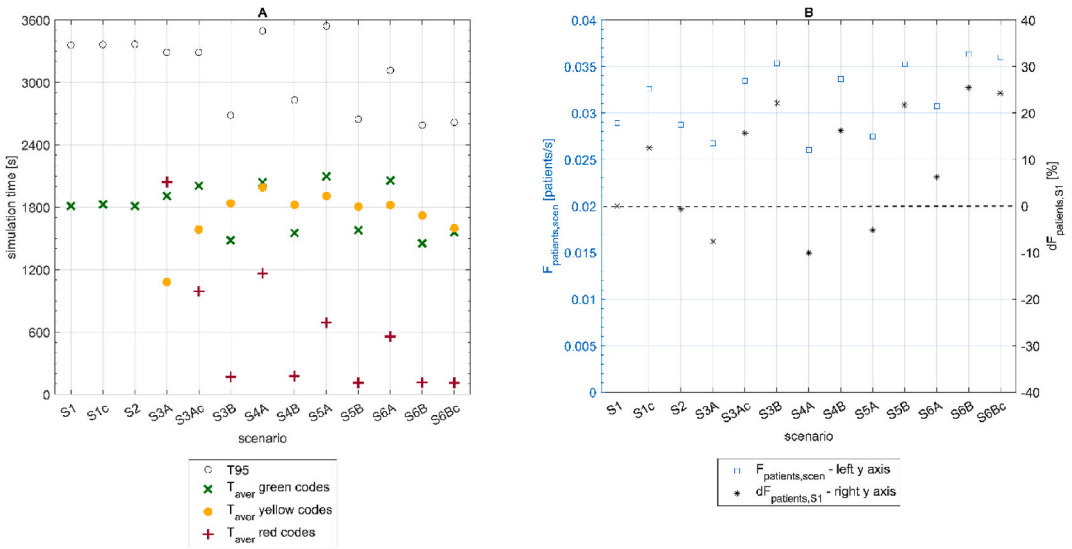

Fig. 4. Comparisons by simulation scenario of: (A) exiting times [s], considering the exit time of 95% of patients (T95) and the average exiting time for patient typology; (B) the overall patients' flow in the given scenario "scen" $F_{patient,\ scen}$ (referenced to the left y axis) and the percentage differences of patients' flow in respect of baseline scenario S1 $dF_{patient,S1}$ (referenced to the right y axis; the dashed black line marks $dF_{patient,S1} = 0\%$).

trigger attraction representing wayfinding tasks. As a results, $F_{patient,S1}$ and $F_{patient,S2}$ are almost equal (and Fig. 4-B). A-type sub scenarios rely on similar interactions among users, but they are amplified by the presence of red-code patients and operators queuing to enter the triage tent. Therefore, Fig. 3 shows that curves for A-type sub scenarios are generally lower than the ones of S1 and S2.

The initial closure of the final exit for green- and yellow-code patients seems to limitedly affect the overall rapidity of the process in case of the presence of green-code patients only, and when red-code patients have specific access to the facility. In this sense, Fig. 3 respectively shows that curves for S1 and S1c, and for S6B and S6Bc are very close one to each other. Nevertheless, when only green-code patients are present, the patient flows seem to increase. In fact, $dF_{patient,S1c} > 0\%$, underlining an increase in the flow-related KPI $F_{patient,S1c}$ in respect to $F_{patient,S1}$ (Fig. 4-B). In this sense, it is worth noting that, in S1c, this effect is due to *T5* increases. The exit opens at 600s, and the first 5 patients only exit at this moment of the simulation. T5 in S1c is hence equal to 600s, while, in S1, to 249s, while *T95* for S1c and S1 are essentially the same (about 3360s). Therefore, considering that $F_{patient}$ depends on the ratio between the exited patients (90 patients in both the scenarios) and the time difference between *T95* and *T5* (about 2850s in S1c and about 3100s in S1), $F_{patient,S1c} > F_{patient,S1}$. Specific value details to support these outcomes are reported in Appendix B. A similar effect, considering the same reasons and phenomena related to the final exit opening time, can be also noticed in S3Ac, indeed.

In addition, the initial closure of green- and yellow-code exit seems to have different impacts depending on the specific operational conditions. In fact, S6B and S6Bc curves (Fig. 3) have the same initial slope within the range from 0 to about 300s. This time span is characterized by the completion of treatment of red-code patients, who access and move in the facility with related assisting operators through specific paths and exit. Hence, T_{aver} for red-code patients in these scenarios is almost the same, since it is not influenced by the closure of the main exit of the field hospital, which is indeed used by green- and red-code patients. Then, after 300s, S6Bc has a horizontal plateau due to the closure of the main exit for green- and yellow-code patients. When this exit opens at 600s, S6Bc curve rapidly increases due to the exit of patients waiting at the trigger placed after the medical tents exits, and it assumes a slope trend similar to the one of S6B. On the contrary, in scenario S3Ac, it can be noticed that, after 600s, the slope of the curve is initially higher than the one of S3A (i.e. between 600s and about 1200s), and then they are almost similar. It can be noticed a beneficial impact in red-code patients' assistance during this time range, as also noticed by Fig. 4-A. Since the queuing along the yellow and the green-code patients' paths is initially also affected by the closure of the related exits, the priority of red-code patients and operators in entering the field hospital seems to assume a prevalent role in crowd organization, accelerating the related red-code patients' flows. As an output, T_{aver} for yellow-code patients in S3Ac increases (both due to the initial exit closure and to this flow effects), and the value is almost equal to the one of S6Bc.

Implementing solutions with 4 operators rather (i.e. S5 and S6) than 2 (S3 and S5) increases the rapidity of the patient flow, as expected, especially when combined to B-type sub scenarios. In this sense, not dividing entrance paths for red-code patients in case of 4 operators seems to limit the effectiveness of such a strategy, as in the case of S5A, as shown by $dF_{patient,S1} < 0\%$ and by the increase in *T5* (compare with Appendix A).

Fig. 4-A also stress some the role of priority of patients and operators in accessing the facility. The performance of green-code patients is mainly influenced by general queueing phenomena. A shown by Fig. 4-B, T_{aver} of green-code patients is almost in the same range (between 1500 and 2100s) in all the simulated scenarios. In fact, they still represent the 70% of the whole simulated patient sample for simulation scenarios from S3 to S6, and, in these scenarios, they have the lower movement priority. In A-type sub scenarios, they should divide access with both yellow- and red-code patients, and thus their T_{aver} is always higher than those of B-type sub

scenarios. In addition, since yellow-code patients have an intermediate priority, in A-type scenarios, their T_{aver} is always lower than the one of green-code patients, as expected, due to the amplification of queuing phenomena in facility access and movement. In B-type sub scenarios, values seem to be higher essentially since they can have priority access to the facility in respect green-code patients, but they also move significantly slower than green-code patients. Nevertheless, results on yellow-code patients could have indeed a lower validity, being them indeed the 20% of sample. Moreover, it is worth noting that specific differences in each scenario between A and B-type sub scenarios could be affected by randomness variations of initial positions, still leading to different effects in patients' priority while entering the triage tent.

Finally, the implementation of wayfinding solutions seems to increase the rapidity of the process, especially considering B-type sub scenarios. In fact, Fig. 3 shows how S6B are the most rapid curves. Nevertheless, in A-type scenarios, some differences among the rapidity of the process exist. While the whole patient flow ($F_{patient,\ scen}$ in Fig. 4-B) increases in S4A and S6A if compared, respectively, to S3A and S5A, local differences in curves slope (Fig. 3) trace some secondary effects in crowd organization. In S4A and S6A, patient flows are affected by the combination between the tent capacity (implying that patients should wait before proceeding on their flow), and the waiting time for medical treatment inside the tents. In S3A and S5A, the process is also affected by the time spent to looking for the path to be followed within the field hospital, implying longer local horizontal plateau related to the activation of these seeking and waiting behaviours in absence of direct wayfinding support. In addition, this impact seems to be more relevant in case of four operators, due to the additional interactions between them and the yellow- and green-code patients, although no specific red-code patients' entrance is implemented, as in A-type sub scenarios. This hence led to the overall increase in the operational rapidity, as shown by $F_{patient,S6A} > F_{patient,S5A} \approx F_{patient,S4A} \approx F_{patient,S3A}$.

3.2. Assessment based on the effects of (over)crowding

For each simulation scenario and sub scenario defined in Table 2, Figs. 5 and 6 relates to the KPIs concerning the assessment of localized effects of (over)crowding in the field hospital layout. In particular, Fig. 5 shows *the boxplot of patient density in critical areas of the field hospital*, and thus considers the entrance to the triage tent (Fig. 5-A), and the two considered triggers, that are the area to enter the medical tents (Fig. 5-B) and the area placed after the medical tents exits (Fig. 5-C). Fig. 6 shows *the patient density in critical areas of the field hospital over the simulation time*, by focusing on the entrance to the triage tent, since it has the highest values and densities that are often higher than the critical considered thresholds of 3 and 1.5 patient/m^2 (compare Fig. 5).

As expected, the adoption of separate access to the facility for red-code patients, as in B-type sub scenarios, reduces local density values, since the strategy better organizes the entrance in the field hospital, and thus organizes the crowd in the first access area. As pointed out by Figs. 5 and 6, the reduction in median densities values reaches up −33% for S3B, while those for maximum values

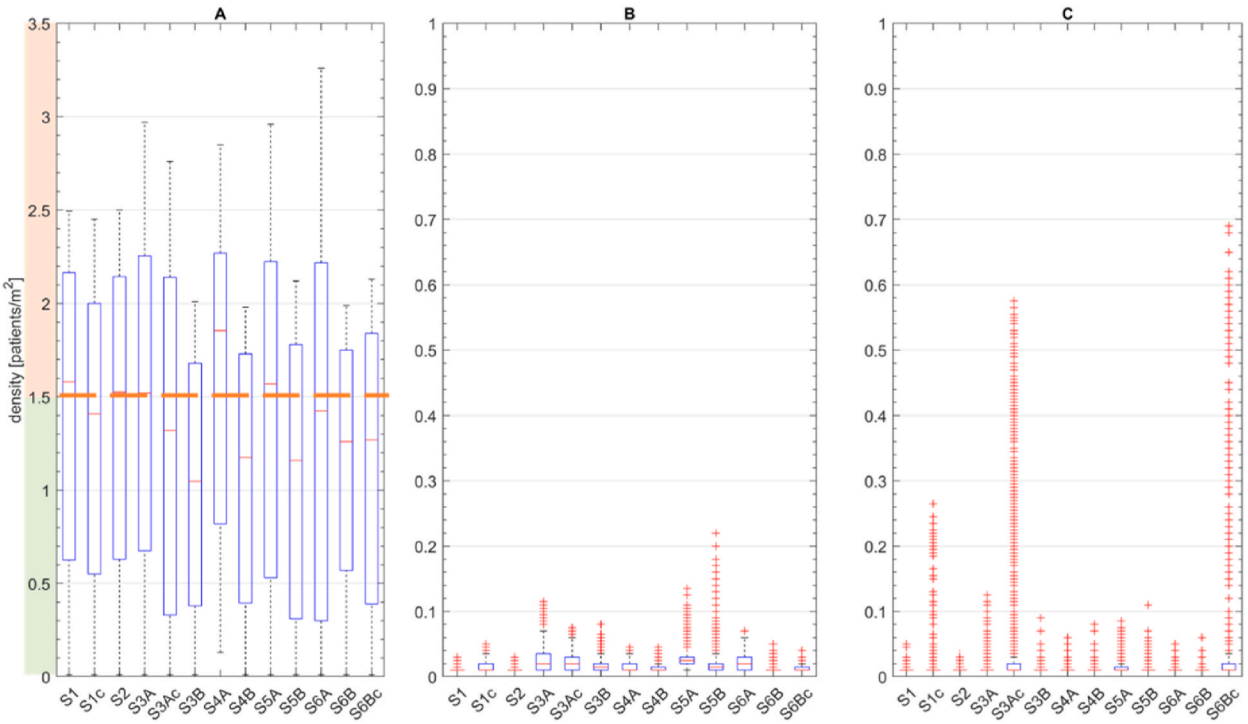

Fig. 5. Boxplot of patient density in critical areas of the field hospital: (A) entrance to the triage tent, where the orange dashed lines divides the critical (red colours on the y axis) to the comfort (green colours on the y axis) density values; (B) access area to the medical tents; (C) exit areas from the medical tents.

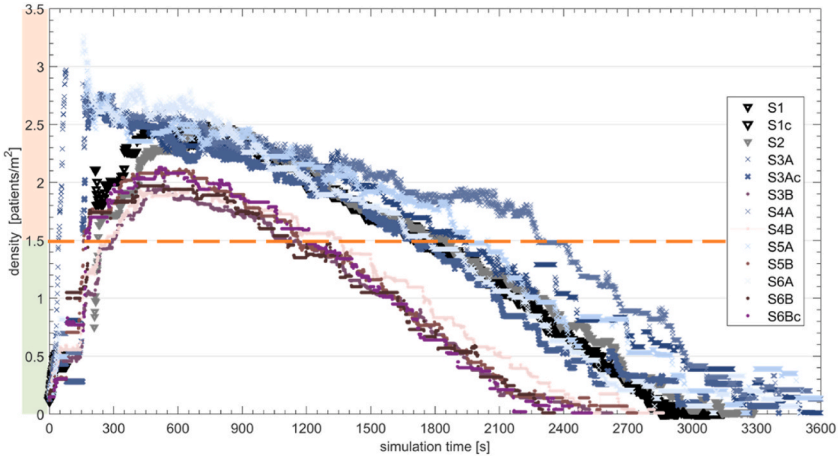

Fig. 6. Time series of patient density in the waiting area at the entrance of the triage tent of the field hospital over the simulation time, by simulation scenario. Black lines refer to S1 and S2 as scenarios with only green codes simulated. Blue curves have a comparable or lower performance than S1 and S2 scenarios, while purples ones have a higher performance in terms of density conditions. The orange dashed lines divides the critical (red colours on the y axis) to the comfort (green colours on the y axis) density values.

reaches up to about −54% for S6B, especially at the entrance of the triage tent. Nevertheless, critical (over)crowding conditions among patients are not generally reached in all the considered scenarios, essentially because of the crowd organization to ensure the access to patients with higher priority levels (i.e. operators and assisted red-code patients). Therefore, the boxplot visualization in Fig. 5-A also point outs that up to about or more than 50% of conditions in all the simulation generally does not lead to uncomfortable conditions, being the median values generally lower than the 1.5 patients/m^2 threshold. Critical threshold of 3.6 patients/m^2 is not reached by maximum density values and values over 3 patients/m^2 appears only for a very limited time. The same effects are also visible over time, according to Fig. 6.

In view of the above, the main effects of crowding are related to the entrance area (Fig. 5-A) and not to the parts inside the field hospital (Fig. 5-B and Fig. 5-C). Comparing such remarks with the temporal evaluation of crowding levels at the entrance area (Fig. 6), it could be possible to argue that crowd management can be a priority before the patients entrance in the facility, but related interventions (e.g. by deploying staff or specific queuing areas/paths to support entrance flows) could have higher value in the first minutes of facility operation (i.e. about to 600s, since after this moment, densities sensibly decrease in all the simulated scenarios).

Conversely, the implementation of crowd management strategies inside the facility could be not relevant in respect to the noticed effects of crowding. The triage tent capacity is lower than the medical tents ones, and permanence timings in the triage and green-/yellow-code tents considered in simulation are quite similar. Therefore, densities in the area to enter the facility tents (Fig. 4-B) are limited in view of the limited number of patients waiting at the same time in this area.

Indeed, a beneficial effect in the reduction crowding levels can be retrieved if implementing wayfinding solutions, as expected. Fig. 5-C shows how the range of densities in scenarios adopting wayfinding solutions (S4 and S6) is lower than the ones in which trigger attraction is present (S3 and S5).

The densities of patients in the area placed after the medical tents exits (Fig. 5-C) is higher in the "c" scenario than in the others, since the exit opens after 600s from the simulation starting and thus patients' waiting time considerably increases. Nevertheless, since this condition is retrieved only for a limited simulation time, it essentially seems to have lower statistical relevance, representing maximum values (detected as outliers) in the S1c, S3c and S6Bc density boxplot distribution shown in Fig. 5-C. Moreover, reached densities are always lower than the 1.5 patients/m^2 threshold for standing in comfort conditions, because waiting patients are limited (about 15 patients as shown by the sloped graph area in Fig. 3 in a neighbourhood of 600s – please also compare with results analysis in Section 3.1).

Finally, in view of Fig. 5 outcomes, three main scenarios can be considered to explore microscopic (over)crowding effects in terms of *the patient density in critical areas of the field hospital* as shown by the maps in Fig. 7. The *patient density* in reference scenario S1 (Fig. 7-A), the "worst" one S3A (Fig. 7-B) and the "best" one S6B (Fig. 7-D) are herein shown at *discrete significant simulation time* referred to events involving the entrance area of the triage tent: when about the maximum of density reached for A-type sub scenarios, that is about 150s, and for B-type sub scenarios, that is about 600s; and when density for B-type sub scenarios tents to 0. In addition, S3Ac (Fig. 7-C) and S6Bc (Fig. 7-E) are also assessed by these maps to compare the effects of final exit closure on the patient density in the field hospital. The maps show the extent of crowding areas from 0.6 to 3.6 patients/m^2, by scale colour from blue to red. These outcomes graphically underline.

- **the effects of the exit closure in S3Ac and S6Bc and their differences in patient flow management effects**: in S3Ac (Fig. 7-C), all the patients are gathering near to the trigger, seeking and exchanging information; in S6Bc (Fig. 7-E), some patients can still identify the exit by moving towards it although it is still closed, thanks to wayfinding signage;

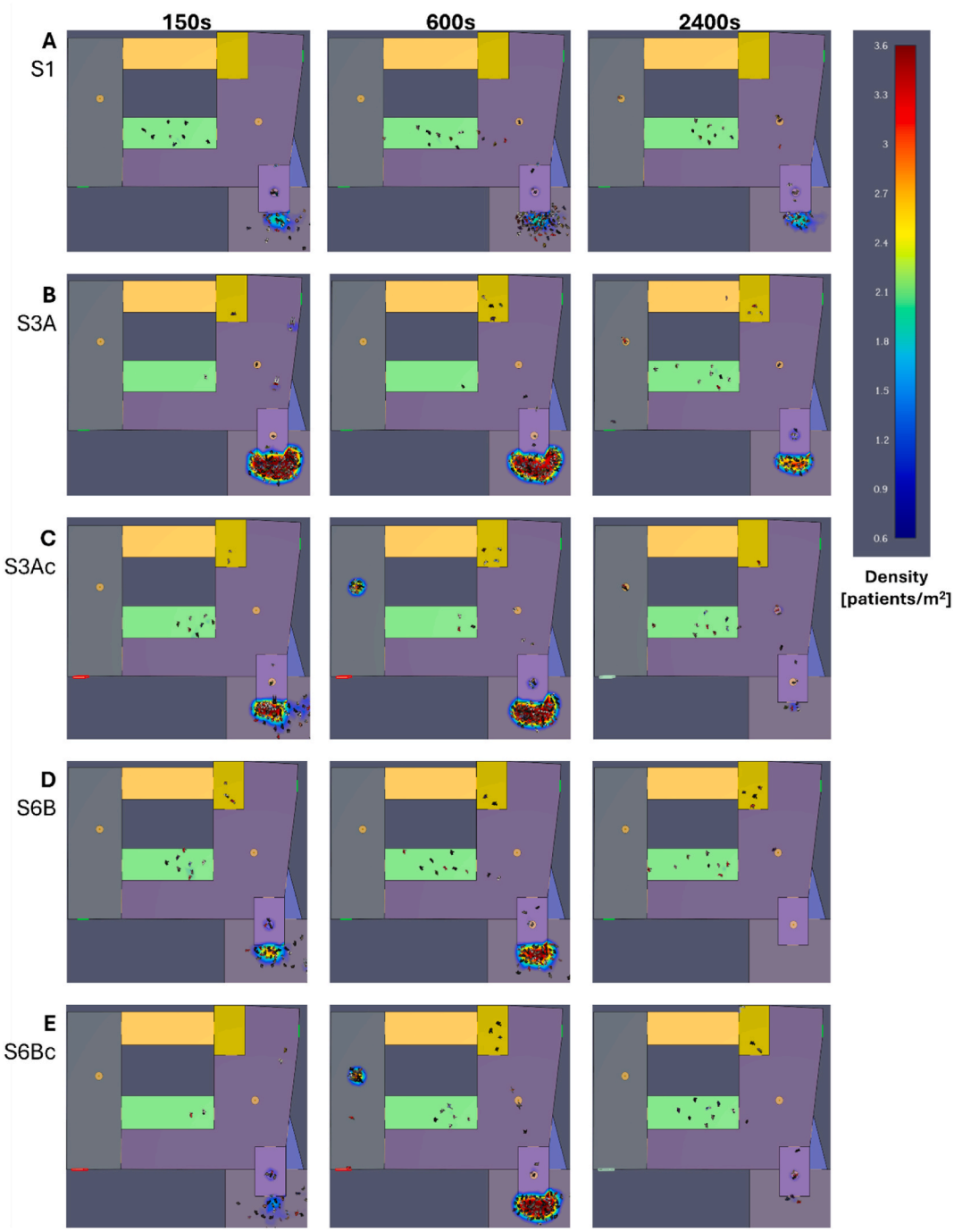

Fig. 7. Maps of the patient density in critical areas of the field hospital at discrete significant simulation times (i.e. 150s, 600s, 2400s) for: (A) S1; (B) S3A; (C) S3Ac; (D) S6B; (E) S6Bc.

- **the impact of combining different patient typologies with different priorities in respect to the baseline scenario in S1, especially focusing on 600s scenarios.** In S1, densities al generally lower since patients autonomously organize the queue without any priority. In S3A and S3Ac, densities are higher since red-code patients and assisting operators should enter the triage tent trying to move towards the other queuing patients (who have a lower priority). In S6B and S6Bc, densities are in an intermediate range since red-code patients and assisting operators move towards a parallel access way.

4. Discussion

4.1. Key findings on case study application

Based on the simulation results and their convergence using Monte Carlo criteria, several key findings can be highlighted from an overall perspective. As expected, lower overall performance levels, particularly in terms of rapidity and localized crowding effects, were observed where red-codes patients were not provided with a dedicated access to the facility. Conversely, enabling red-code patients to enter through a separate line could substantially improve performance.

A dedicated access for red-code patients reduces queuing phenomena from the very beginning of the EMT operation. This organizational measure also lessens the interferences that causes high crowding, particularly at the entrance of the triage tent with density values exceeding 3 patients/m^2. Even under improved conditions, however, the intermediate comfort threshold of 1.5 patient/m^2 was still exceeded during waiting periods, especially for patients requiring little or no medical assistance.

Quantitatively, separating red-code patients' pathways from yellow- and green-code patients improved overall patient flow by up to +30% (patients/s), and reduced maximum density at the triage entrance by up to −54% (patients/s).

The influence of wayfinding solutions inside the field hospital appeared more limited, with effects mainly associated with local density variations in areas where patients seek or wait for assistance. Their effectiveness also depends strongly on the configuration of the trigger influence values (i.e., behavioural response threshold governing patients' movement decisions).

Overall, the best-performing scenario was the one combining: (a) dedicated access for red-codes patients, (b) a higher number of operators providing movement-related assistance, and (c) patient wayfinding support within the facility. In contrast, the least-performing scenario involved: (a) a common access route for all patients, (b) a standard operator allocation, and (c) no internal wayfinding support. These differences are particularly evident when examining basic KPIs related to operational rapidity, such as P_{1h} and $dF_{patient,S1}$.

Simulation results also highlight that crowd-management actions must be carefully planned both at the arrival area and at the entrance to the triage tent. Deploying trained staff to support patient movement, organizing queuing lines, and defining patient paths could substantially mitigate local interactions that would otherwise lead to overcrowding and reduced access efficiency.

4.2. Implication of the study

This study demonstrates the value of combining real data, simulation models, and KPI-based analysis (as presented in the conceptual flowchart) to create a practical decision-support framework. KPIs derived from fire safety engineering have proven to be effective and reliable for analyzing patient flows, giving decision-makers rapid tools to assess differences in facility organization and management approaches.

Among the KPIs proposed, those describing the overall patient flow in the given scenario "*scen*" $F_{patient,\ scen}$ [patients/s] are suitable for comparative assessment. They can be easily expressed in relative terms and used to compare design alternatives, for instance through percentage terms, as expressed by $dF_{patient}$ in respect to a reference basic condition such as standard organization or current management rules).

To assess localized crowding, heat maps of patient density [patients/m^2] at selected time intervals can visually represent typical local interactions and microscale behaviours. These maps can be linked to discretized conditions such as Levels of Service (LoS), which qualitatively classify crowd dynamics from free-standing and free movement to critical contact conditions.

This methodological approach could be integrated into existing decision-support tools to enable rapid scenario testing prior to EMT deployments. Such integration would support decision-makers in planning efficient facility layouts, allocating resources, and optimizing crowd-management strategies based on quantifiable performance indicators.

4.3. Limitations and future work

This study has several limitations. First, the convergence of results, assessed through Monte Carlo criteria, supports the numerical stability of simulation outputs, thus ensuring that implications can be reasonably derived from results and their interpretation through KPIs. Nevertheless, this work does not provide a complete validation of the application to the specific EMT model considered by this work. This process would need further comparisons with data about patient dynamics and individual movement, along with general timings and behaviours from field experiments (i.e. in real world operational contexts). Nevertheless, this limitation does not hinder from underlining how the proposed methodology can be incorporated into decision-support systems, introducing agent-based behavioural simulation to better understand the operational implications of individual movements and interactions between patients, staff members, and physical layout of the health care facility. Similarly, although the simulations were based on a real field hospital layout, the results are inherently specific to that configuration. In the absence of a standardized rule for tasking and area placement, each future deployment would require adaptation of the model to local site. Additional analysis using alternative layout configurations will be needed to improve the generalization of the model and identify performance variations across different design options.

Furthermore, due to limited data collected during real deployments, certain aspects, such as detailed patient and staff dwell time, queuing behaviours, and task-related performance durations, could not be fully simulated. This highlights the need for systematic data collection during actual deployments and training exercises, as well as the crucial role of a dedicated data manager within field team. Enhanced empirical datasets from real-world experiments or operational conditions during crisis, in different EMTs, would enable

stronger validation of the model and the simulation of additional components, such as patient dwell time inside tents or operator-specific response time variability. Similarly, additional expert validation of simulation results, as well as sensitivity analysis on the adopted setups of behavioural variables, could be performed to increase the reliability of results under several scenarios.

Some caveats should be also pointed out considering the $F_{patient,\ scen}$ indicator, which depends on how the 5% and 95% of patients exit the EMT, through the time difference between *T95* and *T5*. Lower the time difference between *T5* and *T95*, higher the $F_{patient,\ scen}$, and thus higher the operational rapidity. Nevertheless, this indicator must be jointly assessed with time-related KPIs. In particular, we can state that "higher the $F_{patient,\ scen}$, higher the operational rapidity" only if different scenarios are characterized by similar values in *T5*. Conversely, when several scenarios share similar *T95* values, those with the higher the $F_{patient,\ scen}$ is potentially characterized by better operational rapidity under "normal" flow conditions, but no information of potential problems related to *T5* are implicitly reported. Under such conditions, having high *T5* implies the presence of some problems for the patient flow exit from the EMT (in this work, e.g. for S1c and S3c, the delayed opening of the EMT exit), but a high $F_{patient,\ scen}$ still demonstrates that no additional operational issues in patient outflow appear once the initial problems have been solved. Future work could manage the connection of these two time- and flow-based KPIs to create unified metrics, according to the involvement of EMT stakeholders in their definition. This kind of task could be replicated for the whole KPIs, supporting their validation in application contexts.

Considering the definition of KPIs, it is worth noting that density-related ones for (over-=) crowding assessment are based on patients/m^2 as leading unit of measurement, thus mainly considering patients as crowd to be evaluated. In fact, in the current work, the focus refers to performance KPI considering patients, operators are placed in tents, or they move to support patients, and patients represent the whole number of simulated occupants. Nevertheless, future works could adopt occupants (patients plus staff) to estimate density by including other typologies of staff members and operators (e.g., supporting patients during waiting times and queueing, performing additional operations in the EMT layout, such as cleaning, maintenance, material transfer, coordination, and supervision).

Finally, the integration of Virtual Reality (VR) for result visualization represents a promising direction for both training and decision-making. Immersive simulations combining patient movements with real-time quantitative overlays can support more intuitive understanding of patient and operators' movement and flows, as well as of the overall dynamics in EMT management under multiple scenarios. As demonstrated in emergency evacuation research [49], VR-based visualization can foster strong engagement among operators and improve preparedness-related decision-making.

5. Conclusion

As demonstrated in this study and further supported by application in hospital environments hosted in buildings, patient flow simulation can play a pivotal role in the design, management, and optimization of operations in EMTs, as well as in addressing emerging operational issues. Simulating patient movement across different facility configurations can assist decision-makers in identifying the most efficient layout, preventing bottlenecks, and improving overall operational performance. This work innovatively demonstrates how the use of computer-based simulation tools in EMTs offers several advantages thanks to KPI-based analysis devoted to detecting the main issues in patient flows and dynamics during EMT use.

First, such tool can highlight specific activities or processes that may be adapted to facilitate patient movement and improve resources utilization. This result is obtained by creating, for the first time at the authors' knowledge, a conceptual model on microscopic patient flows in EMT, defining behavioural rules and individual features for each simulated patient and operator, and by associating variability in simulation parameters according to a probabilistic standpoint. Moreover, the implementation of the conceptual model in an agent-based simulator (Pathfinder) is innovatively provided by avoiding source-code modifications, and thus just using a setup-based approach. This can ensure the quick replicability of the approach by decision makers. At the same time, KPIs respectively related to operational rapidity and (over-)crowding conditions in the EMT have been innovatively defined to support this analysis, building upon previous research on behavioural assessment in emergency scenarios (i.e. evacuation).

Second, simulations can support the rethinking and redesigning of EMTs according to deployment contexts, considering factors such as site constraints, intended use, and environmental conditions. Building on the insights of this work, the proposed KPIs can be adopted and integrated to evaluate to evaluate how spatial organization further enhance EMTs effectiveness. Finally, simulation environments can also be used for teams training and preparedness, enabling staff to familiarize themselves with patient-flow dynamics and anticipate potential challenges during real operations.

The results presented in this paper could be used as a foundation for further research on patient-flow modelling in field hospitals. We recommend that computer simulation be integrated into the verification process of EMTs within the WHO EMT classification. In this sense, a crucial next step will be the systematic collection of real-world data to validate and refine the proposed model, thereby ensuring its reliability and applicability across diverse field hospital configurations.

CRediT authorship contribution statement

Gabriele Bernardini: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sergio Beneitez Pajares:** Writing – review & editing, Writing – original draft, Resources. **Marco D'Orazio:** Writing – review & editing, Validation, Supervision, Conceptualization. **Enrico Quagliarini:** Writing – review & editing, Validation, Supervision, Conceptualization. **Andrea Bartolucci:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

APPENDIX A

Table A.1
Simulation results outline by investigated scenario: KPIs to assess the operational rapidity concerning the overall patient flow. "n.a.": the value is not assessed since $dF_{patient,S1}$ is calculated having the same reference and current scenario, according to Equation (2).

Scenario	P_{1h} [patients]	95% of exited patients [patients]	T5 [s]	T95 [s]	$F_{patient,\ scen}$ [patients/s]	$dF_{patient,S1}$ [%]
S1	99	95	249	3358	0.029	n.a.
S1c	99	95	602	3364	0.033	12.6
S2	99	95	236	3366	0.029	−0.7
S3A	89	85	297	3289	0.027	−7.6
S3Ac	100	95	601	3289	0.033	13.2
S3B	100	95	137	2683	0.035	13
S4A	94	90	228	3494	0.026	−10.1
S4B	100	95	156	2831	0.034	14.6
S5A	97	95	265	3543	0.027	−5.2
S5B	100	95	93	2646	0.035	12.7
S6A	100	95	189	3116	0.031	3.8
S6B	100	95	111	2589	0.036	26.5
S6Bc	100	95	114	2616	0.036	26.9

Data availability

Main data are included in the appendix. Further details can be requested via email

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