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HDSS: A Hospital Design Support System architecture

Zhuoran Jia [a,b,*], Pirouz Nourian [c], Peter Luscuere [a], Cor Wagenaar [a,d]

[a] Faculty of Architecture and the Built Environment, Delft University of Technology, Julianalaan 134, Delft, 2628 BL, The Netherlands
[b] Guangzhou Urban Planning Design & Survey Research Institute, No. 10 Jianshe Dama Road, Zhujiang Planning Building, Yuexiu District, Guangzhou, 510045, China
[c] Faculty of Geo-Information Science and Earth Observation, University of Twente, Hallenweg 8, Enschede, 7522 NH, The Netherlands
[d] Faculty of Arts, University of Groningen, Oude Boteringestraat 34, Groningen, 9712 GK, The Netherlands

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ABSTRACT

Hospital layout design plays a crucial role in ensuring operational efficiency. This study presents a Hospital Design Support System, a data-driven framework that integrates the Four-Step Transportation Model, Discrete-Event Simulation, and Exploratory Network Analysis to systematically assess hospital layouts. The HDSS evaluates four key operational criteria: spatial crowdedness, patient waiting times, patient walking distances, and difficulty in wayfinding. Hospitals exhibit spatial and operational characteristics akin to small cities and factories, making transportation planning and Discrete-Event Simulation highly applicable in evaluating hospital layout performances in terms of the four operational criteria. Exploratory Network Analysis further reveals the inherent structural tendencies that impact hospital efficiency and resilience. Additionally, evaluation mechanisms, including aggregation, relativisation, and interpretation, translate disaggregated simulation outputs into actionable metrics, enabling comparative assessment of design alternatives. This study contributes a systematic approach to hospital layout evaluation, offering valuable insights for architects and policymakers aiming to enhance hospital layout design.

1. Introduction

The layout of a hospital has a profound impact on its overall functionality, driven by two key factors. First, from a functional perspective, medical procedures within hospitals are inherently complex. Second, from a spatial perspective, hospitals resemble small cities, where corridors are similar to streets, and functional units parallel different land uses. Consequently, the integration of these factors highlights that hospital layout significantly influences users' visibility and walkability. When designing a hospital, architects are not merely constructing a building but developing a complex system that, if not carefully planned, may present various risks and challenges. To enhance the design of hospital systems, this study proposes incorporating early operational insights into the design process through the development of a decision support system, referred to as the Hospital Design Support System (HDSS).

The purpose of the HDSS is to help architects assess the overall functional effectiveness and efficiency of hospital configurations. To elicit such an operational "big picture", this research needs to make simplifications, abstractions, and analogies to replicate, reveal, and simulate (model) the functioning of a hospital as a system. In this regard, the proposed approach differs from commonly studied simulation modelling experiments, such as way-finding analyses in hospitals. Even though these two types of endeavours (ours and theirs) are related, they serve completely different purposes. This research focuses on simulating the macro level operation within the hospital, such as the patient movement pattern within the entire hospital building, rather than the micro level movements, such as the patient's detailed trajectory inside a certain room or corridor. To this end, a hybrid simulation framework is developed, combining both macro- and micro-level modelling techniques. Specifically, the macro-level Four-Step Transportation Model is applied for generating patient movement patterns within the entire hospital layout, the micro-level Discrete-Event Simulation (DES) models each patient's trajectory between spatial units, and a micro-level Random Walk simulation is used to represent the wayfinding behaviour of first-time visitors, who may get lost and visit several incorrect spatial units before finding the correct one. It is acknowledged that Agent-Based Simulation is also a popular tool for simulating wayfinding/safety; however, it is ideal when the focus is on modelling detailed wayfinding behaviour, or local interactions with other users or the environmental elements (Helbing and Molnár, 1995; Gwynne et al., 1999; Kretz et al., 2006), e.g., how patients navigate a hallway or respond to obstacles within a room. Our study investigates wayfinding

* Corresponding author at: Faculty of Architecture and the Built Environment, Delft University of Technology, Julianalaan 134, Delft, 2628 BL, The Netherlands.
E-mail address: zhuoran6103@hotmail.com (Z. Jia).

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behaviour at a higher level of abstraction, where patients are modelled as moving from one spatial unit to another; the detailed simulation of wayfinding behaviour inside the spatial unit is beyond the scope of this research. Hence, the Agent-Based Modelling approach is excluded from our methodology. It is important to note that this framework prioritises macro-level abstract simulation over micro-behavioural fidelity. The simulation assumes a steady-state operational environment where routes are unobstructed. While Shortest Path analysis assumes rational wayfinding, the Random Walk Simulation is introduced to account for stochastic, non-rational movement patterns. These assumptions imply that the results represent the layout structural resilience of the system—i.e., its underlying capacity to support movement—rather than resilience under extreme or rapidly changing conditions.

This study's methodological choices are defined in relation to the research objective of devising a spatial decision support system to help architects, building managers, and hospital planners to assess (ex-ante or ex-post) the efficiency and efficacy of hospital configurations, practically in objectively comparing various alternatives with regard to multiple operational optimal criteria. The central analogy of this system regarding geographical land-use transport interaction networks as analogous to the designated functional labels of rooms and their effects on the transport flows across the corridors of the hospital is based on the spatial metaphor of the hospital as an "indoor city" and the operational metaphor of the hospital as a "service-assembling factory". The remainder of the paper is structured as follows: Section 1.1 introduces the research problems and the necessity of developing an HDSS. Section 1.2 presents a literature review and identifies the research gap. Section 1.3 introduces the research approach and Section 1.4 outlines the research contributions. Section 2 describes the methodology for developing the HDSS. Section 3 presents the research results based on the case study. Finally, Section 4 concludes our contributions, limitations and potential future research directions.

1.1. Research problem

This section explains the necessity and objectives of the HDSS. The main design challenges related to hospitals can be summarised as (Jia et al., 2023):

- Overcrowding: whether the assumed room capacities are reasonable and consistently integrated across different functional areas to ensure optimal patient flow and operational efficiency.
- Long Patient Waiting Times: Are the circulation routes and functional zones configured to facilitate rapid patient transitions and minimise bottlenecks that contribute to delays in care delivery?
- Long Patient/Staff Walking Distances: Are the spatial relationships between key departments and areas optimised to minimise unnecessary movement and promote efficient workflows for both patients and staff?
- Difficulty in Wayfinding: Whether the layout incorporates clear and intuitive navigational cues to enable both patients and staff to easily orient themselves and swiftly navigate the hospital without confusion or delay.

These design challenges are not trivial and cannot be easily answered by human intuition. Specifically, Overcrowding is fundamentally linked to how effectively space is distributed and how well the layout supports fluctuating operational demands. Estimating room capacities based solely on intuition or expectation often results in overestimation or misalignment relative to the intended operational function. In contrast, simulation modelling provides a rigorous framework for validating these assumptions and assessing the compatibility of capacities across different functional areas. Additionally, the long walking distances (and thus the time wasted on and the fatigue resulting from walking the corresponding paths) are related to how the spatial configuration is arranged, not only in terms of the unlabelled graph structure but also how different rooms are positioned within it as to their operational purpose. The aggregate effects of such decisions can only be studied concerning the whole network structure of the hospital building and its node attributes. Furthermore, wayfinding difficulties emerge when the spatial organisation does not provide coherent pathways. In a well-designed hospital, each room and corridor is not only functionally defined but also strategically placed to support a logical flow that minimises confusion. Reliance solely on intuition or experiential judgement is insufficient to ensure such spatial coherence; instead, simulation modelling is essential to quantitatively evaluate a hospital configuration's performance in terms of wayfinding efficiency. This study argues that to address these questions/challenges systematically, a Hospital Design Support System (HDSS) consisting of simulation models and an exploratory network analysis module needs to be constructed to assess the hospital layout performances in terms of overcrowding, patient waiting time, patient walking distance, and difficulty in wayfinding.

1.2. Related studies

This section presents a literature review of the relevant studies and identifies the key research gaps. In particular, it examines studies that have applied the Four-Step Transportation Model, Discrete-Event Simulation, Agent-Based Modelling, Exploratory Network Analysis, or Decision Support Systems in hospital contexts.

Kara and Bilgic (Kara and Bilgiç, 2021b) utilised the Four-Step Transportation Model for forecasting hospital trip demand, thereby supporting informed decision-making on hospital location and capacity planning. In a related study (Kara and Bilgiç, 2021a), the authors employed the Four-Step Transportation Model to estimate the number of home-to-hospital trips at the urban scale. However, both studies operate at an urban scale and do not address trip estimation among departments or rooms within hospitals. Similarly, Naser et al. (2015) applied the Four-Step Transportation Model to estimate the number of trips generated by hospitals in the city of Amman based on their floor areas and bed counts. Abu-Ameerh and Al-Trawneh (Abu-Ameerh and Al-Trawneh, 2007) developed a Four-Step Transportation Model to estimate the number of vehicle trips attracted to hospitals in Jordan based on the number of staff, the number of beds, and the hospital's gross floor area. These studies also remain at the urban scale and consider only external travel to hospitals. There is a notable scarcity of studies applying the Four-Step Transportation Model at the building scale to estimate trips among spatial units within hospitals.

Most studies that apply DES or ABM in hospital contexts focus on management aspects, such as testing scheduling policies or appointment strategies, whereas only a few use these methods to evaluate hospital layout performance (Jia et al., 2023). Among these studies, Iskander and Carter (Iskander and Carter, 1991) applied a DES model to evaluate alternative layout design strategies for a day care centre in a university hospital, with a focus on mitigating overcrowding. Valipoor et al. (2021) utilised DES for assessing different layout designs of an emergency department to address overcrowding. Cubukcuoglu et al. (2020) developed a DES tool for examining different hospital layout designs to minimise patient waiting times. J. Morrice et al. (2020) evaluated the layout designs of a care unit in a university hospital, targeting reductions in both patient waiting times and lengths of stay. Vahdatzad (Vahdatzad, 2018) employed DES to evaluate alternative layout design strategies for an outpatient clinic with the aim of minimising patient walking distances. Cai and Jia (Cai and Jia, 2019) applied DES for assessing the layout design of a surgical suite to reduce staff walking distance. Vahdat et al. (2019) implemented DES for assessing the layout design of an outpatient clinic, aiming at minimising patient walking distance. O'Hara (O'Hara, 2014) developed a DES model to optimise the layout design of an intensive care unit by minimising nurse travel distances. Schaumann et al. (2020) applied Agent-Based Modelling (ABM) for reducing crowdedness, staff travel distance, and patients' interruption of staff in a medicine ward. In a similar study (Schaumann et al., 2019), the authors employed an ABM approach for comparing two outpatient clinic design alternatives in terms of reducing overcrowding. Tang and Chen (Tang and Chen, 2021) utilised the ABM approach to test layout improvement strategies for reducing the spread of infectious disease in an infection unit of the hospital. Zamani (Zamani, 2019) integrated ABM with exploratory network analysis (ENA) to evaluate alternative emergency department layout designs in terms of wayfinding difficulty. Lee et al. (2020) applied ABM to assess the performance of a hospital nursing unit's layout design in terms of reducing staff walking distances. Most of the reviewed studies that applied DES or ABM focus only on assessing a single functional unit layout of the hospital, such as the emergency department, the outpatient department, or the nursing ward, etc. Research applying DES or ABM to evaluate the overall hospital layout performance remains scarce. Furthermore, these studies used specific patient flows as input data for the DES/ABM simulation; although these patient flow data can precisely replicate the operations in the studied hospitals, they cannot be generalised to other hospitals, hence limiting the generality of the developed simulation tools.

Kim and Lee (Kim and Lee, 2010) used Exploratory Network Analysis (ENA) to assess different types of hospital ward layout design in terms of difficulty in wayfinding. Lu and Bozovic-Stamenovic (Lu and Bozovic-Stamenovic, 2009) applied ENA approaches for assessing hospital layout designs with a focus on wayfinding performance. Tzeng and Huang (Tzeng and Huang, 2009) employed ENA techniques to evaluate an outpatient department's layout design performance with respect to wayfinding difficulty. Pouyan et al. (2021) utilised ENA to assess five types of ward layout configuration in terms of wayfinding performance, including corridor configuration, racetrack configuration, radial configuration, cluster configuration, and duplex configuration. The authors concluded that the corridor and radial configuration have better performance in reducing wayfinding difficulties. Lacanna et al. (2019) applied ENA to evaluate patients' wayfinding behaviour in the indoor public areas of a hospital. Zwart and Voordt (van der Zwart and van der Voordt, 2015) used ENA approaches to assess the layout design performance of a hospital ward regarding difficulty in wayfinding. Similarly, most ENA approaches concentrate on specific sections of the hospital—such as wards or outpatient departments—while only one reviewed study (Lu and Bozovic-Stamenovic, 2009) examines the design of the entire hospital layout.

In Taboada et al.'s studies (Taboada et al., 2011, 2013), they developed a Decision Support System (DSS) for the emergency department using ABM as the main simulation approach to simulate and evaluate different scheduling policies, to reduce overcrowding in the emergency department of a hospital. Baril et al. (2014) developed a DSS with DES as the main simulation tool for testing different staff scheduling policies and resource allocation strategies in a hospital with the aim of reducing patient waiting times. Cho et al. (2019) developed a clinic DSS using DES as the main simulation approach for optimising the clinician's scheduling policy. Viana et al. (2020) developed a DSS for an outpatient clinic combining the simulation approaches of ABM and DES to evaluate different policies of clinical pathways and appointments scheduling, intending to minimise patient waiting times and lengths of stays. All reviewed studies on hospital DSSs have been conducted primarily from a management perspective, emphasising the influence of policy and strategy on operational efficiency. To the best of the authors' knowledge, no prior study has developed a hospital DSS aimed specifically at assessing how layout configurations affect hospital operational efficiency.

In summary, three key research gaps can be identified. First, existing research employing transport planning or simulation modelling tends to operate at either a large scale—such as the application of the Four-Step Transportation Model at the urban level—or at a micro scale, where DES or ABM is applied at the departmental level. There remains a notable scarcity of studies conducted at the building scale, specifically those that use the Four-Step Transportation Model or DES/ABM to evaluate the performance of an entire hospital layout. Second, all reviewed studies applying simulation modelling (either DES or ABM) rely on predefined operational information, such as patient flow, as input data for the simulation. This operational information is specific to the hospital under study and cannot be generalised to other hospitals, thereby limiting the broader applicability of the simulation tools. Moreover, these tools are only applicable to existing hospitals where operational data, such as patient journeys, are available. They cannot be used in the design of new hospitals, where such operational information does not yet exist. Third, all reviewed studies developing hospital DSS focus exclusively on the management aspects of hospitals, such as staff scheduling policies. To the best of the authors' knowledge, no study has developed a hospital DSS that evaluates the impact of building layouts on hospital operational efficiency. This research aims at filling these gaps by developing a Hospital Design Support System.

1.3. Research approach

The approaches employed in this research include the Four-Step Transportation Model, the Discrete-Event Simulation model, and the Exploratory Network Analysis model. The following text explains in detail the rationale for incorporating these approaches into the proposed HDSS framework.

The structural organisation of hospital buildings shares remarkable similarities with that of small cities. From a mathematical perspective, both hospitals and cities can be modelled as network graphs consisting of nodes and edges, where nodes represent spatial units (e.g., rooms in hospitals, or areas/land uses in cities) and edges denote the connections between these units. This structural resemblance also enables the application of the Four-Step Transportation Model—the framework that is widely used in urban transportation planning—to simulate internal transportation within hospitals, such as the movement of patients. The Four-Step Transportation Model helps address the current limitation of existing hospital simulation tools and DSSs, which rely on predefined patient flow data and are therefore limited in their applicability to new hospital design scenarios where such data are unavailable. By integrating the Four-Step Transportation Model, the HDSS can estimate traffic flows or patient movement patterns, enabling simulation and analysis even in cases where empirical patient flow data do not yet exist. Hence, our HDSS will include a Four-Step Transportation model for simulating the city-like character of hospitals.

The structure of processes in hospitals can be represented by patient journeys, where patients go through a series of medical processes in different functional units in hospitals (e.g., see operational information in Table 1). This procedural nature makes hospitals analogous to factories, where in factories products are produced through a series of processes, and in hospitals medical services are produced through a series of procedures. This procedural similarity between hospitals and factories makes Discrete-Event Simulations a suitable tool for simulating the medical procedures in hospitals. Discrete-Event Simulation (DES), a modelling approach that is commonly applied in simulating the operation of manufacturing systems, models the operation of a system as a sequence of events that occur at distinct points in time. Each event marks a change in the system's state, and the simulation advances from one event to the next (Hillier and Lieberman, 2015). Our HDSS will include a DES model for simulating the factory-like character of hospitals.

The use of simulation modelling is necessary to predict and provide an explanation for the patterns of use or operation of the building as they might emerge or appear out of the statistical superposition of many usage pathways of individual (hypothetical) users of the building. However, the basic assumptions behind simulation modelling and the evaluation reports resulting from the aggregation of the numeric simulation results are related to the macroscopic view of the interactions of people with the building, which implicitly implies a principle of rationality. This implicit assumption of rationality also

Table 1
Exemplified descriptions of four types of information in a Hospital Configuration Model (Jia et al., 2025a).

Information type	Explanation	Example
Geometric Information	Room boundary defined by a sequence of 3D points.	{'RECEPTION': ['−20, 34, 4', '−20, 29, 4', '−19, 29, 4', '−19, 39, 4', ' −20, 34, 4']}
Topological Information	A network graph composed of nodes and edges.	{'Graph1': [{"node1": {"id": "room1"}, "node2": {"id": "room2"}, "edge1":{"id": "e1"}}]}
Semantic Information	Room name	{'Department$Imaging': ['Radiology']}
Operational Information	A patient's journey through the hospital, represented as a sequence of rooms the patient must visit.	{'patient_journey_1': ['Entrance', 'Registration', 'Diagnosis', 'Pharmacy', 'Exit']}

brings about the use of mostly deterministic mathematical models of behaviour under other assumptions, namely the implicit or explicit assumption of the building working under normal steady-state business-as-usual conditions. In brief, these assumptions pave the way towards optimising or adapting the building configuration for the assumed ways or patterns of usage. However rational and necessary this adaptation is, one cannot assume that a perfectly adapted or optimised building for such presumably rational and ordinary or typical ways of usage might be resilient to working conditions that can be regarded as unusual, stressful, extra-ordinary, or irrational (for whatever reason, including the psychological aspects of the usage that have been disregarded in the interest of the bigger issues). In short, for various reasons related to such uncertainties, it is customary in any engineering design practice to introduce "redundancies" into the design of a system or structure, to be prepared for every unaccounted circumstance. One can argue that the art of engineering is to introduce such redundancies reasonably while having a clear view of the barely sufficient backbone structure or system. The inherent difficulty of taking such uncertainties into account is the fact that one needs to deal with the so-called unknown unknowns, and yet, for ensuring resilience in the face of uncertainties, a designer precisely needs to be prepared to include provisions for dealing with such unknown and unpredictable eventualities. In the case of building configurations, or spatial network configurations in general, a relatively established way of reflecting on such eventualities is to use exploratory network analysis methods to look into the structural tendencies of the network structure in attracting or repelling certain behavioural patterns, in facilitating or hindering certain distribution patterns, the likelihood and the shape of inherently random diffusion and spread patterns (of e.g. contamination), and to reflect on worst-case scenarios of maximal usage due to maximal (deterministic or stochastic) flows through network arteries. In contrast to the simulation modelling workflows that are systematically structured to produce clear performance metrics for assessing conditions, it is hard or even futile to think of restructuring all kinds of metrics to assess such uncertainties and reflect on the necessity of redundancies. Instead, this study argues that a suite of tools for exploratory network analysis in the hands of a reflective practitioner is more likely to be useful for revealing the patterns that might be invisible to the mere human intuition of the designer, but quite intuitive and informative when visualised. In short, the decision to provide such a complementary tool suite for exploratory analyses is to foster the art of provisioning a reasonable amount of design redundancies without putting too much unnecessary structure on the exploratory process. The simulation modelling tools provide the apparatus for the science of engineering in dealing with the rational and predictable aspects of building operations, while the exploratory analysis tools are to provide the mechanisms in support of the art of engineering in dealing with the irrational and unpredictable aspects of building operations. This is to explain and justify the reasons why the exploratory analysis part of the toolkit does not include aggregative evaluation tools and remains only a visual inspection tool for studying patterns at a disaggregated level.

1.4. Contributions

This research contributes to the field by filling the research gaps discussed in Section 1.2. It develops an HDSS that combines the methodological approaches of the Four-Step Transportation Model, the DES model, and the Exploratory Network Analysis model for evaluating the hospital layout design in terms of operational efficiency. This study bridges a critical gap in the literature regarding the application of transport planning and simulation modelling for building-level hospital layout assessment. Unlike existing approaches that operate at the single departmental scale or the urban scale—where the hospital is treated as one studied area—the proposed HDSS enables comprehensive simulations at the building scale through the integration of the macro-level Four-Step Transportation Model and the micro-level DES approach. It also addresses the research gap in current simulation-modelling studies that rely on predefined operational data, such as patient flows. The high specificity of these data not only limits the generalisability of the resulting tools to other hospitals but also restricts their applicability to renovation scenarios where patient data can be readily obtained. The proposed HDSS overcomes this limitation by supporting both the renovation of existing hospitals and the design of new facilities. For renovation scenarios, the HDSS's DES model can incorporate available operational information, such as patient journeys, as simulation input. For new hospital design scenarios or situations where the operational information is not available, the Four-Step Transportation Model within the HDSS can generate generalised patient movement patterns, which can then be used by the DES model as input for simulation and performance analysis. Furthermore, the HDSS's Four-Step Transportation Model and DES model can only simulate steady-state hospital scenarios based on rational, undisrupted user routing. By integrating ENA into the proposed HDSS, the system can reveal hidden spatial risk patterns that conventional simulation overlooks by exposing the inherent structural tendencies of hospital layouts. This, in turn, enhances the overall resilience of the software. Lastly, this study addresses the gap in existing hospital DSS research, which focuses exclusively on evaluating the effects of management policies on hospital operational efficiency while neglecting the influence of layout design. By incorporating layout configuration into the simulation, the proposed HDSS evaluates hospital performance through both operational and spatial lenses.

2. Methodology

This section first described the generation of the Hospital Configuration Model (HCM), which serves as the foundational dataset enabling the implementation of HDSS functionalities. It then introduced how the HDSS is built by developing a Four-Step Transportation Model, DES model, and exploratory network analysis model to simulate hospital operations and assessing performance metrics such as crowdedness, patient waiting times, patient walking distance, and difficulty in wayfinding.

2.1. Hospital configuration model

As previously discussed, hospitals exhibit spatial structures akin to small cities. This spatial structure can be effectively represented using a Hospital Configuration Model (HCM). The HDSS is designed to provide robust and transparent assessment mechanisms for evaluating the performance of various hospital layout designs through simulation modelling and exploratory network analysis approaches. Both approaches require a foundational dataset or structure to function properly. An HCM fulfils this requirement. The HCM is a layout representation model of the hospital system that incorporates four key types of information: geometric, topological, semantic, and operational. Jia et al. developed a methodology (Jia et al., 2025a) and software (Jia et al., 2025b) for semi-automatically generating HCM from hospital Building Information Models (BIM) or Industry Foundation Classes (IFC) models. A detailed explanation of the four types of information included in an HCM is illustrated in Table 1 and summarised in the following text:

- **Geometric Information**
  The geometric data in the HCM captures the physical structure of the hospital, including the boundaries and 3D spaces of rooms and corridors (Jia et al., 2025a). This data is defined using mathematical constructs such as:
  - **Vertices and Edges**: Each room is modelled as a polygon, characterised by a set of vertices (3D coordinates) and edges connecting them. The polygonal data is obtained from BIM/IFC models using software tools like Revit and Dynamo. For a detailed example of room polygon data, refer to the geometric information in Table 1.
  - **Mesh Representation**: The 3D spatial geometry of each room is represented as a mesh, constructed using a mesh representation algorithm developed with the COMPAS library in Python (Van Mele et al., 2017).
- **Topological Information**
  Topological information represents the spatial relationships among the functional units of the hospital, structured as a network graph comprising (Jia et al., 2025a):
  - **Nodes**: Each spatial unit, such as a room or corridor, is represented as a node. Each node is associated with a set of attributes, such as a unique identifier, room name, and floor area.
  - **Edges**: An edge between two nodes indicates an adjacency relationship between the corresponding spatial units. Each edge is assigned a weight corresponding to the Euclidean distance between the connected nodes.

  The nodes and edges are derived from BIM/IFC models using tools like Rhino and Grasshopper, and the network graph is constructed in Python with the NetworkX library (Hagberg et al., 2008). For a simplified illustration of a hospital network graph, refer to the topological information in Table 1. The topological information of the HCM explicitly represents the structure of the hospital building.
- **Semantic Information**
  Semantic information assigns meaning to spatial units by connecting them to their functional roles (Jia et al., 2025a). Examples include:
  - **Room Names**: Identifying spaces such as diagnostic rooms and waiting rooms.
  - **Organisational Hierarchy**: Associating rooms with specific departments to facilitate functional grouping.
    The extraction of semantic information from BIM/IFC models is implemented using Python, with the resulting data organised as a Python dictionary. A Python dictionary is a data structure that organises data as key–value pairs (e.g., key: value) (Python Software Foundation, 2026). For an example of the extracted semantic information, refer to the semantic information in Table 1.
- **Operational Information**
  Operational information encapsulates patient journeys within the hospital, detailing the sequential movement of patients through various rooms during medical procedures (Jia et al., 2025a). The patient journey data is represented as a Python list, where each element corresponds to a room the patient visits during their journey. For a simple example of the patient journey, please see operational information in Table 1.
  It is to be noticed that in Jia (Jia et al., 2025a)'s methodology, the operational information of the HCM is extracted from the patient journey data in an existing hospital, i.e., Panyu Central Hospital in Guangzhou, China (Peng, 2022). Although this operational information can be used to perfectly replicate the patient movements in Panyu Central Hospital, the simulation model applying this data can become highly specific and overly rigid, limiting itself to generalising to other hospitals. This study aim to model general patient movement patterns across different hospitals rather than precisely predict specific patient journeys in a certain hospital. The primary goal is to develop a robust model that remains applicable across a variety of cases, rather than being finely tuned to fit specific data. This is supported by the theory of model parsimony, where simplicity and broad applicability are valued over detailed accuracy (Vandekerckhove et al., 2014). To achieve this, the Four-Step Transportation Model, a widely used framework in transportation planning to predict travel demand and analyse traffic patterns in urban areas (Ortúzar and Willumsen, 2011), is applied in this research to obtain general operational data of patient journeys that is applicable in random hospitals. The general patient journeys generated by the Four-Step Transportation Model are also stored in the form of a Python list, similar to the one illustrated in Table 1.

Fig. 1 is a flow chart for illustrating the procedure of extracting HCM from the BIM/IFC files. The methodology starts with importing the hospital BIM/IFC file into Autodesk's Revit and Dynamo, and extracting the geometric information (i.e., room boundaries, stair boundaries, and door locations) and semantic information (i.e., room names and areas). The extracted geometric information was then put into Grasshopper for generating topological information, which is a network graph. Specifically, the node of the graph is generated by calculating the centre point of each room boundary or stair boundary. There are two types of graph edges, namely, horizontal edges and vertical edges. The horizontal edges are generated by connecting the room/stair's centre point to its corresponding door location point. The vertical edge is made by connecting the same stair's centre point at different floor levels. Once the geometric information and semantic information are extracted and the topological information is generated, these types of information are imported into Python and encoded in an XML-based exchange format. The HCM is further developed following the model-view-controller pattern, which is a popular design pattern in the field of software and program development (tutorialspoint, 2026). Under this design pattern, the HCM is organised into three separated yet interconnected parts, namely, data model, view, and controller (Reenskaug and O. Coplien, 2009). The data model component of the HCM contains all the raw data, including geometric information, topological information, and semantic information, and these types of information are stored in JSON format due to its advantage of high editability and readability compared to XML format Ohori et al. (2022). The JSON-based schema of the HCM's data model is illustrated in Fig. 2. The view component of the HCM can access the information contained in the data model component and organise it into a more human-readable manner. Specifically, the view component of the HCM organises the geometric information into a mesh representation using the COMPAS library in Python (Van Mele et al., 2017). The mesh representation intuitively visualises the geometric information. Furthermore, the resulting mesh representation can serve as input for the preprocessing of the HCM's geometric information (e.g., voxelization), thereby enabling the integration of the ABM simulation model into the HDSS in future research. The view component also organises the topological

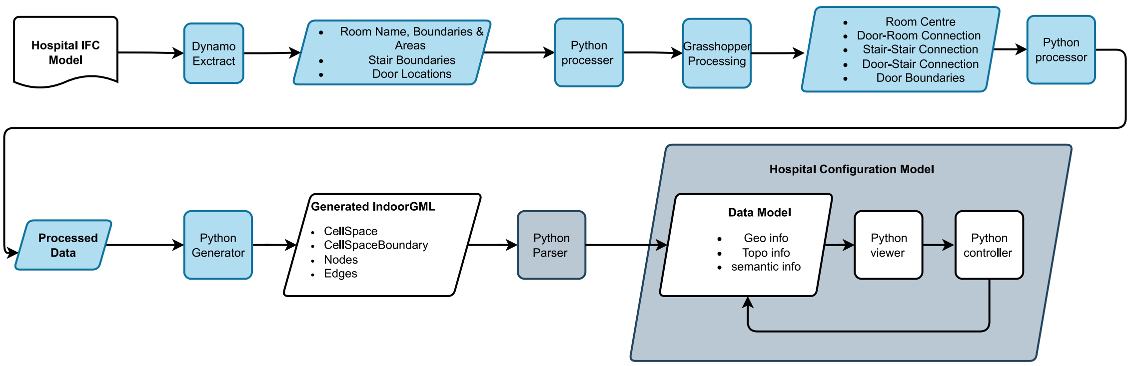


Fig. 1. The procedure of extracting HCM from Hospital BIM model, image source: (Jia et al., 2025a,b).

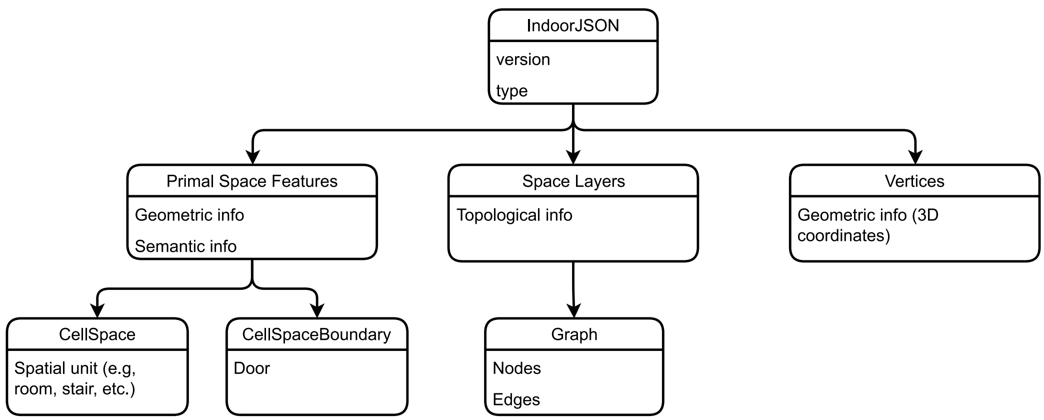


Fig. 2. The HCM's data schema, image source: (Ledoux, 2020).

information contained in the data model into a network graph using the NetworkX library in Python (Hagberg et al., 2008), thereby enabling the development of HDSS's simulation and analysis functions based on the manipulation and analysis of the hospital network, such as optimal path determination and centrality measures using ENA. Semantic information contained in the data model, such as room names and areas, is also organised by the view component and incorporated into the network graph as node attributes. The controller component of the HCM acts as an intermediary between the data model and the view components. It intercepts events from the view component and performs the corresponding updates on the data model. For example, when a geometric visualisation request is issued, the controller retrieves the relevant geometric information from the data model and invokes the view component to generate the corresponding mesh representation.

The structural organisation of hospital buildings shares remarkable similarities with that of small cities. From a mathematical perspective, both hospitals and cities can be modelled as network graphs consisting of nodes and edges, where nodes represent spatial units (e.g., rooms in hospitals, or areas/land uses in cities) and edges denote the connections between these units. This structural resemblance also enables the application of the Four-Step Transportation Model—the framework that is widely used in urban transportation planning—to simulate internal transportation within hospitals, such as the movement of patients. Hence, our HDSS will include a Four-Step Transportation model for simulating the city-like character of hospitals.

2.2. Four-step transportation model

As mentioned in the above section, the Four-Step Transportation Model will be applied to model the city-like character of hospitals. This subsection first provided a brief introduction of the Four-Step Transportation Model, it then explained in detail how our framework utilises the Four-Step Transportation Model to model the patient movement patterns in hospitals.

The Four-Step Transportation Model is a widely used framework in transportation planning for evaluating, assessing, designing and planning transportation systems. It provides a structured approach to understanding how people or goods move within a defined area, such as a city, region, or network (Ortúzar and Willumsen, 2011). The Four-Step Transportation Model consists of four sequential steps, namely, trip generation, trip distribution, mode choice, and route assignment. The following text explains each step in detail with a contrived example. Please note that the numbers and all other aspects of this example are hypothetical. Although hypothetical, the consistency between the first two steps of this modelling approach is demonstrated by the correspondence between the row sums and column sums of Table 3, which align with the values in Table 2 for generated and attracted trips, respectively, with both totals summing to the same value.

- Step 1: trip generation
  Trip generation involves estimating the number of trips originating from and arriving at each zone within the study area. Trips originating from a zone are referred to as "productions", while trips arriving at a zone are termed "attractions" (Kadiyali, 2011). The Four-Step Transportation Model needs to preserve the balance between total travel productions and attractions, which means that the total number of trips produced across all zones must be equal to the total number of trips attracted (Ortúzar and Willumsen, 2011):

$$\sum_{i=1}^{n} P_i = \sum_{j=1}^{n} A_j \tag{1}$$

  where:

  - P_i: Total trip productions in zone i,

Table 2
Trip generation in a virtual hospital project (Jia et al., 2023).

Spatial units	Production	Attraction
	Estimated number of pedestrians in 1 day	Estimated Number of pedestrians in 1 day
Reception hall	50	28
Emergency room	30	26
Diagnosis room	10	20
Imaging room	20	17
Pharmacy	5	24
Total	**115**	**115**

– A_j: Total trip attractions in zone j,
– n: Total number of zones.

In the context of a hospital design project, the trip generation step focuses on predicting the number of patients travelling to and from each spatial unit. Table 2 provides an example of the estimated number of trip productions and attractions at each spatial unit in a hypothetical hospital. For simplicity reasons, the hypothetical hospital only has five spatial units, which are the reception hall, emergency room, diagnosis room, imaging room, and pharmacy. Notably, the proposed example demonstrates strict adherence to the production-attraction equilibrium principle (formula (1)), with total trip productions balancing total trip attractions.

• Step 2: trip distribution
This step distributes the trips generated in Step 1 (trip generation) between origin and destination zones, and it determines the number of people from each origin to each destination by producing an origin–destination matrix (Kadiyali, 2011). A trip distribution model (e.g., a gravity model) estimates the origin–destination matrix, which shows the number of trips travelling between each pair of origin and destination (Ortúzar and Willumsen, 2011). In the context of hospital design, this step calculates the number of patients moving between each origin and destination. Table 3 presents an example illustrating the computed number of patients travelling between the five spatial units of the hypothetical hospital.
It is essential to highlight that in the Four-Step Transportation Model, step one (trip generation) provides the total number of trips—referred to as productions and attractions—that serve as inputs for step two (trip distribution). The trip distribution process must adhere to these totals for each zone (Ortúzar and Willumsen, 2011). This relationship is termed “zonal constraints” and can be formulated as (Ortúzar and Willumsen, 2011):

$$\sum_{j=1}^{n} T_{ij} = P_i \quad \forall i \in \{1, 2, \dots, n\} \tag{2}$$

and

$$\sum_{i=1}^{n} T_{ij} = A_j \quad \forall j \in \{1, 2, \dots, n\} \tag{3}$$

Where:

– P_i: Total trip productions in zone i,
– A_j: Total trip attractions in zone j,
– T_{ij}: Number of trips from zone i (origin) to zone j (destination),
– n: Total number of zones.

This relationship is also demonstrated in Tables 2 and 3, where the sum of trips originating from each spatial unit in the origin–destination matrix (Table 3) corresponds to the trip production for each spatial unit in Table 2. Similarly, the sum of trips arriving at each spatial unit in the origin–destination matrix (Table 3) matches the trip attraction for each spatial unit in Table 2.

• Step 3: mode choice
This step predicts the mode of travel for each pedestrian (Kadiyali, 2011). In the context of the Four-Step Transportation Model applied to a hospital, travel modes for patients may include walking, wheelchair use, or transportation on a hospital bed.
• Step 4: route assignment
This step takes the origin–destination matrix (e.g., Table 3) generated in step 2 as input, and assigns each trip in the matrix a specific path (Kadiyali, 2011). In the Four-Step Transportation Model of a hospital, each trip can be assigned the shortest-distance path to simulate a scenario in which patients navigate to their destination using the optimal route. Alternatively, a random path can be assigned through a random walk simulation to represent situations where patients become disoriented, visiting multiple incorrect locations before reaching their intended destination.

The subsequent sections provide a detailed explanation of how each step of the Four-Step Transportation Model was applied to model patient journeys using the generated HCM as input.

2.2.1. Trip generation

This step estimates the number of trip productions and trip attractions for each zone. In this study, a zone is defined as a spatial unit within the hospital, such as a room, corridor, or stair. The number of trips productions/attractions for each zone is calculated based on its area attribute. Specifically, this research uses the room capacity to determine the number of trip productions and attractions for each spatial unit, and the capacity of each spatial unit is calculated based on its area:

$$P_i = A_i = \text{Room Capacity} = \frac{Area_i}{S_i} \tag{4}$$

where:

• P_i: Total trip productions in spatial unit i,
• A_i: Total trip attractions in spatial unit i,
• $Area_i$ is the area of the spatial unit i(e.g., in square metres),
• S_i is the space requirement per person (this study defines space requirement as 5 square metres per person according to the space guidelines for healthcare facilities (Hospital Concepts, 2012)).

The calculated trip production and attraction at each node are stored in the form of a Python dictionary. In the Python dictionary of trip production and attraction, the key is the node id and the value is the number of trips. Table 4 gives an illustration of generated trip productions and attractions in this step. Please note that for clarity and simplicity reasons only a few of the generated trips are shown in this table, for the complete data please refer to thisrepository. Some node has zero trips because this node is not a room or corridor, instead it is a door which does not have an area. Algorithm 1 presents the pseudo-code for the trip demand estimation method.

Table 3
Trip distribution in a virtual hospital project.

	Reception hall	Emergency room	Diagnosis room	Imaging room	Pharmacy	ΣO
Reception hall	N/A	20	10	10	10	50
Emergency room	10	N/A	5	5	10	30
Diagnosis room	5	2	N/A	2	1	10
Imaging room	10	3	4	N/A	3	20
Pharmacy	3	1	1	0	N/A	5
ΣD	28	26	20	17	24	115

Algorithm 1 Trip Generation and Impedance Calculation.

Require: Graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, node area attributes $\{a_i\}_{i \in \mathcal{V}}$, default space requirement σ.
Ensure: Origin vector $\mathbf{O}$, Destination vector $\mathbf{D}$, Distance matrix $\mathbf{M}$.

Step 1: Node Capacity and Demand Generation
for each node $i \in \mathcal{V}$ **do**
  if a_i is numeric and $a_i > 0$ **then**
    $c_i \leftarrow \lfloor a_i / \sigma \rfloor$ ▷ Calculate room capacity
    $O_i \leftarrow \mathrm{int}(c_i)$, $D_i \leftarrow \mathrm{int}(c_i)$
  else
    $O_i \leftarrow 0$, $D_i \leftarrow 0$ ▷ Non-walkable or undefined space
  end if
end for
Step 2: Shortest Path Impedance Calculation
for each pair $(i, j) \in \mathcal{V} \times \mathcal{V}$ **do**
  if a path exists between i and j in $\mathcal{G}$ **then**
    $M_{i,j} \leftarrow \mathrm{ShortestPathLength}(i, j, \mathrm{weight} = \mathrm{distance})$
  else
    $M_{i,j} \leftarrow \infty$
  end if
end for
return $\mathbf{O}, \mathbf{D}, \mathbf{M}$

2.2.2. Trip distribution

This step distributes the trips generated in step 1. Specifically, this step estimates the number of patients travelling from each origin to each destination by producing an origin–destination matrix. In this research, the origin–destination matrix is constructed by using a simple gravity model, which can be formulated as follows:

$$T_{ij} \propto P_i A_j \cdot f(d_{ij}) \tag{5}$$

where:

- T_{ij}: Number of trips between nodes i and j,
- P_i: Trip production at node i,
- A_j: Trip attraction at node j,
- $f(d_{ij})$: Impedance function between nodes i and j, in this study, an inverse-square impedance function, $f(d_{ij}) = d_{ij}^{-\beta}$ is adopted, where d_{ij} denotes the shortest-path distance between nodes i and j, and β is the impedance parameter, which is set to 2, consistent with classical gravity-based spatial interaction models originally proposed by Zipf (Zipf, 1946). However, this parameter may be calibrated using empirical movement tracking data in future work. The shortest-path distance between nodes i and j is calculated using Dijkstra's algorithm (Dijkstra, 1959) and can be computed as

$$d_{ij} = \sum_{(u,v) \in \pi_{ij}^*} w_{uv} \tag{6}$$

where:

- π_{ij}^* represents the shortest path connecting nodes i and j;
- $(u, v) \in \pi_{ij}^*$ denotes an edge along this path;
- w_{uv} is the weight associated with edge (u, v), defined as the Euclidean distance between the connected spatial units.

Table 4
Results of trip generation.

Node ID	Production	Attraction
0	12	12
1	17	17
2	57	57
3	5	5
...	...	...
501	0	0

From a transportation planning perspective, a hospital can be conceptually divided into two parts: the external connections to the outside world, such as entrances and exits, and the internal system encompassing the remainder of the hospital. The Four-Step Transportation Model is applied specifically to the internal system of the hospital. Consequently, the graph representing the internal system (i.e., the hospital graph excluding entrance and exit nodes) must adhere to the principles of total trip balance (Eq. (1)) and zonal constraints (Eqs. (2) and (3)).

However, the origin–destination matrix generated by the simple gravity model (Eq. (5)) does not follow the zonal constraints principle. The sum of trips originating from (arriving at) each spatial unit in the origin–destination matrix is proportional, but not equal to, the trip production (attractions) for each spatial unit. Hence, the origin–destination matrix needs to be adjusted to follow the zonal constraints principle. This study applied the Algebraic Iterative Proportional Fitting (AIPF) algorithm developed by Nourian et al. (2024) for adjusting the origin–destination matrix. The AIPF algorithm is designed for adjusting a matrix A to satisfy given target row and column sums while minimising the squared error. It ensures that the adjusted matrix $\tilde{A}$ satisfies the constraints (Nourian et al., 2024):

- Row sums of $\tilde{A}$ equal the target row sums ($\mathbf{r}$).
- Column sums of $\tilde{A}$ equal the target column sums ($\mathbf{c}$).
- Both row and column sums add up to the same total.

Algorithm 2 presents the pseudo-code for the trip distribution method and the AIPF procedure used to balance the initial trip matrix.

2.2.3. Mode choice

In this step, all patients are assigned the walking travel mode; wheelchair or hospital bed transportation are excluded in this study. However, the model is flexible, and these alternative travel modes can be assigned to different patient groups in future studies.

2.2.4. Route assignment

For this step, as introduced earlier, two specific paths are assigned for each trip. One is the shortest-distance path to simulate the scenario

Algorithm 2 Doubly-Constrained Trip Distribution via AIPF (Nourian et al., 2024).

Require: Origin vector $\mathbf{O}$, Destination vector $\mathbf{D}$, Distance matrix $\mathbf{M}$, tolerance ϵ, max iterations K, regularisation parameter δ.
Ensure: Adjusted Trip Matrix $\mathbf{T}^*$.

Initialization:
Construct seed matrix $\mathbf{T}^{(0)} \in \mathbb{R}^{|\mathcal{V}|\times|\mathcal{V}|}$ where:
$T^{(0)}_{i,j} \leftarrow \begin{cases} \frac{O_i \cdot D_j}{M^2_{i,j}} & \text{if } i \neq j \text{ and } 0 < M_{i,j} < \infty \\ 0 & \text{otherwise} \end{cases}$
$\mathbf{R} \leftarrow \mathrm{diag}(\mathbf{O})$, $\mathbf{C} \leftarrow \mathrm{diag}(\mathbf{D})$
$k \leftarrow 0$, error $\leftarrow \infty$
while error $> \epsilon$ **and** $k < K$ **do**
  Row Balancing Step:
  $\mathbf{r}^{(k)} \leftarrow \sum_j T^{(k)}_{i,j}$ ▷ Current row sums
  $\mathbf{P} \leftarrow \mathrm{diag}(\max(\mathbf{r}^{(k)}, \delta))$ ▷ Apply regularization to avoid zero-division
  $\mathbf{T}^{(k+1/2)} \leftarrow \mathbf{R}\mathbf{P}^{-1}\mathbf{T}^{(k)}$
  Column Balancing Step:
  $\mathbf{c}^{(k)} \leftarrow \sum_i T^{(k+1/2)}_{i,j}$ ▷ Current column sums
  $\mathbf{K} \leftarrow \mathrm{diag}(\max(\mathbf{c}^{(k)}, \delta))$
  $\mathbf{T}^{(k+1)} \leftarrow \mathbf{T}^{(k+1/2)}\mathbf{K}^{-1}\mathbf{C}$
  Convergence Check:
  error $\leftarrow \sum_i(\sum_j T^{(k+1)}_{i,j} - O_i)^2 + \sum_j(\sum_i T^{(k+1)}_{i,j} - D_j)^2$
  $k \leftarrow k + 1$
end while
return $\mathbf{T}^{(k)}$ as $\mathbf{T}^*$

in which patients reach their destination using the optimal route, and another is the random path, modelling situations where patients become disoriented and visit multiple incorrect locations before arriving at their intended destination. The following text describes how to obtain these two types of paths in detail:

- Shortest-distance path:
  This study assigns the shortest-distance path to each trip in the adjusted origin–destination matrix $\tilde{A}$. Specifically, for the element $\tilde{A}_{ij}$ in the adjusted matrix $\tilde{A}$, if $\tilde{A}_{ij} > 0$ (i.e., there exists paths between nodes i and j), the shortest-distance path between nodes i and j is determined using Dijkstra's algorithm (Dijkstra, 1959) and is expressed in Eq. (6). Algorithm 3 presents the pseudocode for computing the shortest paths based on the adjusted matrix $\tilde{A}$.

Algorithm 3 Shortest Path Assignment from OD Matrix.

Require: Adjusted Trip Matrix $\mathbf{T}^*$, Graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$.
Ensure: A set of shortest paths $\mathcal{P}_{short}$.

$\mathcal{P}_{short} \leftarrow \emptyset$
for each origin $i \in \mathcal{V}$ **do**
  for each destination $j \in \mathcal{V}$ **do**
    $N_{i,j} \leftarrow \mathrm{round}(T^*_{i,j})$ ▷ Obtain integer trip count
    if $N_{i,j} > 0$ **then**
      $\pi_{i,j} \leftarrow \mathrm{Dijkstra}(\mathcal{G}, i, j, \text{weight} = \text{distance})$ ▷ Find shortest path
      for $k = 1$ **to** $N_{i,j}$ **do**
        Append $((i, j), \pi_{i,j})$ to $\mathcal{P}_{short}$
      end for
    end if
  end for
end for
return $\mathcal{P}_{short}$

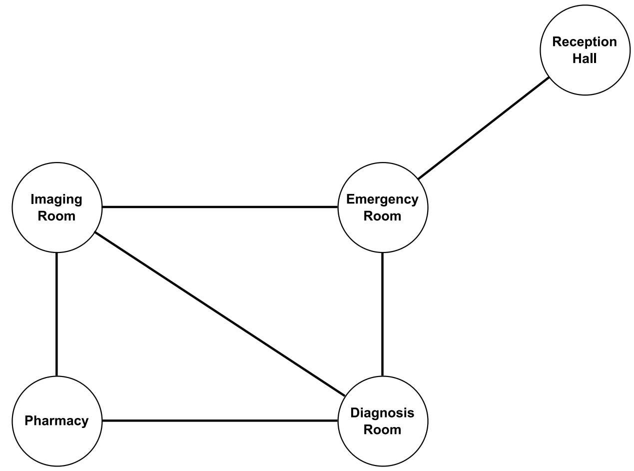


Fig. 3. An illustrative example of a Random Walk Simulation model.

- Random path:
  Hospitals are large-scale, complex environments, where visitors often become disoriented, leading them to take unintended detours before arriving at their intended destinations. This deviation results in actual travel paths being longer than the shortest possible route, reflecting the difficulty in wayfinding. This study uses random walk simulation to obtain a random path for each trip, emulating scenarios where patient agents become lost and deviate from the shortest path, thereby following a longer route to their destinations.
  Random walk simulation (RWS) is a mathematical modelling technique used to represent stochastic (random) movement patterns in various domains, such as urban mobility (Douglas, 1995). In a random walk, an agent moves step by step in a random direction according to predefined probabilities, making it a valuable tool for simulating uncertain, unpredictable, or exploratory movement behaviours. The key characters of RWS can be summarised as follows (Douglas, 1995):

  - Stochastic Process: The movement of agents follows a probabilistic rule rather than a deterministic path.
  - Step-Based Movement: At each step, the agent selects its next position based on a probability distribution.
  - State Dependence: The future position depends on the current position and transition probabilities.

  An illustrative example of the RWS model is presented using the hypothetical hospital consisting of five spatial units, as introduced in Section 2.2. Fig. 3 represents this hospital environment as an undirected graph, where each node corresponds to a spatial unit within the facility. The agent's origin is the "Reception Hall", and the destination is the "Pharmacy". The simulation assumes that the agent begins at the origin node and moves to a randomly selected connected node at each step until reaching the destination. At each step, the agent chooses one of its neighbouring nodes with equal probability. For example, a possible random walk path could be as follows:

  1. Start at "Reception Hall", move to "Emergency Room" (only available choice).
  2. Move to "Diagnosis Room" (choices: "Imaging Room", "Diagnosis Room").
  3. Move to "Imaging Room" (choices: "Emergency Room", "Diagnosis Room", "Pharmacy").
  4. Move to "Pharmacy" (choices: "Emergency Room", "Diagnosis Room", "Pharmacy"), reaching the destination.

Algorithm 4 presents the pseudocode for generating stochastic paths via random walk simulation.

Algorithm 4 Stochastic Path Generation via Random Walk.

Require: Graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, Set of deterministic trips $\mathcal{P}_{det}$ where each entry is $((o, d), \pi)$.
Ensure: Set of stochastic paths $\mathcal{P}_{rand}$.

function GetSingleRandomPath($s, t, \mathcal{G}$) ▷ Generate one stochastic trajectory
  $v_{curr} \leftarrow s$
  $\pi_{rand} \leftarrow [s]$
  while $v_{curr} \neq t$ **do**
    $\mathcal{N}(v_{curr}) \leftarrow \{u \mid (v_{curr}, u) \in \mathcal{E}\}$ ▷ Identify adjacent nodes
    if $\mathcal{N}(v_{curr}) = \emptyset$ **then break**
    end if
    $v_{next} \sim \text{Uniform}(\mathcal{N}(v_{curr}))$ ▷ Stochastic node selection
    Append v_{next} to π_{rand}
    $v_{curr} \leftarrow v_{next}$
  end while
  return π_{rand}
end function

Main Procedure: GetFullRandomPaths($\mathcal{P}_{det}$)
$\mathcal{P}_{rand} \leftarrow \emptyset$
for each $((o, d), \pi) \in \mathcal{P}_{det}$ **do**
  $\pi_{rand} \leftarrow$ GetSingleRandomPath($o, d, \mathcal{G}$)
  $\mathcal{P}_{rand} \leftarrow \mathcal{P}_{rand} \cup \{((o, d), \pi_{rand})\}$
end for
return $\mathcal{P}_{rand}$

In summary, the final outputs of the Four-Step Transportation Model consist of two sets: one representing the shortest paths and the other capturing random paths, both of which describe patient movements under different conditions within the hospital. Fig. 4 presents a visualisation of the patient movement patterns with the shortest path, using the HCM as input. In this figure, red lines represent the volume of trips between spatial units, with thicker lines indicating a higher number of trips. These outputs are instrumental in achieving the HDSS's ability to evaluate patient walking distances and wayfinding challenges. However, the Four-Step Transportation Model is not suitable for evaluating overcrowding and patient waiting times, as it does not incorporate temporal considerations or time-related measurements. To address this limitation, an alternative approach is required. Discrete event simulation emerges as an optimal solution, as it explicitly models time-dependent processes and can effectively capture people density over time and patient waiting times.

2.3. Discrete event simulation

The HDSS's Discrete Event Simulation (DES) model is employed to capture the factory-like dynamics of hospital operations and address the limitation of the Four-Step Transportation Model, particularly in assessing crowdedness and patient waiting times. This section begins with a concise introduction to DES, followed by a detailed explanation of how our framework leverages DES to simulate patient journeys within hospitals. A Discrete-Event Simulation (DES) model represents a system in which events occur at distinct time points, triggering changes in the system's state (Hillier and Lieberman, 2015). A DES model comprises the following key components:

- Discrete Event: A discrete event catalyses changes in the system state. In a DES model, the state transitions occur exclusively due to event occurrences (Leemis and Park, 2006). For instance, in a hospital DES model, a patient's walking distance changes only when they move to another room.

Table 5
Specification of the DES Model components and logic.

Component	Logic/Parameter	Description
Entities	Patient Agents	Agents instantiated for specific Origin–Destination pairs with unique IDs.
Resources	Spatial units (Rooms)	Modelled as `simpy.Resource`. Capacity determined by: $C = \lfloor \text{FloorArea}/5m^2 \rfloor$.
Events	1. Generation 2. Traversal 3. Service Request 4. Release	Discrete events that trigger state transitions (e.g., occupancy updates, start of waiting).
Queue Rule	FIFO (First-In-First-Out)	The default queue discipline for `simpy.Resource`.
Distributions	Inter-arrival: Exp(λ = 5 min) Service: Exp(μ = 5 min)	Exponential distributions capture stochastic operational variability.
Traversal	Speed = 60 metres/min	Deterministic movement: Time = Distance/Speed.
Sync Logic	Blocking Mechanism (`yield request`)	If a node reaches full capacity, the incoming agent process is suspended until a resource slot is released.

- Clock: The clock tracks the simulation's progression over time. Since time is a critical variable in DES, system state variables evolve dynamically as the simulation advances (Leemis and Park, 2006). For example, in a hospital DES model, a patient's total walking distance increases as time progresses.
- Random Number Generators: These generate random variables essential for DES models (Leemis and Park, 2006), such as patient inter-arrival rates or the duration of medical services.
- Statistics: This component aggregates and analyses simulation results, including key performance metrics such as patient waiting times and total walking distances (Leemis and Park, 2006).
- Termination Condition: The simulation concludes once a predefined condition is met (Leemis and Park, 2006). For example, in a hospital DES model, the simulation may terminate when a specified number of patients have been discharged.

The DES model within our framework is designed to utilise patient movement patterns of shortest paths derived from the Four-Step Transportation Model as primary input data, enabling the simulation of operational processes within hospitals. Specifically, the DES model instantiates a patient agent corresponding to each shortest path in the movement pattern dataset, thereby simulating the spatiotemporal dynamics of patients traversing their respective shortest paths. The patient agent starts with the first node in the respective shortest path, and moves node by node through the path, until it reaches the last node. The patient agent stays at each node except for nodes representing connecting units (i.e., doors) for a random period to simulate diagnosis, treatment or other medical services. Since each node has a capacity defined in the previous Four-Step Transportation Model (formula (4)), if the number of patient agents at a node reaches its capacity, the node becomes unavailable, and the next patient reaches the node need to wait until the node becomes available again (e.g., one or more patient agents move to the next node). Table 5 specifies the components and logic of the DES model, including entities, events, resources, service-time distributions, queue rules, and how journeys sync with room capacities. Algorithm 5 presents the pseudo-code of the HDSS's DES model. The main output of the DES model includes each patient agent's total waiting time during the traversal of the respective shortest path. The patient's total waiting time is calculated as follows:

$$W_{\text{total}} = \sum_{i=1}^{N} W_i = \sum_{i=1}^{N} (T_{\text{enter},i} - T_{\text{arrive},i}) \tag{7}$$

where:

- W_{total}: the patient's total waiting time across all nodes in the path,
- W_i: the waiting time at node i,
- $T_{\text{enter},i}$: the time the patient enters node i,
- $T_{\text{arrive},i}$: the time the patient arrives at node i,
- N: the total number of nodes in the path.

Algorithm 5 HDSS Discrete-Event Simulation Logic.

Require: Graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, Trip Matrix $\mathbf{T}^*$, Path set $\mathcal{P}$, node areas $\{a_i\}$, space parameter σ, walking speed v, mean service time μ, mean inter-arrival time λ.
Ensure: Log of agent trajectories $\mathcal{L}_{agent}$ and resource utilization $\mathcal{L}_{util}$.

Procedure: InitializeResources
for each node $i \in \mathcal{V}$ **do**
  $c_i \leftarrow \lfloor a_i/\sigma \rfloor$ ▷ Define capacity of node i
  if $c_i > 0$ **then**
    Create resource $\mathcal{R}_i$ with c_i available servers.
  end if
end for

Procedure: PatientProcess(o, d, π) ▷ Logic for a single agent
$t_{start} \leftarrow current\_time$
for each edge (u, v) in path π **do**
  $\Delta t_{walk} \leftarrow \text{dist}(u, v)/v$
  Wait for duration Δt_{walk} ▷ Simulate walking
  if v has associated resource $\mathcal{R}_v$ **then**
    Request access to $\mathcal{R}_v$
    $t_{entry} \leftarrow current\_time$
    Queue until $\mathcal{R}_v$ is available
    $\Delta t_{wait} \leftarrow current\_time - t_{entry}$
    $\Delta t_{service} \sim \text{Exponential}(1/\mu)$
    Wait for duration $\Delta t_{service}$ ▷ Perform service
    Release resource $\mathcal{R}_v$
  end if
end for
Log trip metrics $(t_{start}, current\_time, \Delta t_{wait}, \dots)$ to $\mathcal{L}_{agent}$.

Procedure: MasterTrafficGenerator
for each origin-destination pair $(o, d) \in \mathcal{V} \times \mathcal{V}$ **do**
  $N_{trips} \leftarrow \text{round}(T^*_{o,d})$
  $\pi \leftarrow \text{GetPath}(o, d, \mathcal{P})$
  if $N_{trips} > 0$ and π exists **then**
    for $j = 1$ **to** N_{trips} **do**
      $\Delta t_{arrival} \sim \text{Exponential}(1/\lambda)$
      Wait for duration $\Delta t_{arrival}$
      Spawn PatientProcess(o, d, π) as a concurrent process.
    end for
  end if
end for

2.4. Exploratory network analysis

To adequately address concerns related to criticalities and required redundancies in the configuration design of a hospital, the study proposes to include an exploratory Network [Centrality] Analysis suite of tools to allow the designer to 'see' the bottlenecks, the hot spots, the spreaders, invisible corners, the hard-to-guard areas, and the natural clusters and/or similar patterns that result directly from the structure of the network rather than its attributes. Space Syntax theories (and their alternative counterparts) typically discuss these structural tendencies of spatial networks in terms of two essential types of networks: the inter-accessibility network and the inter-visibility network (Azadi et al., 2024). The scope of the work does not allow for incorporating inter-visibility networks and the patterns associated with them because they mainly concern the micro-scale issues inside hospital rooms or halls. In contrast, this research is mainly concerned with those issues that pertain to the macro-scale structure of the configuration related to its inter-accessibility network. Therefore, a suite of tools is introduced to perform a few archetypical network analysis procedures, as described below:

- [*Local*] Closeness Centrality: Closeness Centrality is a measure from network analysis and graph theory that helps quantify how near a particular node is to all other nodes in a network (Pérez-Gosende et al., 2021). Local Closeness Centrality is a variant of the traditional closeness centrality measure that focuses on a node's immediate surroundings rather than the entire network (Nourian, 2016). This means it focuses on the "local" accessibility of resources and interactions. In a hospital network—where hospitals tend to form clusters based on regional, referral, or specialisation patterns—local closeness centrality can provide a more nuanced picture of how well a hospital is connected within its relevant operational community. The Local Closeness Centrality can be computed as follows (Nourian, 2016):

$$C_C(i) = \frac{1}{\sum_{j \in P_i^R} D(i,j)} \tag{8}$$

where:

  - $C_C(i)$: the local closeness centrality measure of the node i,
  - $D(i,j)$: the distance between node i and node j, given by: $D(i,j) = \sum_{k \in \gamma_{i,j}} \zeta_k$, where $\gamma_{i,j}$ is the path from node i to node j, and ζ_k is the weight/cost of the kth edge on that path,
  - P_i^R: the set of nodes within distance R of i, given by: $P_i^R = \{\, j \mid D(i,j) < R \}$.

  When comparing local closeness centrality across different networks or dealing with networks of varying sizes, it is necessary to normalise the centrality measures, given by the previous formula multiplied by the number of nodes within the "local neighbourhood" P_i^R, resulting in Nourian (2016):

$$C'_C(i) = \frac{|P_i^R|}{\sum_{j \in P_i^R} D(i,j)} \tag{9}$$

  This calculation ensures the resulting local closeness centrality is between 0 and 1.
- [*Local*] Betweenness Centrality: Betweenness centrality is a fundamental measure in network analysis that quantifies the extent to which a node acts as a bridge within a network (Pérez-Gosende et al., 2021). It identifies nodes that frequently appear on the shortest paths between other nodes, highlighting their role in facilitating flow or influence distribution. By contrast, Local Betweenness Centrality focuses on a restricted subgraph. This is particularly useful in spatial or architectural contexts (e.g., in hospitals), where designers might only need to assess the impact of a node on routes in its immediate vicinity or within a functional zone. The Local Betweenness Centrality is calculated as follows (Nourian, 2016):

$$B_C(i) = \sum_{s \neq t \in P_i^R} \frac{\sigma_{s,t}(i)}{\sigma_{s,t}}, \tag{10}$$

where:

  - $B_C(i)$: the local betweenness centrality measure of the node i,
  - P_i^R: the set of nodes within distance R of node i.
  - $\sigma_{s,t}$: the total number of shortest paths between nodes s and t (both in P_i^R).

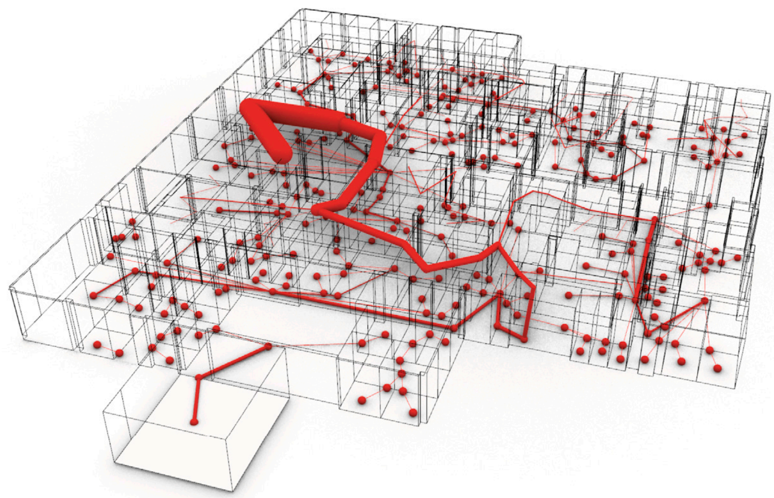


Fig. 4. Visualisation of patient movement patterns.

- $\sigma_{s,t}(i)$: the number of those shortest paths that pass through i.

To compare local betweenness scores across different hospital networks, one can include a normalisation factor based on the size of P_i^R. For example, if P_i^R has $|P_i^R| = M$ nodes, one might normalise as follows (Nourian, 2016):

$$B'_C(i) = \frac{2}{(M-1)(M-2)} \sum_{s<t \in P_i^R} \frac{\sigma_{s,t}(i)}{\sigma_{s,t}}, \tag{11}$$

where $s < t$ indicates summing only over unique unordered pairs. This scaling ensures that $B'_C(i)$ falls between 0 and 1 under the assumption that i cannot be on a shortest path to or from itself.

- [*Local*] Eigenvector Centrality: Eigenvector centrality assigns a score to each node such that a node is considered important if it is connected to other nodes that are themselves important (Pérez-Gosende et al., 2021). In other words, not all connections are equal—a connection to a highly influential node boosts the score more than a connection to a less influential one. Local Eigenvector Centrality is a variation of the traditional eigenvector centrality that focuses on a node's influence within a confined or "local" region of a network rather than across the entire graph. For evaluating a complex building network such as a hospital, local eigenvector centrality is more practical because it captures the immediate, spatially relevant connectivity that underlies day-to-day operations and helps pinpoint locally critical nodes (such as specific corridors or doorways) that could be essential for traffic flow. The computation of local eigenvector centrality is restricted to a subgraph centred on node i. Let:

  - $S(i)$ be the local neighbourhood of i, typically defined as the k-hop neighbourhood (i.e., nodes reachable from i within k steps).
  - $A^{(local)}$ be the adjacency matrix of this subgraph.
  - λ_{local} be the largest eigenvalue of $A^{(local)}$

The local eigenvector centrality can be obtained by Nourian (2016):

$$E_C(i) = \frac{1}{\lambda_{local}} \sum_{t \in A} a_{i,t} x_t^{(local)}, \tag{12}$$

The Eq. (12) can also be written in a vector form as:

$$\mathbf{E}_\mathbf{C}^{(local)} = \frac{1}{\lambda_{local}} A^{(local)} \mathbf{E}_\mathbf{C}^{(local)}$$

Which simplifies to the eigenvector equation:

$$A^{(local)} \mathbf{E}_\mathbf{C}^{(local)} = \lambda_{local} \mathbf{E}_\mathbf{C}^{(local)} \tag{13}$$

This shows that $\mathbf{E}_\mathbf{C}^{(local)}$ is the eigenvector of the local adjacency matrix $A^{(local)}$ corresponding to the largest eigenvalue λ_{local}. For the purpose of cross-network comparison, the local eigenvector centrality is normalised through the computation of a normalised local adjacency matrix $N^{(local)}$ (Zaki and Meira, 2014):

$$N^{(local)} = \mathrm{diag}(A^{(local)}\mathbf{e})^{-1} A^{(local)}$$

Where:

- $\mathbf{e}$ is the vector of ones.
- $\mathrm{diag}(A^{(local)}\mathbf{e})$ is a diagonal matrix containing the row sums of $A^{(local)}$, i.e., the local out-degrees.

Then the normalised local eigenvector centrality satisfies the equation:

$$\mathbf{E'}_\mathbf{C}^{(local)} = (N^{(local)})^T \mathbf{E'}_\mathbf{C}^{(local)} \tag{14}$$

Fig. 5 illustrates the connectivity between the Four-Step Transportation Model, the DES model, and the ENA model. Specifically, all three models rely on the HCM as the primary input. Furthermore, the DES model dependently utilises the patient path data generated by the Four-Step model.

2.5. The evaluation mechanisms

This section elaborates how to deal with the outputs of the three models within the HDSS (i.e., Four-Step Transportation Model, Discrete-Event Simulation model, and Exploratory Network Analysis model) to enable informed decision support.

2.5.1. The evaluation mechanisms for simulation modelling

Both simulation models within the HDSS generate disaggregated outputs. Specifically, the Four-Step Transportation Model produce a large set of patient travel paths in the hospital, while the Discrete-Event Simulation (DES) model outputs detailed patient-level simulation data, including patient ID, arrival time, departure time, total waiting time, origin, and destination. Although these outputs provide a granular representation of patient flows within the hospital environment, it is hard to make effective assessments on these outputs due to their

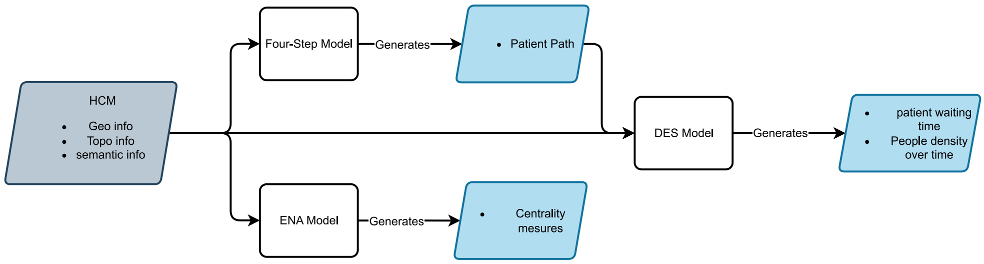


Fig. 5. A flow chart illustrating how Four-Step, DES, and ENA models connect.

disaggregated nature. To be able to use these outputs to make effective assessments and informed decisions, the following three steps need to be taken:

- Aggregation: The aggregation process refers to the method of summarising and consolidating disaggregated simulation results into higher-level statistical metrics or grouped datasets (Law, 2007). This process is used to extract meaningful insights by computing averages, totals, distributions, or other summary statistics from individual simulation outputs (Law, 2007). For example, in a hospital simulation, different individual patient waiting times can be aggregated to derive an average waiting time.
- relativisation: The relativisation process involves the normalisation or standardisation of the aggregated simulation outputs to facilitate comparison across different spatial scales (Banks, 2010). This process typically transforms absolute values into relative indicators, such as ratios or percentages, allowing for meaningful comparison and analysis across different scales (Banks, 2010). For instance, the average patient waiting times in different hospitals with varied scales can be relativised based on the total times spent in hospitals.
- Interpretation: Functional unit interpretation refers to the process of harmonising relativised simulation outputs by adjusting them to a common functional unit, ensuring comparability between different datasets or scenarios (ISO (the International Organization for Standardization), 2006). This is particularly useful when results come from models with different scales, units, or baseline assumptions. In hospital simulations, for example, the relativised waiting times can be interpreted by defining a functional unit such as "percentage of total time spent per patient" to enable direct comparisons between different hospital layouts.

The HDSS is engineered to evaluate the efficiency and effectiveness of hospital layouts by assessing four key quality criteria: public spatial crowdedness, patient waiting time, patient walking distance, and wayfinding difficulty. In order to assess these quality criteria, the disaggregated indicators of the four quality criteria are first identified from the simulation results. Specifically, for assessing crowdedness in public spaces, the disaggregated indicator is the average people density in each spatial unit over a period T, which can be calculated as:

$$\bar{\rho}_i = \frac{1}{T}\int_0^T \rho_i(t)\,dt \tag{15}$$

where:

- $\rho_i(t)$ is the people density in spatial unit i at time t, and is calculate as

$$\rho_i(t) = \frac{C_i(t)}{Area_i} \tag{16}$$

where $C_i(t)$ is the number of people simultaneously presented in spatial unit i at time t.
- $Area_i$: the area of spatial unit i.

The disaggregated indicators for patient walking distance are each patient's total walking distance, which is straightforward according to the shortest paths generated by the Four-Step Transportation Model. The total distance for each path can be calculated as follows:

$$D_p^{\text{shortest}} = \sum_{i=1}^{k_p-1} d(n_{p,i}, n_{p,i+1}) \tag{17}$$

where:

- D_p^{shortest}: the total distance of the patient p's shortest path,
- $n_{p,i}$: the ith node in patient p's shortest path,
- $d(n_{p,i}, n_{p,i+1})$: the distance between node n_i and node n_{i+1} in patient p's shortest path.

For assessing wayfinding difficulty, this study defines the disaggregated indicator as each patient's extra walking distance. The HDSS assigns two paths to each patient agent. One is the shortest path, and another is the random path. Both paths have the same origin–destination pair, but the journeys are different, leading to different total distances. The distance of the random walk paths (D_p^{random}) can be calculated using formula (17) and each patient's extra walking distance is computed as follows:

$$D_p^{\text{extra}} = D_p^{\text{random}} - D_p^{\text{shortest}} \tag{18}$$

where:

- D_p^{extra}: the extra walking distance of the patient p,
- D_p^{random}: the random walking distance of the patient p,
- D_p^{shortest}: the shortest walking distance of the patient p.

For assessing patient waiting time, the disaggregated indicator is each patient's waiting time, which is already recorded by the DES model (see formula (7)).

The following paragraphs discuss how to use the steps of aggregation, relativisation, and interpretation to turn the four disaggregated indicators into the quality criteria that are ready to be used for comparing and assessing different hospital layouts.

For results aggregation, the four indicators are aggregated using their average: average people density in public spaces over a period T, average patient walking distance, average extra walking distance, and average waiting time. Specifically, the average people density in the public area over a period T is calculated as follows:

$$\bar{\rho}_{\text{public}} = \frac{\sum_{i=1}^{M} \bar{\rho}_i}{M} \tag{19}$$

where:

- $\bar{\rho}_{\text{public}}$: the average people density in public areas over the period T,
- $\bar{\rho}_i$: the average people density in public spatial unit i over the period T,
- M: the total number of public spatial units.

The average patient walking distance is computed as follows:

$$\bar{D} = \frac{\sum_{p=1}^{P} D_p^{\text{shortest}}}{P} \tag{20}$$

where:

- $\bar{D}$: the average patient walking distance,
- $D_p^{shortest}$: the walking distance of patient p,
- P: the total number of patients.

Similarly, the average extra patient walking distance can be calculated as:

$$\bar{D}^{\text{extra}} = \frac{\sum_{p=1}^{P} D_p^{\text{extra}}}{P} \tag{21}$$

where:

- $\bar{D}^{\text{extra}}$: the average patient extra walking distance,
- D_p^{extra}: the extra walking distance of patient p,
- P: the total number of patients.

Lastly, the calculation of average patient waiting time is straightforward:

$$\bar{W} = \frac{\sum_{p=1}^{P} W_p^{\text{total}}}{P} \tag{22}$$

where:

- $\bar{W}$: the average patient waiting time,
- W_p^{total}: the total waiting time of patient p,
- P: the total number of patients.

In the step of relativisation, the aggregated simulation results are relativised to enable the comparison between hospitals with different sizes and scales. The average people density in public areas is relativised by comparing it to the total capacity of the public areas. Specifically, the relativised people density in public areas is calculated as follows:

$$\rho_{\text{rel}} = \frac{P_{\text{total}}}{C_{\text{public}}} \tag{23}$$

where:

- ρ_{rel}: the relativised people density in public spaces,
- P_{total}: the total number of patients in public spaces, given by: $P_{\text{total}} = \bar{\rho}_{\text{public}} \cdot A_{\text{public}}$, where $\bar{\rho}_{\text{public}}$ is the average people density in public areas, and A_{public} is the total area of public spaces.
- C_{public}: the total capacity in public spaces, given by: $C_{\text{public}} = \rho_{\text{target}} \cdot A_{\text{public}}$, where ρ_{target} is the target people density in public spaces.

In this formula, the target people density in public spaces ρ_{target} is defined as 0.77 person per square metre according to the FGI Guidelines (Facility Guidelines Institute) (The Facility Guidelines Institute, 2022). However, this number can be adjusted according to different cases. The value of ρ_{rel} ranges from 0 to $+\infty$ (positive infinity), where $\rho_{\text{rel}} > 100\%$ indicates that the population exceeds the designed capacity (overcrowding).

The average patient walking distance is relativised by comparing it to the hospital size. Specifically, The relative walking distance R is defined as:

$$D_{\text{rel}} = \frac{\bar{D}}{D_{\text{total}}} \tag{24}$$

where:

- D_{rel}: the relative patient walking distance,
- $\bar{D}$: the average patient walking distance,
- D_{total}: the total distance of the HCM's network graph, given by: $D_{\text{total}} = \sum_{(i,j)\in E} d_{ij}$ where E is the set of edges in the graph, and d_{ij} is the distance between nodes i and j.

Similarly, the relative patient extra walking distance can be computed as follows:

$$D_{\text{rel}}^{\text{extra}} = \frac{D^{\bar{\text{extra}}}}{D_{\text{total}}} \tag{25}$$

where:

- $D_{\text{rel}}^{\text{extra}}$: the relative patient extra walking distance,
- $D^{\bar{\text{extra}}}$: the average patient extra walking distance,
- D_{total}: the total distance of the HCM's network graph.

The values of D_{rel} and $D_{\text{rel}}^{\text{extra}}$ both theoretically range from 0 to $+\infty$ (positive infinity). In practice, D_{rel} is usually below 100%; however, it may exceed 100% in certain cases, such as in small hospitals with only a few rooms and corridors, where a patient's multi-stop journey requires repeated traversals between spaces, resulting in a total travelled distance that surpasses the overall network length. Likewise, wayfinding difficulty is intrinsically unbounded, as a disoriented patient could, in principle, wander indefinitely.

The relative patient waiting time is obtained by comparing the average patient waiting time with the average patient total time spent in the hospital:

$$W_{\text{rel}} = \frac{\bar{W}}{\bar{W}_{\text{ts}}} \tag{26}$$

where:

- W_{rel}: the relative patient waiting time,
- $\bar{W}$: the average patient waiting time,
- $\bar{W}_{\text{ts}}$: the average patient total time spent in hospital, given by: $\bar{W}_{\text{ts}} = \frac{\sum_{p=1}^{P} W_p^{\text{ts}}}{P}$, where W_p^{ts} is the total time spent by patient p in the hospital, and P is the total number of patients.

The value of W_{rel} is bounded between 0 and 1 (100%), representing the percentage of total time spent waiting.

In the step of interpretation, a functional unit is defined for each relativised quality criterion to ensure fair comparisons. For example, the functional unit for relative people density in public spaces is defined as "occupancy percentage per square metre". Under this definition, a relative people density of 10% per square metre in a hospital's public areas indicates that, on average, only 10% of the hospital's capacity is utilised per square metre. Similarly, the functional unit for relative patient walking distance is defined as "percentage of hospital size per patient". Consequently, a relative walking distance of 5% of hospital size per patient implies that the average distance walked by a patient corresponds to 5% of the total hospital size. Notably, this same functional unit is also applied to quantify the relative patient extra walking distance. Furthermore, the functional unit for relative patient waiting time is defined as "percentage of total time spent per patient". Thus, a relative patient waiting time of 20% of total time per patient signifies that, on average, a patient's waiting time constitutes 20% of the overall time spent in the hospital.

Table 6 summarises the mathematical formulas used to derive the disaggregated indicator, aggregated quality criterion, and relativised quality criterion for each of the four hospital design challenges. Additionally, the table presents the functional units associated with these design challenges.

2.5.2. Interpretation of exploratory network analysis results

In the exploratory network analysis, centrality measurements are inherently disaggregated and normalised, with each node in the graph assigned a unique value between 0 and 1. As a result, this study does not apply the same evaluation mechanisms as those used in simulation modelling. Instead, the centrality measures are interpreted to analyse their implications for hospital layout design and spatial connectivity.

Fig. 6 illustrates the results of Local Closeness Centrality measures of the HCM's network graph. The local region is defined as the subgraph

Table 6
A summary of the HDSS's evaluation mechanisms.

	Disaggregated indicator	Aggregated quality criterion	Relativised quality criterion	Functional unit
Spatial Crowdedness	$\bar{\rho}_i = \frac{1}{T}\int_0^T \rho_i(t)\,dt$	$\bar{\rho}_{\text{public}} = \frac{\sum_{i=1}^{M}\bar{\rho}_i}{M}$	$\rho_{\text{rel}} = \frac{P_{\text{total}}}{C_{\text{public}}}$	Occupancy percentage per square metre
Patient walking distance	$D_p^{\text{shortest}} = \sum_{i=1}^{k_p-1} d(n_{p,i}, n_{p,i+1})$	$\bar{D} = \frac{\sum_{p=1}^{P} D_p^{\text{shortest}}}{P}$	$D_{\text{rel}} = \frac{\bar{D}}{D_{\text{total}}}$	Percentage of hospital size per patient
Difficulty in Wayfinding	$D_p^{\text{extra}} = D_p^{\text{random}} - D_p^{\text{shortest}}$	$\bar{D}^{\text{extra}} = \frac{\sum_{p=1}^{P} D_p^{\text{extra}}}{P}$	$D_{\text{rel}}^{\text{extra}} = \frac{D^{\bar{\text{extra}}}}{D_{\text{total}}}$	Percentage of hospital size per patient
Patient Waiting time	$W_{\text{total}} = \sum_{i=1}^{N}(T_{\text{enter},i} - T_{\text{arrive},i})$	$\bar{W} = \frac{\sum_{p=1}^{P} W_p^{\text{total}}}{P}$	$W_{\text{rel}} = \frac{\bar{W}}{\bar{W}_{\text{ts}}}$	Percentage of total time spent per patient

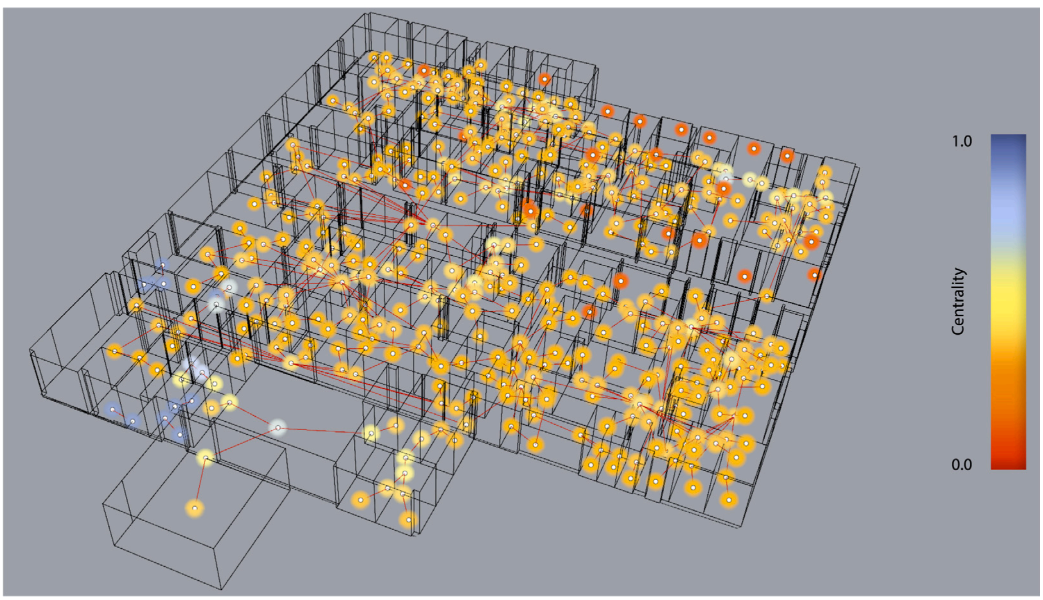


Fig. 6. Local Closeness Centrality ($R = 5$) measures of the HCM's graph.

induced by all nodes reachable within a radius of five edges from the target node. The nodes coloured in blue represent spatial units with relatively high local closeness centrality, indicating their centrality and strong connectivity within the local region of the hospital network. These areas are beneficial for accessibility and efficient movement, making them optimal locations for reception areas or nurse stations, where rapid communication and coordination are essential. In contrast, the nodes shown in red correspond to spatial units with lower local closeness centrality, signifying more remote or isolated locations within the network. These areas are likely to serve specialised or lower-traffic functions, such as patient rooms or recovery areas, where reduced interaction with other hospital units is appropriate.

Fig. 7 presents a visualisation of the local betweenness centrality measure for the HCM graph, with the local region defined as the subgraph induced by all nodes within a five-edge radius. The spatial units represented by blue nodes exhibit high local betweenness centrality, indicating that they frequently lie along the shortest paths between other spatial units within the local region of the hospital network. As critical passageways or "bridges", these areas facilitate connectivity between different clusters or departments within the hospital. Due to the high volume of movement through these spaces, they have the potential to become congestion points. The HDSS's exploratory network analysis model can identify these key areas, which enables architects to implement strategic design interventions early in the planning process to optimise circulation and mitigate bottlenecks. Conversely, the spatial units denoted by red nodes have relatively low local betweenness centrality, meaning they are rarely traversed as part of the shortest paths between other rooms. Their relative isolation may be advantageous for functions that require a controlled or quieter environment, such as therapy rooms or private offices, where minimal disruption is desirable.

Fig. 8 illustrates the local eigenvector centrality metric for the HCM graph, with the "local" region defined as the subgraph induced by all nodes reachable within a five-edge radius. The nodes coloured in blue represent spatial units with high local eigenvector centrality; they are connected to other highly connected rooms, making them influential within the local region of the hospital layout. Their positioning helps in the rapid dissemination of people or information. Such rooms are key in facilitating efficient movement and may be ideal for central functions like lobbies, nurse stations, or emergency triage areas. In contrast, because they are integrated into a broader cluster of well-connected spaces, any issues here (e.g., hospital-acquired infection) could affect a larger portion of the hospital. The red nodes are spatial

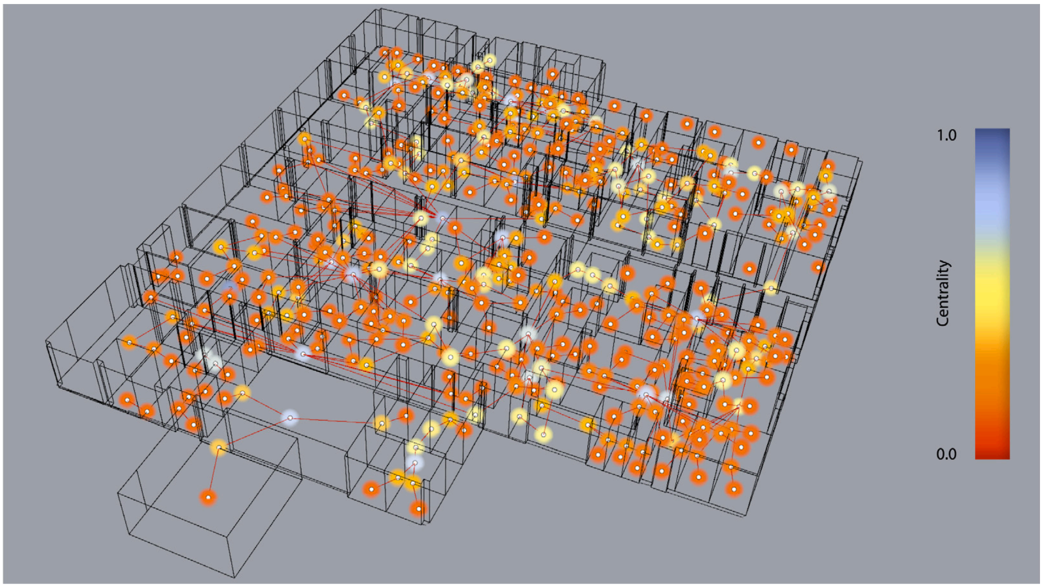


Fig. 7. Local Betweenness Centrality ($R = 5$) measures of the HCM's graph.

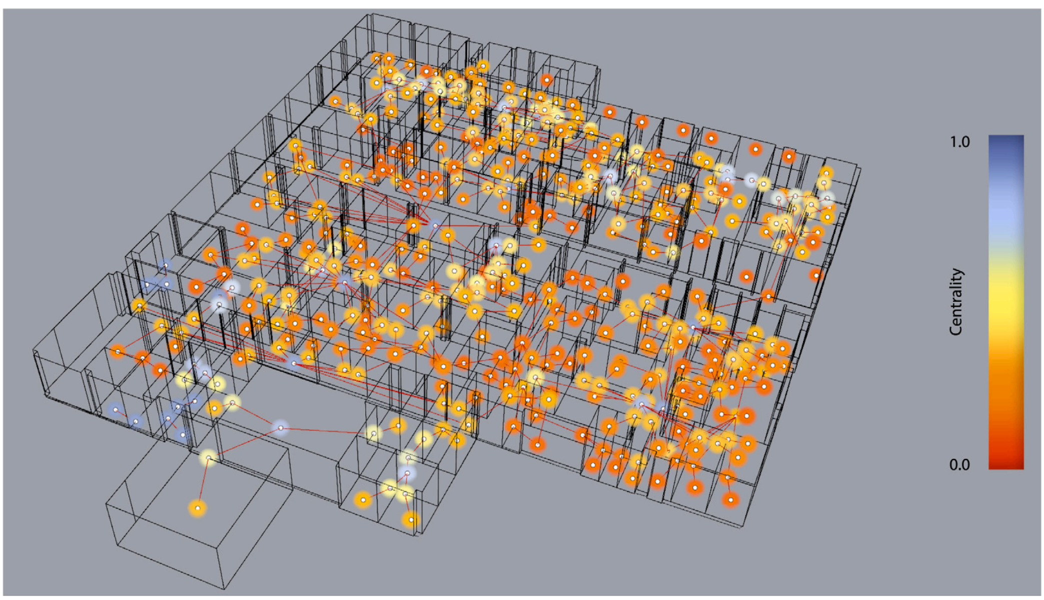


Fig. 8. Local Eigenvector Centrality ($R = 5$) measures of the HCM's graph.

units with lower local eigenvector centrality; these rooms are typically connected to other less connected or isolated areas, reducing their overall influence in the network. Their relative isolation makes them suitable for functions that benefit from lower foot traffic and enhanced privacy, such as patient rooms, specialised treatment areas, or private consultation spaces.

To bridge the gap between abstract centrality metrics and practical design decision-making, Table 7 summarises how each metric links to specific operational goals (Resilience, Wayfinding) and informs tangible design interventions based on the centrality metric visualisations.

3. Research results

3.1. Case study

This study adopts an open-source hospital IFC model as the case study (van Berlo, 2026) and implements the case following the methodology described in Section 2. First, an HCM is extracted from the selected hospital IFC model, as illustrated in Fig. 9, where the red graph is embedded within the transparent building geometry. The HCM is then used as the input for the three core models of the HDSS, i.e., the Four-Step Transportation Model, the DES model, and the ENA Model. Various layouts and scenarios were tested to evaluate the performance of the HDSS. Due to the limited availability of hospital IFC models, only one IFC model was implemented in this study. A different layout was created by modifying this model (e.g., main corridor closure). Accordingly, three different scenarios were designed to evaluate the HDSS's performance of assessing layout resilience and operational sensitivity:

- Scenario A (the baseline scenario): simulates the normal operation within the original hospital layout.
- Scenario B (Sensitivity Test - Peak Load): The patient volume (Trip Generation) was increased by 150% across all spatial units

Table 7
Interpretation of centrality metrics: linking mathematical definitions to architectural design choices.

Centrality metric	Mathematical meaning	Architectural interpretation	Link to design goal	Design action (Visual inference)
Local Closeness Centrality	Mean distance to all other nodes within a local neighbourhood.	Integration/Accessibility: How central a space is.	**Wayfinding Efficiency**	High (Blue): Place Reception /NurseStations here. Low (Red): Place private wards here.
Local Betweenness Centrality	Frequency of appearing on shortest paths.	Through-movement potential: Likelihood of being a “bridge” or bottleneck.	**Resilience /Safety**	High (Blue): Identify “choke points.” Widen corridors or add parallel routes (redundancy) to prevent congestion.
Local Eigenvector Centrality	Connectedness to well-connected nodes.	Influence/Spread: Potential for spreading flow/infection.	**Infection Control**	High (Blue): High risk of cross-contamination. These rooms should be prioritised for isolation.

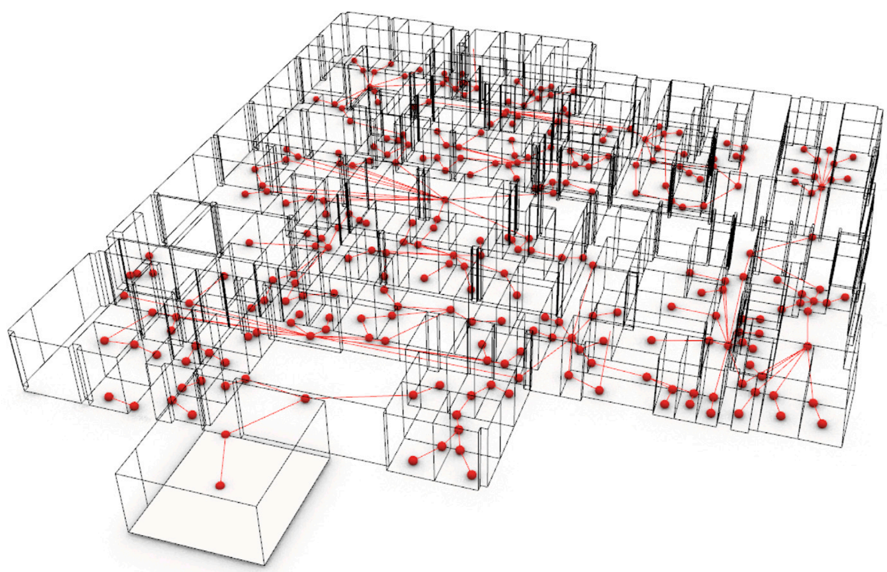


Fig. 9. A visualisation of the HCM, image source: (Jia et al., 2025b).

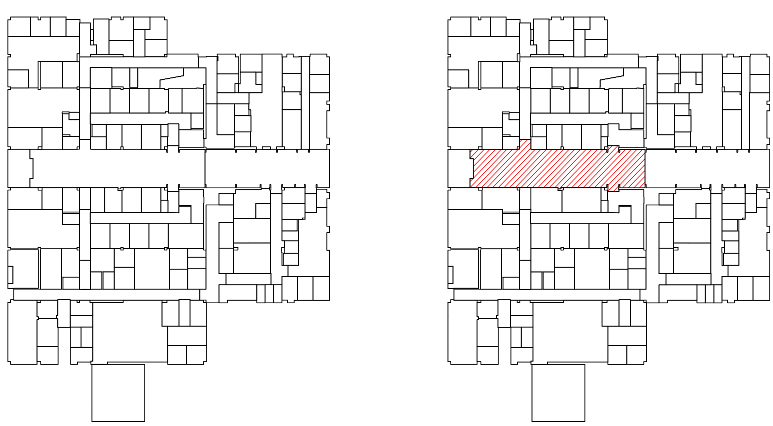


Fig. 10. Various Layouts for simulation (red lines indicate the main corridor closure).

to simulate a peak operational hour. This scenario tests the system’s sensitivity to demand fluctuations.

- Scenario C (Layout Robustness - Corridor Closure): To simulate a variation in hospital layout (representing different layouts), one of the main corridors was removed from the original layout (as illustrated in Fig. 10). This simulates a scenario of maintenance, renovation, or isolation control, forcing agents to seek alternative routes.

3.2. Evaluations

The quantitative results of the above scenario analysis are summarised in Table 8. In the Peak Load scenario (B), while the average walking distance remained unchanged, the average waiting time increased substantially (+260%). In addition, the average people density in public areas increased markedly (+400%) due to the higher patient volume, indicating that certain spatial units (e.g., waiting rooms and

Table 8
Sensitivity and Scenario Analysis.

Metric	Scenario A (Baseline)	Scenario B (Peak Load +50%)	Scenario C (Corridor Closure)
Average Walking Distance	22 m	22 m	25 m (+14%)
Average Waiting Time	10 min	36 min (+260%)	11 min
Average People Density	0.001 person/m^2	0.005 person/m^2 (+400%)	0.001 person/m^2

Table 9
Ablation Analysis.

Metric	Full HDSS	Transport Model Only	DES Only	ENA Only
Avg. Walking Distance	Scenario A	Scenario A	N/A	N/A
Avg. Waiting Time	Scenario A	N/A	N/A	N/A
Average People Density	Scenario A	N/A	N/A	N/A
Difficulty in Wayfinding	Scenario C	Scenario C	N/A	N/A

corridors) were operating under higher pressure during peak hours. These results demonstrate the HDSS's sensitivity in identifying and quantifying the impacts of demand variation. In the Corridor Closure scenario (C), the system successfully captured the effects of layout change: the average walking distance increased by 14% as a result of necessary detours, demonstrating the HDSS's ability to quantify the "cost" of layout modifications. These tests confirm that the HDSS can effectively differentiate between layout alternatives and operational conditions.

A key methodological contribution of this study lies in the hybrid integration of Exploratory Network Analysis (ENA), the Four-Step Transportation Model, and Discrete-Event Simulation (DES). To substantiate the necessity of this integrated architecture, an ablation analysis was conducted (Table 9) to examine the limitations of each component when applied in isolation. Specifically, four configurations were tested: the full HDSS framework, the Four-Step Transportation Model alone, DES alone, and ENA alone. These models were applied to compare the alternative layouts discussed in Section 3.1 (i.e., Scenario A: baseline, and Scenario C: corridor closure). The preferred layout identified by each configuration is summarised in Table 9. The Four-Step Transportation Model is primarily suited to evaluating distance-related metrics, such as average walking distance and average extra walking distance (reflecting potential difficulty in wayfinding). However, it does not capture the temporal quality criterion, including waiting time or crowdedness (measured as average density over time). DES, while capable of detailed temporal analysis, requires predefined patient path information. Without such inputs derived from the transportation model, DES cannot independently evaluate layout alternatives across the full set of quality criteria. ENA provides structural insights at the node level by quantifying centrality measures; however, due to its disaggregate nature (see Section 2.5.2), it does not produce an aggregate performance indicator for overall layout evaluation. Instead, ENA functions as a diagnostic tool for identifying spatial units that may exhibit structural vulnerability or importance, complementing quantitative simulation outputs through visualisation. Together, the ablation results demonstrate that no single method can comprehensively evaluate hospital layouts, thereby justifying the necessity of the proposed hybrid HDSS architecture.

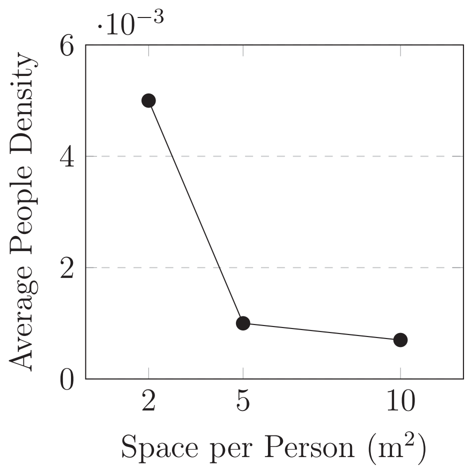
To evaluate the robustness of the proposed HDSS, a parameter sensitivity analysis was conducted on two key assumptions: the space-per-person parameter and the impedance parameter β in the gravity model. First, the space-per-person parameter was varied across three levels (2 m^2, 5 m^2 baseline, and 10 m^2). As illustrated in Fig. 11, average people density exhibits an inverse relationship with available space, decreasing from 0.005 (2 m^2) to 0.001 (5 m^2) and further to 0.0007 (10 m^2). While this proportional change reflects the mechanical impact of capacity adjustment, the operational response shows a markedly non-linear pattern. The average waiting time increases from 4 min (10 m^2) to 10 min (5 m^2 baseline), and sharply to 36 min when the space requirement is reduced to 2 m^2 per person. This escalation indicates strong congestion effects within the Discrete-Event Simulation framework, demonstrating that system performance is highly sensitive to spatial capacity constraints under high-density conditions. Second, the sensitivity analysis of impedance parameter β in the gravity model was tested using values of 1, 2 (baseline), and 5. Fig. 12 shows a consistent monotonic relationship between impedance parameter and average walking distance. When β is reduced to 1, the average walking distance increases to 27.26 m, reflecting weaker distance decay and greater likelihood of long-distance movements. Under the baseline value of $\beta = 2$, the average walking distance is 22.47 m, while increasing β to 5 reduces it to 19.26 m. This trend confirms that stronger impedance effects constrain long-distance interactions and promote more localised movement patterns within the hospital network. Importantly, the variation remains gradual rather than abrupt, suggesting that the overall movement pattern is stable across a reasonable range of impedance assumptions. These findings indicate that the HDSS captures theoretically consistent distance-decay behaviour while maintaining structural robustness under parameter variation.

To verify the internal consistency of the DES model, trace analysis was conducted on the generated patient data logs. This analysis verified that agents correctly followed topological paths and that waiting times were strictly generated only when node occupancy reached the defined capacity limit ($5m^2/person$). Regarding validity, in the absence of sensor data for calibration, expert face validity was established. Simulation outputs were reviewed by experienced hospital architects to assess whether the identified bottlenecks and queuing behaviours represented plausible operational scenarios for the evaluated layouts.

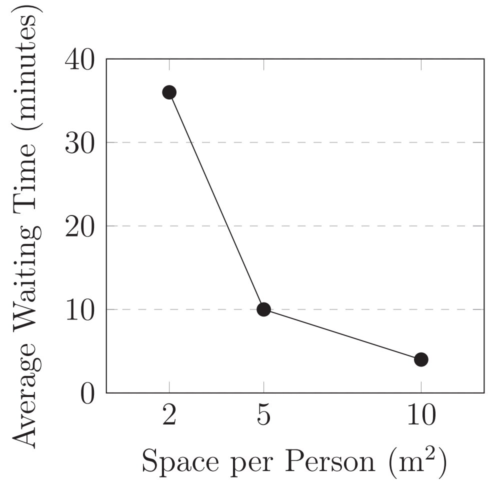
4. Conclusion and discussion

This study presents a comprehensive framework—the Hospital Design Support System (HDSS)—that integrates simulation models and network analysis techniques to evaluate hospital layout performance. By merging the Four-Step Transportation Model, Discrete Event Simulation (DES), and Exploratory Network Analysis, the HDSS provides a multifaceted approach to address key operational challenges such as overcrowding, patient waiting times, excessive walking distances, and wayfinding difficulties.

This study presents significant findings that enhance the field of hospital layout design and simulation modelling. The application of the HDSS revealed that the combined use of macro-scale simulation models and exploratory network analysis yields valuable insights into hospital operations. Specifically, the Four-Step Transportation Model successfully quantified spatial dynamics by simulating patient movement across various functional zones, effectively identifying potential hotspots of congestion and inefficient circulation patterns. Concurrently, the DES model offered a detailed temporal analysis, capturing waiting times and service delays that are critical for evaluating operational performance. Moreover, the integration of Exploratory Network Analysis allowed for the identification of critical nodes—via measures such as local closeness, betweenness, and eigenvector centralities—that



(a) Average people density



(b) Average waiting time

Fig. 11. Sensitivity analysis of space-per-person parameter. (a) Average people density; (b) Average waiting time.

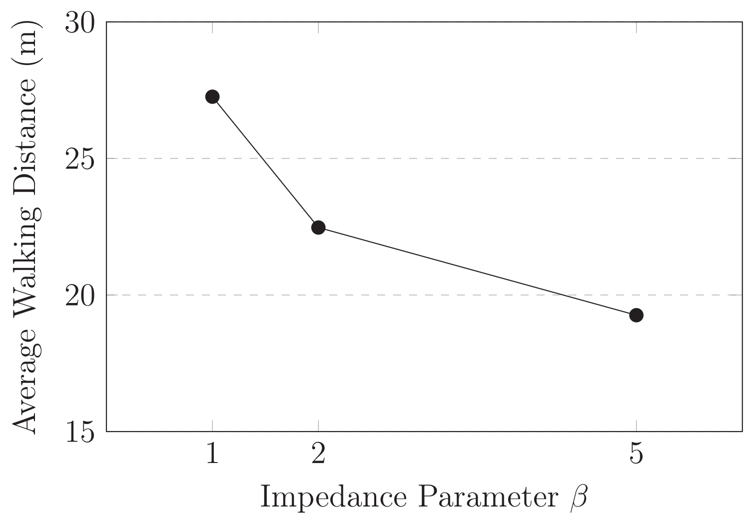


Fig. 12. Sensitivity of average walking distance to impedance parameter β in the gravity model.

are indicative of areas with high connectivity and potential vulnerability to bottlenecks. Together, these findings underscore the effectiveness of the HDSS in providing objective, quantifiable metrics that can inform early design decisions and facilitate the optimisation of hospital layouts.

The primary contribution of this work lies in the development of an integrated decision support system tailored for hospital layout design. Unlike traditional approaches that often rely on isolated simulation or qualitative assessments, the HDSS bridges multiple disciplinary methodologies to create a robust framework for evaluating hospital layout performance. The innovative combination of Transportation Planning with Discrete-Event Simulation and Exploratory Network Analyses not only enhances the accuracy of performance evaluation but also provides a scalable method adaptable to various hospital configurations. Furthermore, another contribution is achieved by proposing systematic evaluation mechanisms—aggregation, relativisation, and interpretation of simulation outputs—that transform disaggregated data into actionable quality criteria. This methodological rigour establishes a new benchmark for assessing complex healthcare environments, promoting a more data-driven approach to architectural design in hospitals.

Despite its strengths, the HDSS framework has several limitations. First, it is important to acknowledge that the current simulation parameters—such as the impedance parameter β in the Four-Step Model and service time distributions in the DES—rely on expert-informed assumptions and standard benchmarks rather than empirical calibration against real-world hospital operational logs. While this limits the system's ability to make precise absolute predictions of traffic volumes or specific wait times for an existing facility, it does not undermine its validity as a design support tool. The primary objective of the HDSS is comparative assessment: it aims to rank the relative performance of competing layout alternatives (e.g., Design A vs. Design B) under consistent conditions. Future research will focus on validating the model against real-world pedestrian tracking data to refine the impedance parameter of the gravity model and the service rate distributions of the DES, a necessary step for evolving the HDSS into a digital twin system for live hospital management. Second, the framework currently lacks integration of real-time operational data, relying predominantly on synthetic or modelled data. Third, the proposed methodology was applied and validated using a single real-world hospital BIM model. While this case study confirms the feasibility and effectiveness of the approach, further research is needed to assess its generalisability across diverse hospital layouts with varying levels of complexity and functional requirements. It is important to delineate the boundaries of the current HDSS implementation.

The framework primarily operates under steady-state assumptions, modelling 'business-as-usual' patient flows based on rational routing (shortest paths) and stochastic service variability. Consequently, it does not currently account for non-routine dynamics, such as panic behaviour during emergency evacuations, complex cognitive wayfinding errors (beyond random walks), or physical collision avoidance in narrow corridors. However, a key strength of the HDSS architecture lies in its modularity. The Hospital Configuration Model (HCM) serves as a robust foundational database where geometric information is defined at the spatial unit (room) level. Crucially, these units can be further discretised into finer grids (tile level) using voxelization algorithms. This flexibility allows future research to integrate Agent-Based Modelling (ABM) or hybrid micro-simulation modules as 'plug-ins' to the existing architecture. By applying voxelization to the HCM geometric data, an ABM model could be deployed to simulate high-fidelity evacuation scenarios or detailed crowd interactions—such as collision avoidance—thereby effectively complementing the macroscopic efficiency analysis provided by the current Four-Step/DES approach.

Addressing these limitations offers avenues for future research. Enhancing model flexibility by incorporating stochastic variations and more nuanced behavioural parameters could further improve the fidelity of the simulations. Additionally, a key avenue for future research involves enhancing the HDSS with real-time data integration, effectively transforming it into a digital twin system for hospital management. By continuously processing live patient movement data through cameras and computer vision sensors, the system could conduct simulation-based analyses to forecast congestion hot spots and identify high-risk zones for contamination. This predictive capability would enable hospital administrators to implement timely interventions, optimising both operational efficiency and patient safety. Beyond hospital management, this digital twin framework has broad applicability across various domains. In urban transportation systems, for example, real-time traffic data could be utilised to simulate congestion patterns, allowing policymakers to devise proactive strategies for traffic mitigation. Similarly, in railway stations, the framework could enhance passenger flow management by identifying potential bottlenecks and optimising crowd movement. These examples underscore the framework's adaptability, demonstrating its potential to support intelligent decision-making in complex, dynamic environments. Lastly, validation of the HDSS against various cases will be essential to refine the models and ensure their applicability in diverse healthcare settings.

In conclusion, while the HDSS framework represents a significant advancement in the evaluation of hospital layout design, its refinement and validation in different contexts remain crucial for realising its full potential in hospital design decision-making.

CRediT authorship contribution statement

Zhuoran Jia: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Pirouz Nourian:** Writing – review & editing, Supervision, Software, Methodology, Conceptualization. **Peter Luscuere:** Supervision, Project administration. **Cor Wagenaar:** Supervision, Project administration.

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.

Data availability

Data will be made available on request.

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