Observational Study

Digital technologies for enhancing evacuation planning in critical care units

A quantitative, experimental simulation

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Abstract

This study aims to evaluate evacuation performance in a high-acuity intensive care unit (ICU) by integrating building information modeling (BIM) and computational simulation and examine how different parametrizations affect the fidelity of predicted evacuation dynamics when compared with data from a real evacuation drill. A detailed BIM model of a tertiary hospital ICU was developed and imported into Pathfinder to simulate 3 protocol-based evacuation scenarios and 1 scenario calibrated with preparation times obtained from a 2024 evacuation drill. Simulations assessed occupant flow, bottlenecks, movement trajectories, and total evacuation times. Architectural constraints, behavioral rules, and patient dependency profiles were incorporated to reflect real operational conditions, including explicit geometric incompatibilities between door widths and ICU bed dimensions. Evacuation times produced with generic parameters showed a gap of up to 7 minutes 40 seconds less than the real drill duration, whereas the empirically calibrated simulation narrowed this difference to 2 minutes 30 seconds. Across all scenarios, bottlenecks consistently emerged at the main critical patient unit exit, primarily driven by architectural constraints such as insufficient door widths relative to bed size, which hindered bed maneuverability and intensified staff circulation conflicts. Flow rates peaked between 0.40 and 0.55 persons/s, with higher occupancy producing more sustained congestion. Preparatory actions for clinically complex patients significantly shaped overall evacuation performance. The integration of BIM and empirically informed simulation enhances the accuracy and operational relevance of evacuation analyses in complex clinical environments. Findings highlight the need for calibration based on real behavioral data and demonstrate how specific architectural mismatches, particularly between door geometry and bed dimensions, act as critical drivers of evacuation bottlenecks. This approach supports more robust risk assessment and emergency planning within critical socio-technical infrastructures.

Abbreviations: BIM = building information modeling, CPU = critical patient unit, ECMO = extracorporeal membrane oxygenation, ICU = intensive care unit, PTAT = preparation time and time to action.

Keywords: agent-based modeling, building information modeling (BIM), computational simulation, emergency preparedness, healthcare facility safety, ICU evacuation, patient evacuation time

1. Introduction

Safety in hospital environments constitutes a fundamental component of comprehensive risk management, particularly in highly sensitive areas such as intensive care units (ICUs), where patient vulnerability and their substantial reliance on life-sustaining technologies markedly increase operational demands during emergency situations.[1,2] ICUs house patients

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The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

This study did not involve the use of patient data or any identifiable personal information. All data analyzed were derived from computational simulations and consisted solely of theoretical and technical parameters related to building modeling and evacuation performance. As no human participants, clinical records, or sensitive information were included, the study was exempt from ethical approval in accordance with institutional and international research guidelines.

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with severely limited or absent mobility and require continuous health care, rendering any evacuation procedure inherently high-risk and dependent on precise technical, human and organizational considerations.[2,3] International literature reports a rise in fire-related incidents within hospital facilities; a trend intensified during the COVID-19 pandemic due to the widespread use of oxygen therapy.[4] This escalation has highlighted the urgency of improving evacuation strategies in technologically complex units such as ICUs.

Although a growing body of research has examined evacuation procedures in healthcare facilities, important limitations persist when these findings are applied to intensive care contexts.[5] Most simulation studies rely on generic parameters that do not accurately represent the operational demands associated with life-support technologies, the heterogeneity of clinical conditions or the significant staffing requirements necessary to ensure safe patient transfers.[6] The scarcity of empirical data from real evacuations in ICUs, compared to general hospital evacuations, further limits insight into how accurately computational simulations reflect actual evacuation dynamics.[7] Consequently, current evidence offers limited insights into complex cases such as evacuations involving advanced therapies.

In parallel with these gaps, advanced digital technologies have assumed a central role in the field of emergency planning. Building information modeling (BIM) enables the accurate reproduction of spatial and functional hospital configurations, generating 3-dimensional models that integrate architectural, technological, and operational data that are crucial for emergency management.[2,8] When combined with simulation software, these models make it possible to recreate hazardous scenarios, anticipate blockages, analyze occupancy flows, and evaluate the effectiveness of different evacuation routes without interfering with healthcare activity.[9] Agent-based computational simulations have become a key methodological approach to representing individual behaviors in emergency situations, facilitating the examination of interactions between occupants, reaction times, and challenges associated with assisted mobility.[10] Recent studies also emphasize the importance of integrating premovement phases into evacuation models, noting that patient preparation can represent a substantial proportion of total evacuation time and varies considerably depending on clinical complexity.[11] This is especially relevant in ICU-related contexts where equipment such as extracorporeal membrane oxygenation (ECMO) systems, ventilators and multiple infusion pumps must be stabilized, secured and sometimes transported together with the patient, while maintaining continuity of therapy and monitoring.[12] These additional steps require careful coordination, more personnel and longer preparation times, making premovement substantially more complex than in other areas.[12]

Despite these advancements, several studies show that simulation models tend to miscalculate evacuation times due to the difficulty of replicating human behavior during high-pressuresituations and the unpredictability of acute clinical scenarios.[13] Architectural constraints common in ICUs, such as narrow doorways or congested corridors, as well as the substantial staffing needed to evacuate patients with high levels of dependency, further complicate attempts to achieve accurate predictions. These challenges reinforce the need to validate simulation outcomes against empirical observations. Meanwhile, emerging research employing virtual reality and immersive simulation environments has proven to be a valuable tool for training healthcare personnel, enhancing decision-making processes and improving coordination during emergencies.[14]

Therefore, the aim of the study was to evaluate the operational behavior of different evacuation strategies in an ICU of a tertiary hospital through computational simulation and BIM modeling of the building. By examining how simulations relate to the conditions observed during a real evacuation drill, the study seeks to advance the comprehension of the factors that shape evacuation performance in high-acuity environments and to contribute to ongoing efforts to strengthen hospital preparedness in critical care settings. In doing so, it contributes to the broader safety science effort to strengthen risk assessment and emergency preparedness in socio-technical systems where human, technological and organizational factors converge.

2. Materials and methods

2.1. Study description

This study adopts a quantitative, experimental simulation approach to evaluate the operational performance of hospital evacuation procedures in an ICU at Hospital Universitario Virgen Macarena, a leading tertiary care teaching hospital in Seville, a region in southern Spain.

The analysis combined detailed building modeling using Archicad with computational evacuation simulations performed in Pathfinder.[15,16] The methodological process was structured in 3 phases: acquisition and analysis of environmental information, instruments and tools, and results and comparative analysis (Fig. 1). A detailed BIM model of the unit was developed, and several evacuation scenarios were executed in Pathfinder.[16] The outcomes of these simulations were compared with empirical data obtained from a simulation performed in 2024.

The study protocol followed the Declaration of Helsinki.[17] This study did not involve the use of patient data or any identifiable personal information. All data analyzed were derived from computational simulations and consisted solely of theoretical and technical parameters related to building modeling and evacuation performance. As no human participants, clinical records, or sensitive information were included, the study was exempt from ethical approval in accordance with institutional and international research guidelines.

2.1.1. Phase 1: Acquisition and analysis of environmental information.

This phase consists of the following components:

Acquisition of architectural drawings: Graphic documentation was provided by the hospital's Technical Department to allow accurate building modeling and subsequent software implementation.

Assessment of building configuration: The architectural documentation was reviewed to identify critical areas, evacuation routes, and the location and dimensions of exits.

On-site visits: The correspondence between the drawings and the actual built environment was verified.

Analysis of ICU occupancy and review of data from a previous evacuation simulation to evaluate existing conditions.

2.1.2. Phase 2: Instruments and tools.

The study relies on the Pathfinder software environment to perform evacuation simulations. This includes the digital modeling of the building in Archicad and Pathfinder, as well as the application of generic parametrization in the 3 defined scenarios. Archicad was chosen for its capacity to create detailed BIM models, while Pathfinder allows robust simulation of occupant behavior and evacuation scenarios in the face of various constraints.[15,16] These simulations allow the evaluation of the efficiency of evacuation routes and the response of occupants in emergency situations. Additionally, a new parametrization based on data from the 2024 simulation was proposed and used to execute a final simulation.

The BIM model and simulation parameters were validated through comparison with floor plans and measurements taken on-site, ensuring accurate representation of spatial constraints and occupant movements. The architectural documentation was used to develop a detailed digital model of the area in Archicad, including all relevant architectural elements that affect evacuation, such as patient rooms, corridors, doors, access points, and expansion areas (Fig. 2). The model was

exported in industry foundation classes format to ensure interoperability with Pathfinder.[16,18] Once imported, the model was parametrized and programmed using unit specific data, such as the number of occupants, occupant behavior, and exit conditions.

2.1.2.1. Definition of scenarios. Three simulation scenarios were defined to study different evacuation strategies:

Scenario 1: Reproduction of the evacuation route followed during the 2024 simulation, from the critical patient unit (CPU) to Intermediate Care. Total number of patients evacuated: 6.
Scenario 2: Evacuation route defined in the ICU evacuation protocol, from the CPU to ICU A, ICU B, and Coronary ICU. Total number of patients evacuated: 6.
Scenario 3: Simulation of maximum occupancy in the CPU following the ICU evacuation protocol, from the CPU to ICU A, ICU B, and Coronary ICU. Total number of patients evacuated: 12.

2.1.3. Phase 3: Results and comparative analysis. After executing the simulations, the evacuation times of CPU occupants, flow rates through the main doors, and simulated paths and speeds were analyzed and compared. Validation was performed by comparing the obtained results with empirical data from the 2024 simulation.

2.1.3.1. Simulation development and parametrization. Four simulations were performed using the previously defined scenarios. Two types of parametrizations were applied to identify

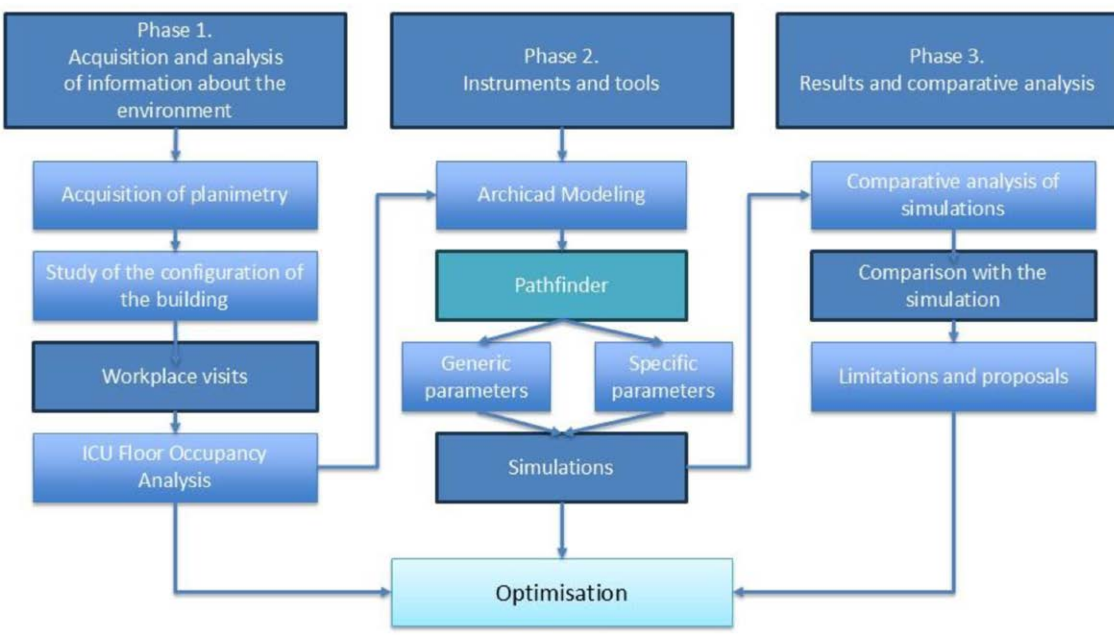

Figure 1. Research methodology workflow. ICU = intensive care unit.

Figure 2. BIM model of the workspace in Archicad 28. BIM = building information modeling, CPU = critical patient unit, ICU = intensive care unit.

which configuration best matched real conditions. A generic parametrization based on previously published studies was used in the first 3 simulations, and a study specific parametrization based on simulation data was used in the fourth simulation.

The first simulation used Scenario 1 and reproduced the evacuation route followed during the 2024 simulation. Generic parametrization was applied.
The second simulation used Scenario 2 and followed the routes established in the ICU evacuation protocol toward ICU A, ICU B, Balcony of Hope, and Coronary ICU. Generic parametrization was applied.
The third simulation used Scenario 3 and followed the same protocol-based routes but with maximum CPU occupancy. Generic parametrization was applied.
The fourth simulation used Scenario 1 and reproduced the 2024 simulation route with the study specific parametrization.

Environmental factors such as lighting and ambient noise were considered constant to focus the analysis on spatial and behavioral constraints. The following elements were configured in Pathfinder prior to running the simulations:

2.1.3.1.1. Doors and beds. Doors and beds constitute the main physical constraints in the evacuation process and were configured using real measurements. ICU beds measure 90 cm in width and 200 cm in length. Door and opening dimensions are shown in Table S1, Supplemental Digital Content, https://links.lww.com/MD/R411.

Due to the limited width of some doors, particularly those in CPU patient rooms, bed evacuation may be hindered. These constraints were integrated into the model to ensure realistic simulation conditions.

2.1.3.1.2. Smoke. Smoke affects visibility and occupant speed during evacuation. Pathfinder includes integrated smoke behavior parameters based on Fridolf et al,[19] method 3, so no additional programming was required.

2.1.3.1.3. Behaviors. Patient and healthcare staff behaviors were configured to ensure replicability of the model across different ICU contexts. Patient behaviors were defined individually in order to allow precise positioning of each patient using waypoints in designated refuge areas, whereas healthcare staff behavior was defined collectively because all personnel shared the common objective of evacuating patients from their rooms. Preparation times were incorporated into the simulation, and staffing was parameterized so that evacuation progressed progressively, starting with patients of lower clinical complexity and continuing with those requiring higher levels of support. Consequently, the most complex patient (who was on ECMO) was evacuated last, involving a greater number of professionals once the evacuation of less complex cases had been completed.

2.1.3.1.4. Individual profiles. Two patient profiles were used: assisted patients in bed, who require bed evacuation, and assisted patients on foot. A single profile was created for healthcare personnel since their attributes and objectives were comparable.

2.1.3.1.5. Individual speeds. Speeds are critical for modeling evacuation performance. Both movement speed toward the safe area and preparation times (PTAT) for patients and staff were considered. The values applied were based on previous studies,[20–22] as shown in Table S2, Supplemental Digital Content, https://links.lww.com/MD/R411. These generic parametrizations were used in the first 3 simulations. Preparation speed was assumed to be identical for both pre-evacuation preparation, including disconnecting of life-support equipment, and patient stabilization at the refuge area.

2.1.3.2. Study specific PTAT parametrization. To better adjust preparation times for ICU patients, a new parametrization was developed using preparation times obtained from the simulation chronology (Annex 1, Supplemental Digital Content, https://links.lww.com/MD/R411). This parametrization was applied in the fourth simulation and used both for pre-evacuation preparation and stabilization.

Preparation time was calculated based on the interval between the start and end of each patient's preparation phase, as shown in Table 1.

Patients with similar preparation times were those with comparable life-support equipment, such as those in rooms 2, 11, and 12. The patient in room 1 presented similar equipment, but the use of invasive ventilation increased preparation time. The patient in room 10 required the longest preparation time, 346 seconds, due to ECMO support.[23] The patient in room 9 had no preparation time because he was able to evacuate on foot (Annex 2, Supplemental Digital Content, https://links.lww.com/MD/R411).

For parametrization, the following were defined: function type, mean distribution, standard deviation, and minimum and maximum reaction time values. A log normal distribution was selected because ICU patient characteristics vary substantially depending on clinical status and day to day unit conditions.

Mean distribution (μ) in seconds:

$$\text{Mean}\,(\mu) = \frac{\sum_{i=1}^{N} X_i}{N} = \frac{219 + 80 + 0 + 346 + 91 + 110}{6} = 141$$

$$\text{Log normal mean}\,(\mu) = \ln\left(\frac{\mu_x^2}{\sqrt{\sigma_x^2 + \mu_x^2}}\right) = \ln\left(\frac{141^2}{\sqrt{111.93^2 + 141^2}}\right) = 4.70$$

Population standard deviation in seconds (σ)

$$= \sqrt{\frac{\sum_{i=1}^{N} (X_i - \bar{X})^2}{N}} = \sqrt{\frac{(219-141)^2 + (80-141)^2 + (0-141)^2 + (346-141)^2 + (91-141)^2 + (110-141)^2}{6}} = 111.93$$

Table 1

Preparation times obtained according to the chronology of the 2024 simulation.

Patient	Start of preparation	Preparation end	Total brew time	Total brew time (s)
Box 1	34″	4′ 13″	3′ 39″	219
Box 2	10″	1′ 30″	1′ 20″	80
Box 9	0	0	0	0
Box 10	52″	6′38″	5′46″	346
Box 11	1′ 14″	2′ 45″	1′ 31″	91
Box 12	51″	2′ 41″	1′ 50″	110

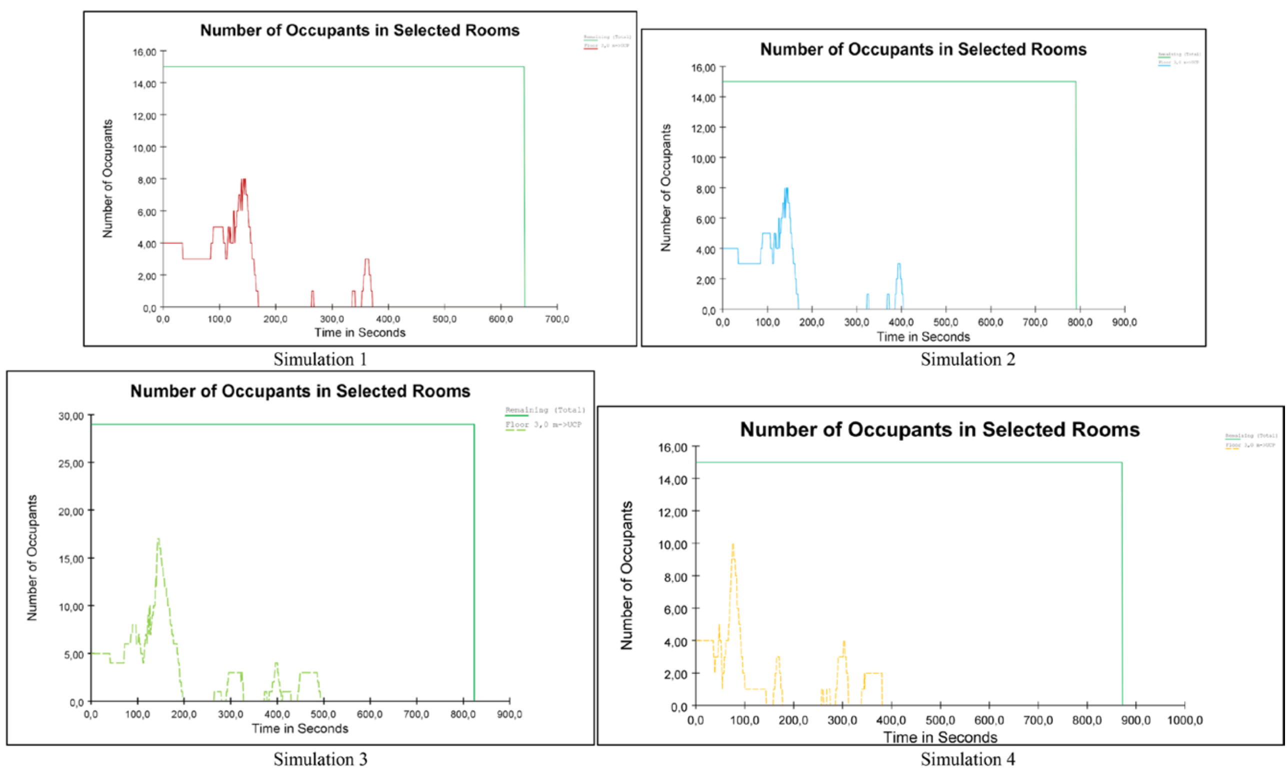

Figure 3. Temporal evolution of the number of occupants within the CPU during the evacuation process across simulations (1–4). CPU = critical patient unit.

$$\text{Log normal standard deviation}\,(\sigma) = \sqrt{\ln\left(1+\frac{\mu_x^2}{\sigma_x^2}\right)} = \sqrt{\ln\left(1+\frac{141^2}{111.93^2}\right)} = 0.97$$

Minimum value: The minimum reaction time was set to 0 because negative values are not feasible.

Maximum value: The maximum reaction time was set to the 95th percentile of the log normal distribution, 542.13 seconds.

3. Results

3.1. General findings

The 4 simulations revealed clear differences in operational evacuation performance depending on the selected route and the parametrization applied. Overall evacuation times ranged from 10 minutes 42 seconds in simulation 1 to 14 minutes 32 seconds in simulation 4. All simulated values were shorter than the time recorded in the 2024 real simulation, which was 17 minutes 02 seconds. Simulations using generic parametrization consistently predicted shorter evacuation durations, particularly in scenarios involving patients with high clinical complexity. In contrast, the study specific parametrization achieved a closer approximation to the behavior observed in the real evacuation.

Across all scenarios, common patterns were identified in occupant flow and spatial distribution. The initial charts showed an abrupt increase in traffic in the main CPU corridor during the first 60 to 100 seconds, followed by fluctuations associated with the repeated movements of healthcare personnel returning to collect patients from individual rooms. Flow rates through the main doors ranged from 0.40 to 0.55 people/s, with the highest values observed in the maximum occupancy scenario. Regarding movement speeds, the fastest segments corresponded to the return trips of healthcare staff, approximately 1.35 m/s, whereas beds moved at approximately 0.3 m/s, highlighting the physical constraints that slowed the evacuation process. Overall, these trends demonstrate the influence of architectural layout, clinical workload, and team composition on overall evacuation dynamics.

3.2. Number of occupants in the CPU

The number of occupants within the CPU over time is shown in Figure 3. The graphs illustrate the initial influx of individuals into the main corridor in all simulations. Subsequent peaks correspond to healthcare staff returning to collect patients who were still inside their rooms and required evacuation. A consistent pattern appears across all scenarios due to the identical architectural configuration and the use of the same behavioral rules and programming conditions.

3.3. Occupant flow

Flow rates through the main doors of the CPU, Balcony of Hope, Intermediate Care, ICU A, ICU B, and Coronary ICU are presented in Figure 4. These graphs represent the number of persons passing through selected doors over time. A sequential and relatively orderly pattern was observed, with intermittent pauses between flow peaks.

In simulation 1 the highest flow peaks occurred between 140 and 230 seconds, reaching approximately 0.45 persons/s. Simulation 2 presented a similar pattern, with its maximum also around 0.45 persons/s in the same time window. Simulation 3 showed extended peaks from 140 to 350 seconds and reached a maximum flow of approximately 0.55 persons/s. Simulation 4 showed peak values between 80 and 310 seconds with a maximum of approximately 0.40 persons/s. The increase in simulation 3 is attributed to the higher total number of occupants compared with the other scenarios. The lower values in

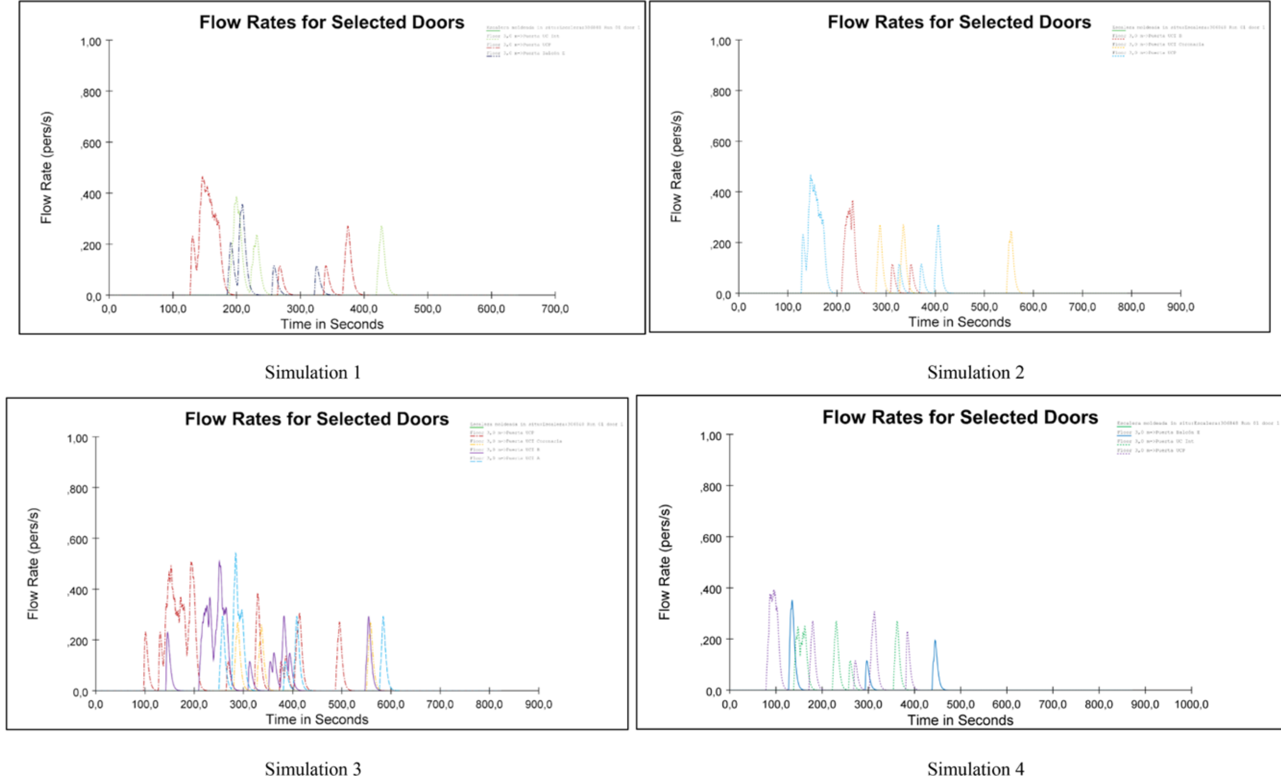

Figure 4. Occupant flow rates through the main CPU exit doors over time for simulations (1–4). CPU = critical patient unit.

simulation 4 reflect longer preparation times, resulting in a more distributed and less concentrated flow.

3.4. Paths and speeds

Figure 5 shows the evacuation trajectories and corresponding movement speeds, where higher speeds are represented in red and lower speeds in blue. All simulations displayed similar exit paths from the CPU due to identical architectural configuration and behavioral programming.

Maximum speeds of approximately 1.35 m/s were recorded during the return movements of healthcare personnel. Bed transport segments reached approximately 0.3 m/s, and assisted ambulatory patients moved at approximately 0.6 m/s. The most critical segments, where bottlenecks appeared, were those in which all occupants converged on the main exit route toward the designated refuge zones. These constrictions may contribute to delays and increase risk during evacuation. The primary bottleneck was consistently located at the CPU exit.

Figure 6 provides a detailed visualization of occupant movement trajectories and associated speed fields across the 4 evacuation simulations, with velocity encoded chromatically in m/s. In all scenarios, a systematic convergence of trajectories is observed at the main CPU exit, where trajectory density increases markedly and movement speeds shift toward lower values, indicating localized deceleration. This area is characterized by overlapping paths and frequent directional adjustments, consistent with bed maneuvering and circulation conflicts between healthcare personnel, thereby visually confirming the CPU exit as a persistent structural bottleneck regardless of the evacuation scenario or parametrization applied. Simulations 1 to 3, which used generic parametrization, exhibit more temporally concentrated flows and sharper accumulations at the exit, with simulation 3 showing the highest degree of spatial congestion under maximum occupancy conditions. In contrast, simulation 4, calibrated with empirically derived preparation times, displays more temporally dispersed trajectories and a more prolonged but less abrupt congestion pattern, reflecting delayed and staggered patient release into the corridor. Overall, the figure illustrates how architectural constraints, bed dimensions and maneuverability, and staff–patient interactions jointly produce localized speed reductions and trajectory accumulation at the CPU exit, providing visual support for the quantitative flow analysis presented above.

3.5. Evacuation times

The evacuation times obtained from the simulations are shown in Table 2. All simulated times fell short of the actual duration. The simulation that most closely matched the empirical time was simulation 4, which differed by only 2 minutes 30 seconds. Simulation 1 showed the greatest deviation with a difference of 7 minutes 40 seconds. Simulations 2 and 3 produced intermediate results, consistent with their shared parameters and evacuation routes.

4. Discussion

The findings of this study indicate that the degree to which evacuation simulations approximate real ICU conditions depends considerably on the suitability of the parameters used to represent both preparation and movement processes. Simulations employing generic parameter sets consistently produced shorter evacuation times than those recorded during the 2024 drill, a tendency also noted in previous investigations where standard models have fallen short in predicting the full duration in complex environments.[13] This discrepancy was especially pronounced in the case of the patient receiving ECMO support in box 10, whose evacuation required many healthcare professionals and whose extensive preparation reflects the clinical and technological demands associated with advanced life-support therapies.[23] This case illustrates how high-dependency scenarios strongly influence

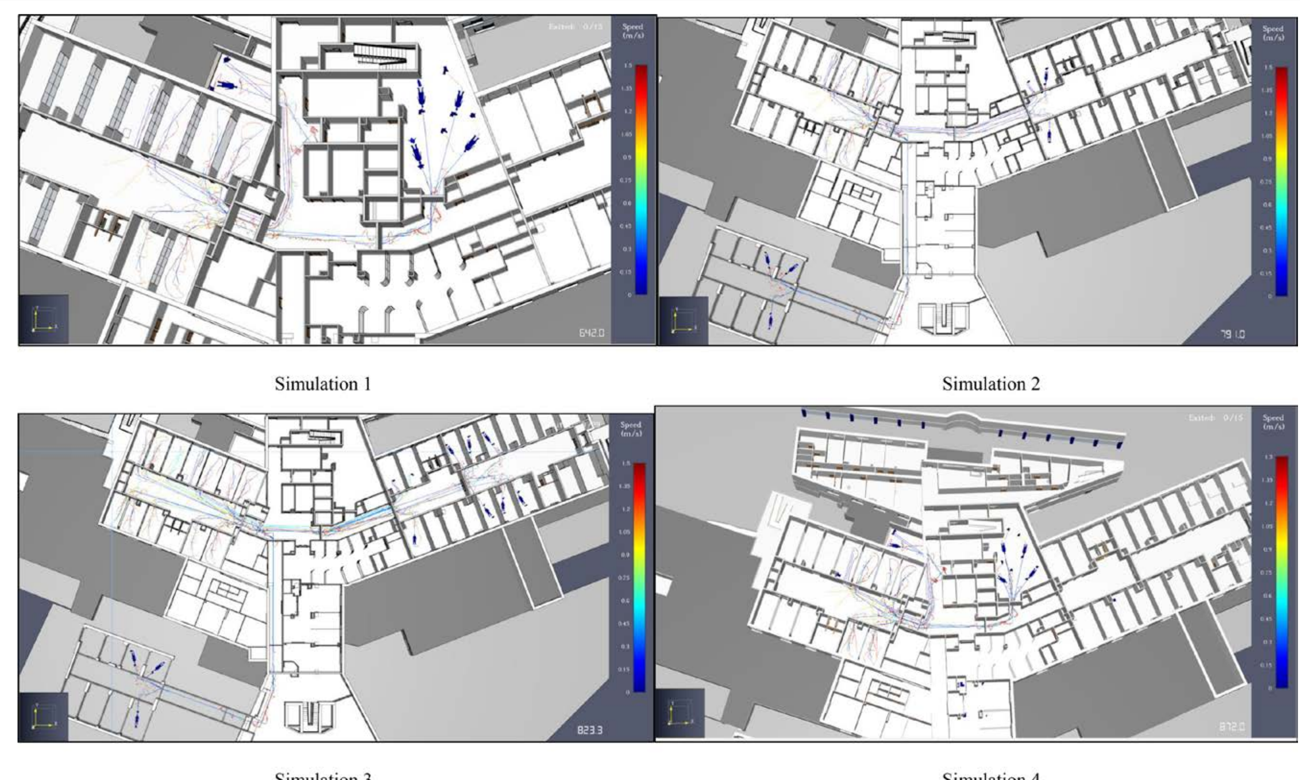

Figure 5. Evacuation trajectories and associated movement speeds of occupants for simulations (1–4).

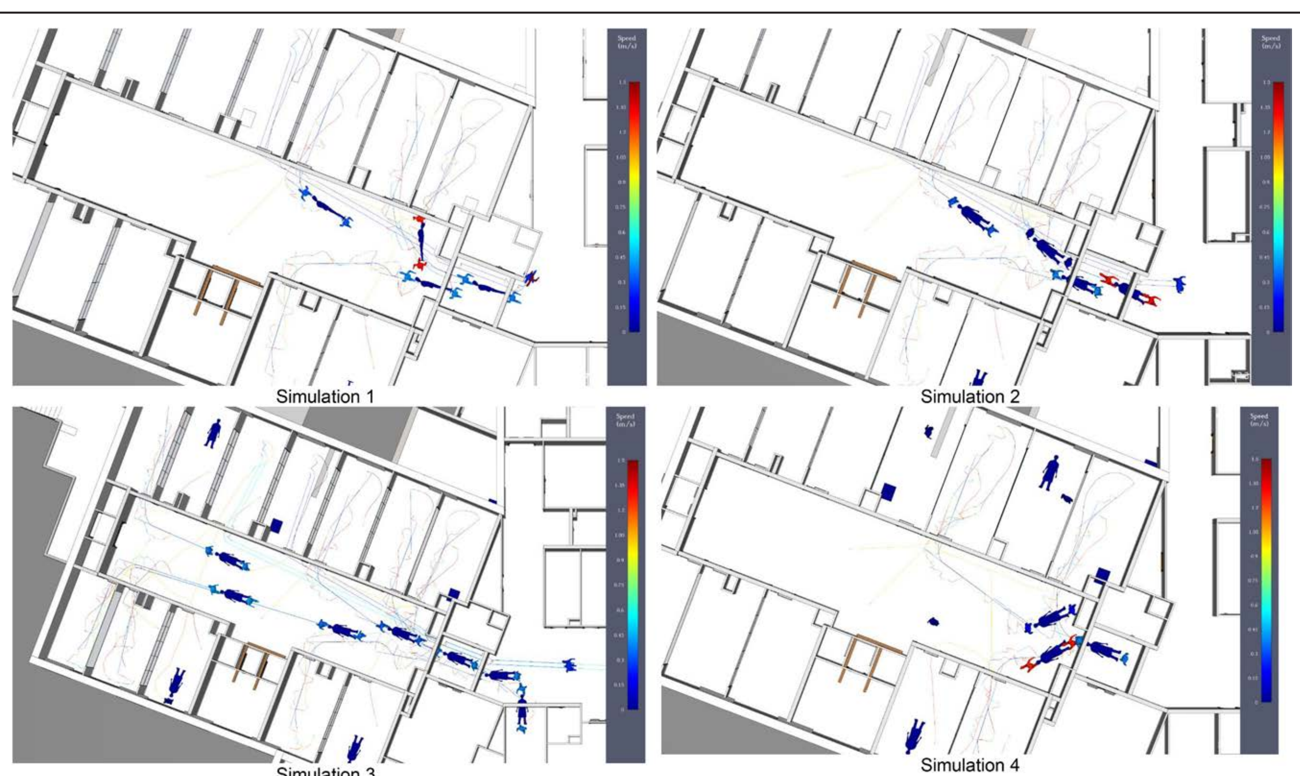

Figure 6. Spatial distribution of evacuation trajectories and speed reductions at the CPU exit bottleneck. CPU = critical patient unit.

overall evacuation dynamics and shows the limitations of applying uniform generic parameters to heterogeneous patient groups.[24]

The comparison of simulations further suggests that models incorporating empirically derived PTAT values may offer a more accurate representation of evacuation behavior.[25] Simulation 4, which integrated preparation times extracted from the real drill, yielded results closer to the empirical duration than those relying on generic values, though some discrepancy remained as the simulated total was slightly less than the actual time. This

Table 2

Times obtained and increase compared to the 2024 simulation.

Evacuations	Total evacuation time (min)	Increased evacuation times (min)
Simulation 2024	17:02	0
Simulation 1	10:42	−7:40
Simulation 2	13:11	−3:51
Simulation 3	13:43	−3:19
Simulation 4	14:32	−2:30

improvement supports the argument that calibration based on observed behavior can meaningfully enhance model fidelity.[25] The contrast between simulations using identical routes but different parametrizations reinforces the idea that preparation processes, particularly those associated with highly dependent patients, constitute a decisive factor in determining total evacuation time, consistent with observations in other hospital evacuation studies.[11]

Analysis of movement trajectories, flow rates and congestion points provides additional insight into how behavioral and architectural factors interact during an evacuation. All simulations identified the exit of the CPU as a persistent bottleneck, reflecting structural limitations such as narrow doorways, corridor constraints and the need to maneuver beds with attached medical equipment. Similar architectural influences on evacuation efficiency have been documented in earlier work.[26] The recurrence of near-identical flow patterns across simulations is likely attributable to the fixed spatial configuration of the ICU and the standardized behavioral rules applied to staff within the model.[27] Longer evacuation routes in simulations 2 and 3 also contributed to extended evacuation times, highlighting the operational implications of directing patients toward more distant expansion areas, as noted in research on evacuation route optimization.[2]

Several limitations emerged from this study. The parametrization developed from the drill data relied on a small sample, which restricts its statistical robustness and generalizability.[28] Additional drills or structured training exercises would yield more comprehensive datasets, enabling the development of more precise parameter distributions. Although the current analysis incorporated all relevant patient types present in the drill, further differentiation based on specific life-support technologies and clinical profiles would improve model accuracy.[29] Moreover, structural constraints identified in the ICU, such as narrow doorways and limited circulation space, reinforce the need to evaluate infrastructural modifications or procedural adjustments to improve evacuation efficiency. These issues align with the observations of architectural influences in previous evacuation literature.[30]

Despite these limitations, the study offers several strengths that enhance the robustness and applicability of its findings. The combined use of detailed BIM modeling and computational simulation enabled a highly accurate representation of the ICU's architectural and operational conditions, exceeding the level of environmental fidelity typically reported in similar research.[31] Furthermore, the incorporation of empirical data from a real evacuation drill provided a valuable benchmark for assessing model performance, strengthening the validity of the comparative analysis.[32]

Beyond the specific ICU setting analyzed, the methodological framework developed in this study was conceived with a modular and highly parametrizable design, which supports its scalability and transferability to other high-risk hospital environments. The integration of detailed BIM-based architectural modeling with agent-based evacuation simulation allows key variables (such as spatial configuration, equipment density, patient dependency profiles, staffing patterns, and preparation times) to be redefined according to the functional characteristics of different clinical units.[33] As a result, the same modeling logic could be adapted to operating rooms, neonatal and pediatric ICUs, or other technologically intensive care areas where evacuation is constrained by fixed equipment, limited circulation space, and highly dependent patients. Previous studies have highlighted that evacuation sustainability in such environments is strongly influenced by unit specific workflows, technological complexity, and patient vulnerability, reinforcing the need for flexible, context-sensitive simulation approaches rather than generic models.[6] In this regard, the present framework provides a scalable tool that can support risk assessment and emergency planning across diverse critical care settings by accommodating both architectural and operational variability.

The findings of this study have implications for grasping the role of computational simulation within ICU emergency planning. Simulations cannot yet replace physical drills, as they do not fully reproduce the behavioral, clinical and contextual variability of real emergencies; however, they offer substantial value as a complementary tool, especially when used alongside drills and staff training.[29] The results of this study show that computational simulations can support the identification of congestion points, the assessment of alternative evacuation routes and the estimation of staff workload, all without disrupting everyday clinical operations.[27] Their ability to test hypothetical scenarios, quantify bottlenecks and visualize velocity fields, flow patterns and evacuation dynamics provides valuable insight into how evacuations may unfold, offering a structured means of anticipating operational challenges and supporting more informed decision-making within a comprehensive preparedness strategy.[34]

Additionally, the findings indicate that simulations remain limited in their ability to replicate behavioral variability, dynamic decision-making and clinical unpredictability, reinforcing that real-world drills continue to be indispensable for capturing these elements and ensuring adequate staff training and coordination, as echoed by previous authors.[14] Continued refinement of empirically grounded parameters, along with expanded data collection and assessment of physical infrastructure, may further enhance the reliability and usefulness of simulation tools in high-acuity hospital environments.

Overall, the findings demonstrate that integrating simulation technologies with empirically grounded parametrization can substantially enhance the accuracy and operational relevance of evacuation analyses in high-acuity clinical settings. This work illustrates how digital modeling and behavioral data can jointly inform risk management, expose latent vulnerabilities and support evidence-based decision-making within complex socio-technical infrastructures. By highlighting both the capabilities and the current limitations of simulation tools, the study reinforces the importance of multidisciplinary approaches that bridge technology, human behavior and organizational processes.

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