A Hospital Design Support System
Addressing Hospital Layout Design Challenges in China

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A Hospital Design Support System

Addressing Hospital Layout Design Challenges in China

Dissertation

for the purpose of obtaining the degree of doctor
at Delft University of Technology
by the authority of the Rector Magnificus, Prof.dr.ir. T.H.J.J. van der Hagen
chair of the Board for Doctorates
to be defended publicly on
Monday, 27 October 2025 at 12:30 o'clock by

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My interest in hospital design began during a clinical design project in my undergraduate architectural studies. Since then, I have been deeply passionate about hospital architecture. I embarked on this PhD research with the goal of deepening my understanding and expertise in hospital architecture. Surprisingly, throughout this journey, I discovered that not only did I gain a more profound insight into hospital design, but I also developed an even stronger interest in another discipline—Operations Research—which has further enriched my perspective.

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Zhuoran Jia
April 2025
Guangzhou, China

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Summary

Hospitals are inherently complex systems, characterized by two distinct dimensions of complexity. First, from a functional perspective, medical procedures inside a hospital are complex. Second, from a spatial and organizational standpoint, hospitals resemble small urban environments, where corridors function as streets and spatial units operate similarly to distinct land uses within a city. This dual-layered complexity underscores the profound impact of hospital layout on users' visibility and walkability within the hospital. Consequently, hospital design extends beyond mere architectural considerations; it entails the creation of a system where inefficiencies and risks can arise if not planned carefully. To enhance the design of the hospital system, we propose the integration of 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 HDSS aims to establish a robust and transparent evaluation framework for systematically assessing hospital layout performance in terms of functionality and operational efficiency.

This dissertation begins with an introduction chapter (chapter 1), which explains the rationales for developing an HDSS. It provides an overview of the research background, objectives, and research questions, while also defining relevant terminology, research scope, and the proposed methodology. Chapter 2 presents a comprehensive literature review, summarizing the key design challenges associated with hospital layout designs in China. These challenges include overcrowding, long patient waiting times, long patient walking distances, and difficulty in wayfinding. The proposed HDSS aims to address these issues through simulation modelling and exploratory network analysis. Since both approaches require a well-structured foundational dataset to function effectively, the development of such a dataset is a prerequisite for the HDSS. To meet this requirement, we introduce the Hospital Configuration Model (HCM), which serves as the foundational dataset for the HDSS. The HCM comprises four types of critical information: geometric, topological, semantic, and operational. Chapter 3 provides a detailed description of the HCM and outlines the methodology for systematically constructing it. Once the HCM is established, we can develop the HDSS to assess hospital layout configurations in relation to the four key design challenges. Chapter 4 describes the developed HDSS, which consists of three core models: a Four-Step Transportation Model which simulates the city-like characteristics of hospitals and evaluates hospital layout performance concerning overcrowding, patient walking distances, and difficulty in wayfinding; a Discrete-Event Simulation Model which captures the factory-like nature of hospitals and assesses hospital layout performance in terms of patient waiting

times; and an Exploratory Network Analysis Model – unlike the previous two models, which focus on functional efficiency, this model evaluates the inherent logic of hospital spatial structures without considering the specific functions or attributes of hospitals' spatial units. In other words, the Four-Step Transportation Model and the Discrete-Event Simulation Model assess the rational aspects of hospital layouts, while the Exploratory Network Analysis Model examines the irrational aspects of hospital layouts. Additionally, the HDSS includes an evaluation mechanism that translates simulation results into actionable insights to support informed decision-making. Specifically, disaggregated outputs from the simulation models are aggregated, normalized, and interpreted using a functional unit, ensuring fair comparisons across hospitals of varying scales. The HDSS serves as a robust decision-support tool for architects, hospital administrators, and head nurses during the early design stages, enabling the identification of optimal hospital layout alternatives. Finally, Chapter 5 presents the conclusion of this dissertation, addressing the research questions, summarizing key contributions, discussing research limitations, and suggesting potential directions for future studies.

1 Introduction

1.1 Background

The life cycle of a hospital project includes the planning stage, designing stage, construction stage, operation stage and maintenance stage. Identifying the problems with the hospital project in the early design stage and improving them is much easier and more cost-effective than identifying and improving the problems during/after the construction stage. The expenditures of a hospital project can be divided into capital expenditures (prepaid costs such as buildings, construction and equipment, etc.) and operational expenditures (day-to-day costs such as staff salaries and utilities, etc.) [1]. Operational expenditures account for approximately 96% of the total costs in hospitals, which is much higher than the capital expenditures (approximately 4%) [2]. This is due to the complexity of the hospital architecture, the complexities of a hospital building are twofold, which include spatial complexity (i.e., hospitals have large scales, multiple functional units connected by public and/or access-limited corridors) and procedure complexity (i.e., different actors accomplishing different types of procedures such as diagnosis, treatment, clinical test, surgeries and cleaning, etc.). These complexities make hospitals eligible to be compared to cities. Hence, when we design a hospital, we are not just making a building, but a system that can have many risks and problems if not treated carefully. There are two ways of making such systems. The conventional way is to make it by intuition, architects design hospitals based on experience or expectation. The other way is to introduce an early operational insight into the design process through simulation. Simulations can form the base of a decision support system by predicting the performance of the system and making evaluations according to the simulation results. Decision support systems are concerned with the field of Operations Research, which has been separated from the field of Architecture for a long time. This research aims to combine the fields of Architecture and Operations Research to develop a Spatial Decision Support System to address the problems with Chinese hospital layout design and reduce hospital expenditures.

1.2 Problem Statement

1.2.1 Problems with hospital design in China

Inappropriate hospital layout design leads to problems such as overcrowding, patients/visitors' difficulty in wayfinding, nurse/patients' long travel distance, and patient long waiting time [3, 4, 5, 6, 7, 8, 9, 10]. These problems/challenges cause not only patient and staff dissatisfaction but also a negative impact on medical outcomes and operational inefficiency, which further lead to high expenditure [11, 12].

1.2.2 High Operational Expenditure in hospitals

A recent study investigating 3501 hospitals' cost structures in the USA shows that the operational expenditures of hospitals (96% of total cost) are much higher than the capital expenditures (4% of total cost) [2]. The high operational expenditures can be caused by operational inefficiency. For instance, a study conducted in a large-scale hospital in the U.S. shows that due to the unsuitable layout design, the annual expenditure caused by the wayfinding system is $220,000 per year or $448 per bed per year in 1990 [13]. The main reason behind this is that doctors/nurses are interrupted by visitors and have to pause their current work and give directions, according to the study results, more than 4,500 staff hours (i.e., two full-time staff positions) were occupied [13].

1.2.3 The complexity of hospitals

As mentioned in section 1.1, it is much easier and more cost-effective to identify the problems and make changes during the design stage and before the construction/operation stage. Specifically, the hospital architectural design stage includes the schematic design phase, the layout design phase and the design development phase. This study aims at identifying problems and make improvements during the layout design phase. Spatial layout design, as one of the most significant phases of the architectural design stage [14], is concerned with identifying appropriate locations and geometries for a set of interrelated functional units to achieve design goals and maximize design performance in line with design preferences [14]. The complexities of hospitals are twofold. Firstly, the building environment itself is complex, the hospital can be compared to a city due to its scale as well as the traffic system (e.g., there are main public corridors and access-limited corridors, which can be regarded as major roads and minor roads in a city). Secondly, different medical and non-medical procedures indicate that the interactions between the actors and the environment are complex. Hence, when we design a hospital, we are not merely designing a building, instead, we are making a system that is prone to have problems mentioned in section 1.2.1. Conventionally, architects design hospital systems by intuition or based on experience and expectation, which can cause dissonance between the envisioned and the actual building performance in terms of the user's behaviour [15, 16]. Alternatively, we can introduce an operational insight during the layout design stage through simulation. Simulation can predict the system performance and make evaluations based on simulation results, which form the basis of a Spatial Decision Support System. A Spatial Decision Support System is concerned with the field of Operations Research, and its interrelated fields such as Facility Layout Planning and Transport Modelling etc. These fields have long been separated from the field of Architecture.

1.2.4 Criticality of procedures

Importance of procedures in the overall functioning of hospitals. People are supposed to follow procedures in hospitals, which means when they walk, they do not walk for fun, and they do not wander. Most movements are purposeful in a hospital, although this is not a full justification for using deterministic models of movement of individuals based on a geodesic, it is a very good reason for simplifying several assessment models, which are supposed to work on aggregate levels. Discrete-Event Simulation models are therefore very well suited to the assessment of hospitals for this clear reason. Therefore, it is clear that for any assessment we shall need some representations related to these procedures, e.g., schedules, designated routes, restricted zones, and most importantly, the expected frequencies of transition between spaces, which are typically summarized in Activity Relations Charts (a.k.a., ARC models or REL charts). For a detailed explanation of a REL chart, please refer to section 3.1.2.2 and figure 3.4 in Chapter 3. A clear-cut data model or mathematical representation of a layout configuration is necessary for any kind of assessment. For the definition of the layout configuration, please see section 1.4.1.9. In short, the layout configuration can be referred to as the 'form' and the procedures can be referred to as the 'function' of a hospital, referring to the architectural jargon. We will need both of these in exact shapes (data models) to be able to perform any systematic assessment.

This research aims to combine the two fields of Operations Research and Architecture to develop a Spatial Decision Support System for improving operational efficiency and reducing operational expenditures in Chinese hospitals.

1.2.5 Use Cases of the Hospital Design Support System

This research aims to develop a Spatial Decision Support System as a Python workflow. To demonstrate the function of the proposed Spatial Decision Support System, four use cases are described by answering the following questions: who would be the user of this system? What questions can this system answer? And at what stage of a project can these questions be answered?

- Use Case 1: The hospital director can use this system to check the crowdedness of a hospital project during the layout design stage.
- Use case 2: The architect can use this system to check how difficult it will be for the first-time visitor to find their way in a hospital project during the layout design stage.
- Use Case 3: The head nurse can use this system to check if their walking distance will be too long in a new hospital project during the layout design stage.
- Use Case 4: The hospital director can use this system to check if the patient waiting time or walking distance will be too long in a new hospital project during the layout design stage.

In short, the proposed Hospital Design Support System is envisaged to be a Multi-Criteria Decision Analysis toolkit for the integral evaluation of design alternatives.

1.3 Research Objectives & Questions

This research aims to combine the knowledge from the disciplines of Operations Research and Architecture to develop a Spatial Decision Support System for addressing the problems and challenges (i.e., overcrowding, long patient/nurse travel distance, long patient waiting time and patient/visitor's difficulty in wayfinding) faced by hospital layout designs in China. The objectives of this research are:

- To develop a tool for Spatial Network Analysis for assessing hospital layout design in terms of visibility and accessibility.
- To develop a tool for simulation modelling for assessing hospital layout design in terms of overcrowding.
- To develop a tool for simulation modelling for assessing hospital layout design in terms of patient and/or nurse walking distance.

- To develop a tool for simulation modelling for assessing hospital layout and procedures (program of requirements) design in terms of patients/visitors' difficulty in wayfinding.
- To develop a tool for simulation modelling for assessing hospital layout design in terms of patient waiting time.

The above-mentioned research aim and objectives can be reached by answering the following research questions:

- How to measure the accessibility and visibility of a spatial unit concerning all other spatial units in a hospital layout?
- How to measure the crowdedness in a hospital layout design?
- How to measure the patient's and/or nurse's walking distance in a hospital layout design?
- How to measure patient/visitor's difficulty in wayfinding in a hospital layout + procedures (program of requirements) design?
- How to measure patient waiting time in a hospital layout design?

The main research objectives would then divide this research into three separate, yet interrelated Work Packages to answer the research questions above.

1.4 Research Terminologies & Scopes

1.4.1 Terminologies

This section introduces the relevant terminologies of this study. The terminologies include hospital types, hospital building types, Geographical Information Systems, Building Information modelling, Operations Research and its interrelated disciplines (i.e., Industrial Engineering and Facility Planning), Graph Theory and Network Analysis, transportation planning, definition of a layout configuration model, simulation modelling, and from analysis to evaluation and decision support. Specifically, this section is structured as follows:

- Hospitals are indoor cities/villages, the scale is big, much bigger than many buildings. (Section 1.4.1.1)

- This makes them hard to navigate, hard to manage logistics, etc. (section 1.4.1.2)
- This means that analyzing their spatial model's integration of BIM and GIS (building scale and geographical scale) is most likely to be necessary. (sections 1.4.1.3 & 1.4.1.4)
- The importance of the layout of a hospital is related to "facilities planning" and facility management in terms of the efficiency and effectiveness (efficacy) of "operations", as in Operations Research. (section 1.4.1.5)
- Why graphs/networks? Navigation and studying operations involving human movement in a complex (non-Euclidean) environment make the use of graphs/networks inevitable. Network models (or hyper-graph/Mesh models) are necessary for modelling walkable 2D manifolds. (section 1.4.1.6)
- Spatial network analysis is particularly challenging because one needs to first model the structure (Geometry and Topology) of space adequately to be able to analyze it as a network. (section 1.4.1.7)
- Transport patterns inside a hospital can be complex, and they need to be planned properly. (section 1.4.1.8).
- What is a layout configuration model? A layout representation of a hospital is necessary for any kind of assessment, e.g., spatial network analysis and simulation modelling. (section 1.4.1.9)
- The Simulation Models include the deterministic model and the stochastic model. This research is aimed at developing deterministic pedestrian simulation models, It is to be noticed that this research is not making a "crystal ball"; it is about Ex-ante assessment based on aggregate patterns, not individual trajectories. Additionally, this research is not about Pedestrian simulations egress, fire egress/fire safety, stampede, etc. (section 1.4.1.10)
- In short, this research is mostly focused on what to do with simulation results, and how to analyze a decision based on simulation results (section 1.4.1.11)

1.4.1.1 Hospital Types

Based on their functionalities, Hospitals can be differentiated into different types such as general hospitals, children's hospitals, university hospitals, specialized hospitals, community health centers, and rehabilitation and support clinics [17]. Hospitals can also be categorized based on ownership, such as private hospitals and public hospitals (including state hospitals, city hospitals, district hospitals, and village hospitals). These types of hospitals are all common in China, and there is another special type of hospital in China, which is the Traditional Chinese Medicine (TCM) hospital [18]. Most hospitals have large scales, their scales are so large that one can compare them to small cities. The large scale makes the hospital hard to navigate and manage the logistics, etc.

1.4.1.2 Hospital Building Types

The current hospital building types can be classified into two main groups – high-rise hospitals and low-rise hospitals. High-rise hospitals are suitable for limited site areas, where all the major departments and functions can be compacted into one single large building complex. A variation of the high-rise hospital type, namely the Breitfuss Model, is popular in Europe; it is also known as the “Wide Foot Model”, “Matchbox on a Muffin”, or “Tower with Technical Blocks”. In comparison, the low-rise hospital has a higher requirement on the size of the site, and it is more flexible and easier to expand due to a clear division of different functions (e.g., inpatient and outpatient) into different building wings so that the construction of one function will not influence the operation of another. The popular forms of low-rise hospitals in Europe include T-type, K-type, and H-type [17]. In China, both types of high-rise hospitals and low-rise hospitals are popular. Both scales of these types of hospitals are large, which makes it difficult to navigate both types of hospitals. Hence, it is appropriate to introduce Geographical Information Analysis (GIS) and Building Information Modelling (BIM)as means of analyzing the spatial models of hospitals.

1.4.1.3 Geographical Information Systems

A Geographical Information System (GIS) mainly consists of a geospatial database management system that is used for systematically storing and retrieving geospatial data, a data processing workbench that can manipulate data for higher-level analysis and decision support, and a data visualization system that can communicate to users by presenting the result of data analysis [19]. The information stored in the geospatial database management system is threefold, namely, geometric information such as room sizes and shapes, topological information such as connectivity and adjacency, and semantic information such as pedestrian density and room functions, etc. [20]. Hospitals can be considered as an analogy of a small city, it is reasonable to use a geographical approach (i.e., the GIS approach) to analyse hospitals. Our research is mainly concerned with the spatial database management system part of GIS. For example, we propose a spatial database management system where a hospital’s geometric information, topological information and semantic information can be stored and retrieved.

1.4.1.4 Building Information Modelling

Building Information Modelling (BIM) consists of a 3D model, a database that contains all the relevant data, and the interoperable software used for building the 3D model [21]. Architects can use BIM software to design buildings and build their virtual models in 3D [21]. The information contained in BIM's database includes geometric information, topological information, attribute information, and geographical information. Our research uses BIM models of hospitals as input and extracts the relevant data (i.e., geometrical, topological, and semantic data) from them and stores the data in the spatial database management system mentioned in section 1.4.1.3 for further analysis.

1.4.1.5 Terminology of Operations Research

The spatial decisions made when designing a hospital layout are related to objectives of higher efficiency and effectiveness of "operations", as in Operations Research (OR). OR is a discipline that can support decision-making by developing and applying advanced analytical methods [22]. When dealing with complicated decision-making problems, Operations Research can find an optimal solution (or optimal solutions) by employing methods and techniques such as mathematical modelling, mathematical optimization, simulation, queuing theory, Markov Decision Process, statistical analysis, decision analysis, etc. The optimal solution identified by an OR process is often a maximized result (e.g., maximized performance or interest) or a minimized result (e.g., minimized cost or distance) [22]. In this study, two interrelated disciplines of OR are discussed, including Industrial Engineering (IE) and Facilities Layout Planning (FLP).

- Industrial Engineering (IE). OR lies in the area of IE. According to IISE [23], IE is "concerned with the design, improvement and installation of integrated systems of people, materials, information, equipment and energy. It draws upon specialized knowledge and skill in the mathematical, physical, and social sciences together with the principles and methods of engineering analysis and design, to specify, predict, and evaluate the results to be obtained from such systems." Industrial engineering approaches such as Lean Thinking and Six Sigma concepts have been applied in healthcare to reduce patient waiting time and reduce overcrowding [24].
- Facility Layout Planning (FLP). Facility layout planning is one of the most important problems in the field of Operations Research and Industrial Engineering [25]. FLP is defined as locating different facilities in a plant area, to achieve the most efficient layout according to certain criteria or objectives while taking into account different constraints such as size and form, etc. [26]. The most common and significant objective related to the efficiency of a layout is the minimization of material handling cost because such cost is proportional to the distance, which depends on the layout [27]. Figure 1.1 presents a hospital-related example of the FLP, wherein eight distinct departments or functional areas are assigned to eight different locations within a hospital building, to minimize walking distances for both patients and staff.

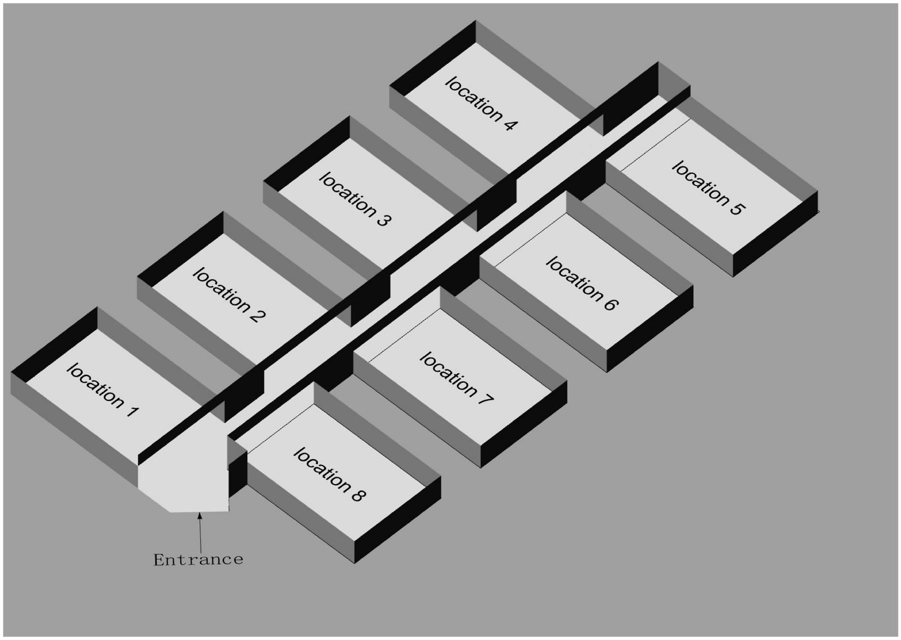

FIG. 1.1 A hospital-related example of the Facility Layout Planning, image source: author

1.4.1.6 Graph Theory & Network Analysis

Graph Theory is a term used in the field of mathematics; it is also known as Network Analysis in the fields of engineering and applied science. these terms can be used interchangeably[59, p. 4]. The terms graph, weighted graph, directed graph, dual graph and coloured graph are introduced respectively in the following:

- Graph/network: A graph/network G is composed of two sets of objects, namely, the set of nodes/vertices $V = \{v_1, v_2, v_3, ...\}$ and the set of links/edges $E = \{e_1, e_2, e_3, ...\}$ [28]. The spatial configuration of a hospital can be represented by a graph. Specifically, nodes can represent rooms/corridors in a hospital, and if two rooms/corridors are directly connected, a link can represent the connection between these rooms/corridors. Figure 1.2(a) shows a small portion of the Panyu Central Hospital in Guangzhou, China. It includes eight rooms and one corridor. Figure 1.2(b) is a graph representation drawn from Figure 1.2(a) and shows the connection relationships between rooms or rooms and corridors. For example, rooms v_1 and v_2 are directly connected, while rooms v_1 and v_6 are not directly connected (connected through room v_2). The degree of a vertex is defined as the number of edges incident to it (e.g., the degree of v_1 is 4 and the degree of v_2 is 2) [28].

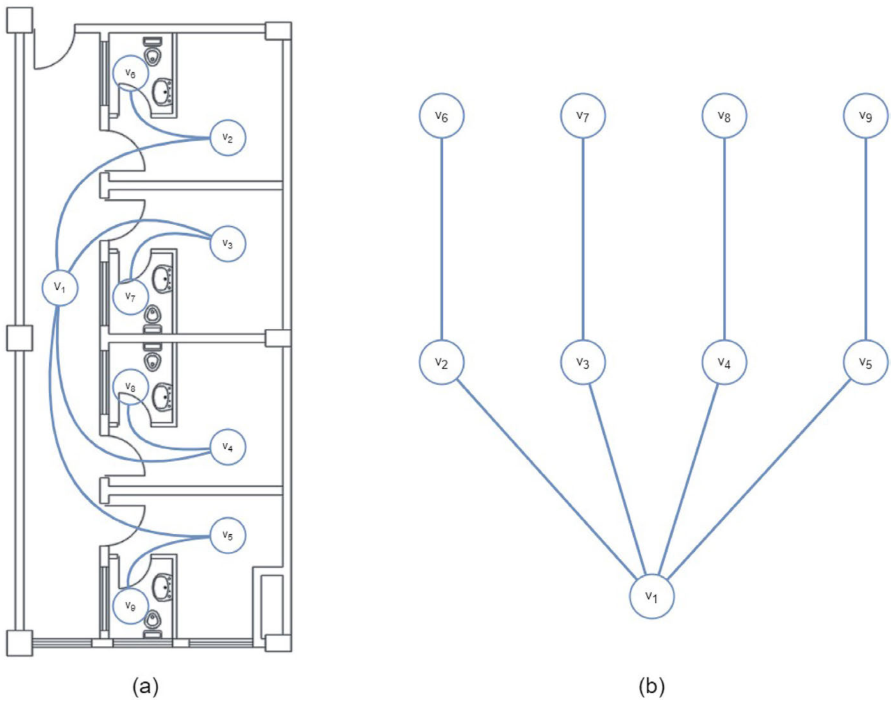

FIG. 1.2 A small portion of the ground floor plan of Panyu Central Hospital (a) and a graph representation showing adjacent relationships among rooms/corridors (b), image source: author.

– Weighted graph: A weighted graph/network means that the edges and/or the vertices are attached with weights [28]. In a network representation of hospital spatial configuration, the links can be assigned weights representing travel distance or travel time, etc. For example, in figure 1.3(a), each edge is assigned a weight related to distance. A path in a graph/network from v_i to v_j is denoted as $p(i, j)$ [28]. For example, in Figure 1.3(a), path $p(1, 6)$ is a sequence of vertices and edges $\{v_1, e_1, v_2, e_5, v_6\}$.

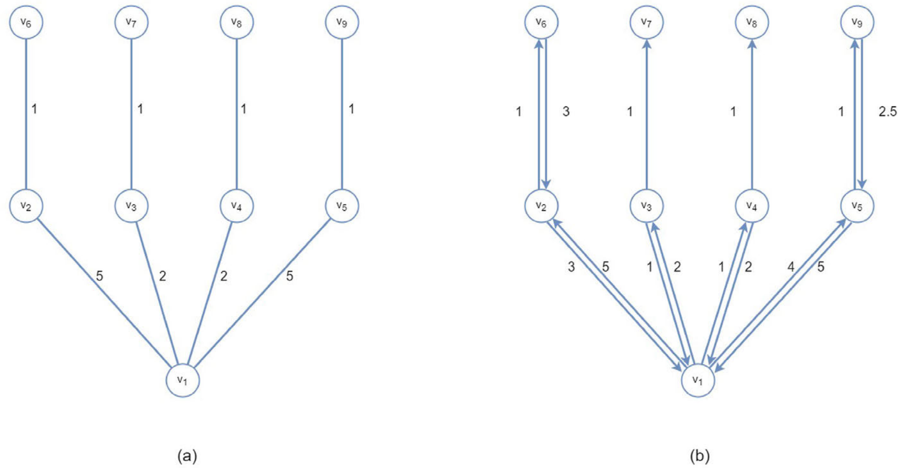

FIG. 1.3 An example of a weighted graph/network, image source: author

- Directed graph: The graphs shown in Figure 1.2 and Figure 1.3(a) are undirected graphs, which means that the edges in these graphs do not have directions. By contrast, the graph in Figure 1.3(b) is a directed graph; each edge in this graph has one or two directions, and the two directions of one edge can have different weights [29]. The shortest path in a weighted graph/network is the path between two nodes such that the sum of the weights of its elemental edges is minimal when weights represent travel distance [29]. For example, in Figure 1.4, the shortest path between v_1 and v_4 is the path highlighted in red.

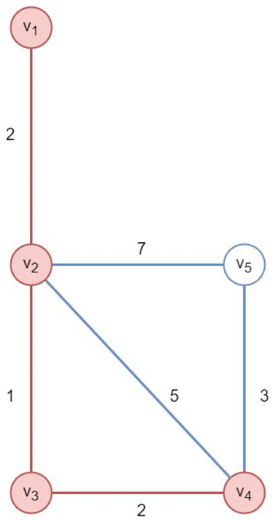

FIG. 1.4 The shortest path in the graph is highlighted in red, image source: author

- Dual graph: Another important concept of Graph theory is the Dual Graph. In a 2D space, the dual graph of its primal graph G is a graph that has a vertex for each face of G and an edge between vertices for each pair of adjacent faces (see Table 1.1) [30], a face in a graph is defined as a region surrounded by a group of vertices and edges [31]. An example of a dual graph can be seen in Figure 7, where the blue graph is the dual of the black graph and vice versa.

TABLE 1.1 Duality of features in 2D space [30]

Primal	Dual
Vertex (node)	Face
Edge (link)	Edge
Face (e.g., a triangle or a polygon)	Vertex

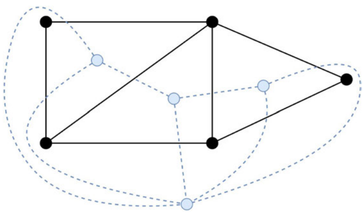

FIG. 1.5 The dual graph, image source: [32]

1.4.1.7 Spatial Network Analysis

Spatial Networks Analysis lies in the field of Graph Theory and is inspired by the study of Social Network Analysis [30]. Spatial Networks are graphs whose vertices/edges are spatial elements (such as rooms, corridors, streets, etc.), the vertices in a spatial network are embedded in a space provided with a metric (e.g., distance) [33]. Figure 1.2(b) is an example of a spatial network, where vertices represent rooms and edges represent direct connections between rooms. Spatial Network Analysis adopted the concept of Centrality metrics from Social Network Analysis, which measures the influences of the vertices in a graph [34]. Four common centrality measures are discussed in this study:

- Degree Centrality: It measures how many other nodes a node is directly connected to (i.e., the degree of a node) [35].
- Closeness Centrality: It measures how close a node is to every other node in the network [35].
- Betweenness Centrality: It measures the frequency of a node serving as a bridge along the shortest path between two other nodes in a network [35].

- Eigenvector Centrality: It measures the influence of both a node and its neighbours in a network. If the node is connected to other nodes with high quality, then its Eigenvector Centrality will also be high [35].

Based on the theory of Spatial Network Analysis, one can calculate the centrality values mentioned above to evaluate the layout design of complex buildings such as hospitals and predict their "potential performances". Specifically, the centrality values can indicate how visible and accessible a spatial unit (e.g., a room or corridor) is concerning all other spatial units in a layout.

1.4.1.8 Transport Planning

Transport planning is concerned with evaluating, assessing, designing and planning transport facilities such as streets, highways, public transport lines, etc., with the objectives of moving people and goods to destinations efficiently and cost-effectively [36]. Since hospitals have similar transport systems to cities (public main corridors and access-limited corridors in a hospital can be compared to major and minor roads in a city), the knowledge from the area of transport planning can be used for designing and evaluating the pedestrian flows and logistics in hospitals. The transport planning process has four steps (i.e., Four-Step Transportation Model):

- Trip generation: this step predicts the number of people starting from and arriving at each zone in the studied area [37]. For example, the trip generation step in a hospital design project can be predicting the number of pedestrians travelling from and arriving at each functional unit in the hospital. Table 4.2 presents an example of trip generation in a virtual hospital with five spatial units, i.e., reception hall, emergency room, diagnosis room, imaging room, and pharmacy.

TABLE 1.2 Trip generation in a virtual hospital project with five spatial units

Functional units	Production (number of patients)	Attraction (number of patients)
Reception hall	50	28
Emergency room	30	26
Diagnosis room	10	20
Imaging room	20	17
Pharmacy	5	24
Total	115	115

- Trip distribution: this step predicts the number of people from each origin to each destination by producing an origin-destination matrix/table [37]. For example, in the case of the hospital design, this step predicts the distribution of the total number of people going from each origin to each destination. Table 1.3 presents a trip distribution matrix/table for the virtual hospital project, serving as an illustrative example.

TABLE 1.3 Trip distribution in a virtual hospital project with five spatial units

	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

- Mode choice: this step predicts the travel modes of the pedestrians [37]. For example, in the case of the hospital, travel modes for patients may include walking, wheelchair use, or transportation on a hospital bed.
- Route assignment: the last step selects the paths between all origins and destinations and hence the total amount of pedestrians on each path will be known [37]. In the case of a hospital, path selection can be based on the shortest path (the path with the shortest travel time).

In this research, the Four-Step Transportation Model will be used for simulating the city-like character of hospitals and evaluating the hospital performance in terms of crowdedness and patient walking distance.

1.4.1.9 Definition of Configuration Model

The configuration model serves as a comprehensive framework for representing the layout of a building system, integrating four critical types of information: geometric, topological, semantic, and operational. Specifically, within the context of a Hospital Configuration Model (HCM), these four types of information are defined as follows:

- 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 [38].
- Topological Information

  Topological information represents the spatial relationships among the functional units of the hospital, structured as a network graph [38].

- Semantic Information

  Semantic information assigns meaning to spatial units by connecting them to their functional roles [38]. Examples of semantic information include Room Names and room areas.
- Operational Information

  Operational information encapsulates patient journeys within the hospital, detailing the sequential movement of patients through various rooms during medical procedures [38].

Table 1.4 presents detailed explanations and examples for each type of information in an HCM.

TABLE 1.4 Exemplified descriptions of four types of information in a Hospital Configuration Model

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']}

1.4.1.10 Simulation Modelling

The Transport Planning and Four-Step Transportation Model predicts the static transportation systems inside a hospital. In this research, it will serve as a base for the dynamic simulation (Simulation Modelling) of hospital transportation. Methods of Simulation Modelling will be applied to achieve the goal of evaluating the hospital layout design at the layout design stage by simulating the dynamics of the hospital and making an assessment based on the simulation results.

To understand simulation modelling, the concepts of system and model need to be explained. A system is defined as a set of related components (e.g., individuals, elements, spaces, etc.) interacting with each other to achieve a certain objective [27]. A model is a representation of a system [39]. Specifically, system models are developed to design, assess, explain, verify and validate a system [28]. Any activity of imagining or speculating how a social dynamic would develop is running a model (e.g., imagining how the hospital-acquired infection would spread inside a hospital) [40]. However, this is an implicit model; our study focuses on explicit models in which assumptions are described elaborately for simulation and thus making informed predictions [40]. One should notice that modelling is not equal to prediction; it has many functions other than prediction. According to Epstein [40], the explicit model's functions include "explain", "guide data collection", "illuminate core dynamics", "demonstrate trade-offs/suggest efficiencies", and "reveal the simple (complex) to be complex (simple)" among others.

System models can be categorized into deterministic models and stochastic models, between which a distinction must be made. When we try to model a system, the values of parameters/variables (e.g., each patient's time spent in the doctor's consulting room) need to be appraised [27]. These parameters/variables can change over time, i.e., they are random variables or their changes are predictable [27]. Deterministic simulation ignores the randomness of the variables and assumes that the variable is constant (e.g., when simulating the situation in a hospital, the deterministic simulation assumes that each patient's time spent in the consulting room is always 15 min) [27]. By contrast, stochastic simulation recognizes the randomness of the variables (e.g., each patient's time spent in the consulting room is a random variable with a mean of 15 min) [27].

A system model can also be static or dynamic [41]. A static system model represents a system at a certain point in time, while a dynamic system model shows how a system's state variables change with time (e.g., a patient's walking distance in a hospital can increase with time) [42]. A dynamic system model can be further divided into continuous or discrete system models [41]. In a continuous system model, the state variables of the system change continuously over time (e.g., the position of the Earth relative to the sun) [43]. Conversely, in a discrete system model, the state variables of the system only change at discrete points in time [43]. For example, patients arrive at the hospital at 8:01, 8:15, 9:20, etc.

Figure 1.6 illustrates the categories of the system model. Three types of system models (i.e., Agent-Based Modelling, Discrete-Event Simulation and Random Walk Simulation) are introduced in the following. These three types of models are classified as stochastic, dynamic, and discrete system models [41].

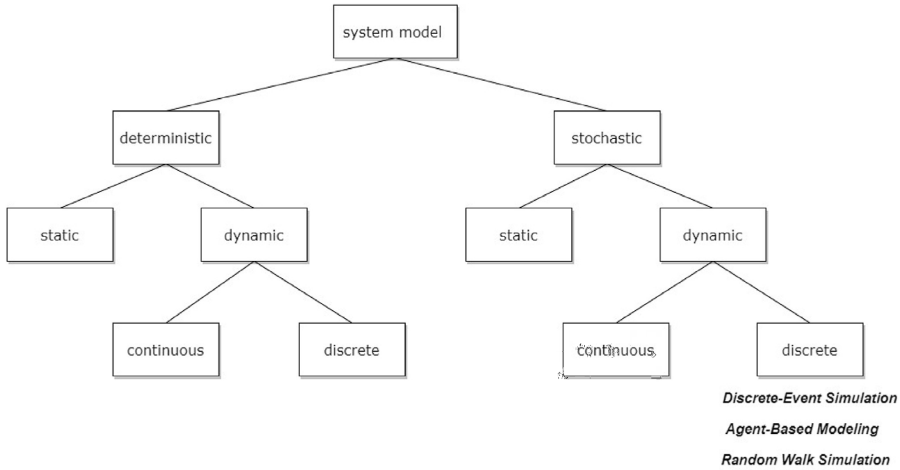

FIG. 1.6 System model categories, image source: [41].

An agent-based model is defined as a computer program composed of autonomous, heterogeneous, and active agents, and the interactions between agents and between agents and the environment [44]. Agents are small computer programs and can represent any type of entity [44, 45]. In the case of a hospital agent-based model, agents can be people (i.e., patients, visitors, nurses, doctors, etc.). The agent environment is the space where agents interact [45], it can be a graph/network as introduced in section 1.4.1.6 [44]. The characteristics of agents are introduced in the following:

- Autonomy: agents are autonomous entities and their behaviours are not directed by central controllers; they are able to make independent decisions [45].
- Heterogeneity: agents can have different attributes such as roles, ages, jobs, etc. [45]. For example, in an agent-based model of a hospital, agents can include different roles such as patients, nurses, doctors and visitors.
- Active: patients are active entities in terms of:Goal-directed: agents can be assigned to different goals [45]. For example, in the agent-based model of a hospital, a patient-agent can be assigned goals of finding their doctors, getting healed and being discharged. Perceptive: agents can be enabled to perceive their surroundings, other agents as well as the whole structure of the environment (i.e., a mental map) so that agents know the locations of obstacles and their destinations [45]. Bounded Rationality: agents have a finite ability to make adaptive and inductive decisions to achieve their goals [45].
- Interactive: agents can interact with other agents and/or the environment [45].Mobility: agents can move in the environment [45]. For example, in the hospital agent-based model, agents can move in order to achieve their goals, such as wayfinding.

- Adaptation/Learning: agents can be adaptive; they can be enabled to change their state according to previous states, to memorize/learn [45]. For example, patient-agent can be enabled to memorize their path during wayfinding so that they will not repeat the wrong path.

Agent-based modelling (ABM) can be applied for hospital design/evaluation with the aim of simulating the flow in the hospital space or examining the crowd congestion in public corridors or waiting areas, to name but a few.

A Discrete-Event Simulation (DES) is the model of a system where events occur at different instants in time, which leads to changes in the system state [46]. A DES model is composed of:

- Discrete-event: the state variables of a DES model do not change continuously, they only change at discrete time instances due to events occurring at different time instances [41]. For example, the number of patients in a hospital only changes if a new patient comes in or a current patient is discharged.
- Clock: a clock tracks the simulation time, the DES model is dynamic because time is a significant variable, i.e., the state variables of the system are different at different points in time [41]. For example, the number of patients in a hospital can vary at different points in time.
- Random number generators: a DES contains randomized variables (e.g., patient inter-arrival rate can be randomised) [41].
- Statistics: it tracks the system's statistics [41], e.g., patient mean waiting time, the total number of people inside the hospital, etc.
- Ending Condition: the simulation will end when the ending condition is met, e.g., the simulation is set to end at a certain simulation time [41].

In this research, DES will be applied to simulate the factory-like character of hospitals and evaluate hospital performance in terms of patient waiting time.

A Markov chain is a stochastic system model whose state transitions from one to another, the system changes its current state to the next state at each point in time, and it is changed based on a transition probability [27]. A Markov chain has three attributes: the number of possible states is finite [27]; the probability of transitioning from one state to another is only dependent on the current state, not on any earlier history (it is memoryless) [27]; the transition probability from one state to another is constant [27]. Here we present an illustrative example of an RWS model using the hypothetical hospital consisting of five spatial units, as introduced in Section 1.4.1.8. Figure 4.2 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

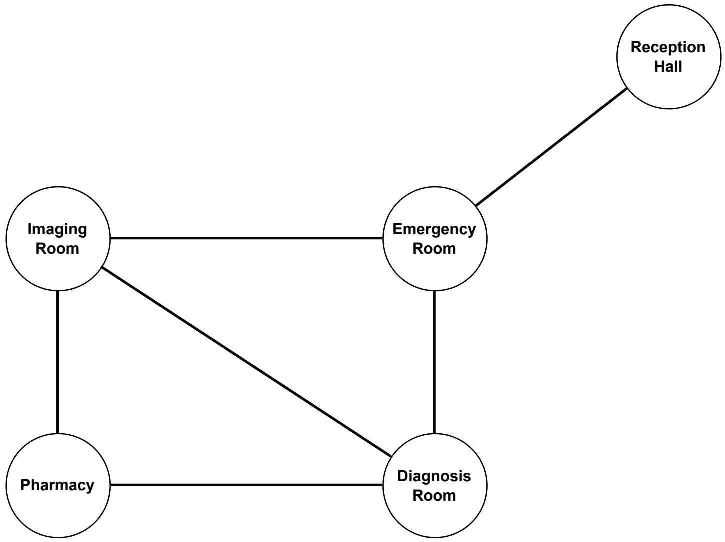

FIG. 1.7 An example of a Markov Chain/RWS model, image source: author.

of its neighboring 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.

Thus, the random walk path, expressed as a Python list, is: [“Reception Hall", “Emergency room", “Diagnosis Room", “Imaging Room", “Pharmacy"]. This example demonstrates the stochastic nature of the random walk process, where agents navigate the hospital environment without prior knowledge of the optimal path. In this research, RWS will be used to evaluate the hospital’s performance in terms of difficulty in wayfinding by simulating situations where patients become disoriented, visiting multiple incorrect locations before reaching their intended destination.

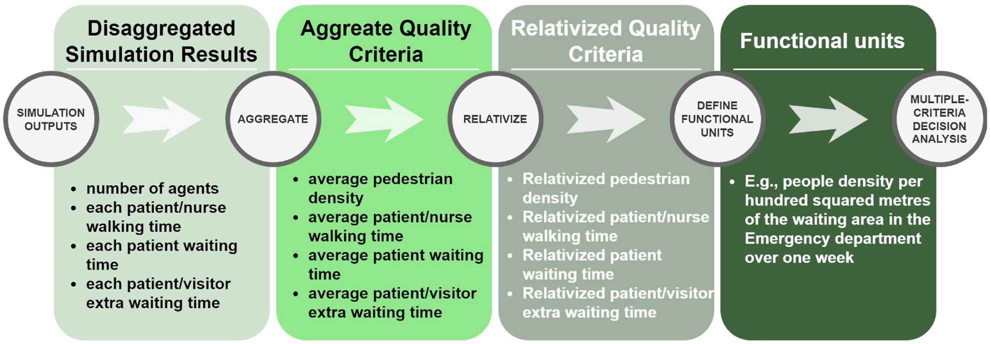

FIG. 1.8 The necessary steps between analysis, evaluation and decision support, image source: author.

1.4.1.11 From Analysis to Evaluation and Decision-Support

Generative [simulation] models such as Discrete-Event Simulation (DES) and Random Walk Simulation (RWS) produce spatially disaggregate results. However, a decision-maker concerned with making better decisions about the whole building would be required to take at least four important steps to be able to use such information (see also Figure 1.8):

- Spatial Aggregation and Temporal Aggregation: the simulation results are disaggregate, e.g., it might contain the number of pedestrians in each spatial unit in the hospital, or each pedestrian's time spent on walking and waiting. These disaggregate results need to be aggregated for ease of comparison, e.g., the aggregate forms of the results can be the average pedestrian density over time, average pedestrian walking time and waiting time, etc.
- Relativization: the aggregate results need to be further relativized/normalized. For instance, it is unfair to compare the average pedestrian walking distance in a large hospital with a relatively small hospital, because the walking distance in a large hospital will be naturally longer. Hence, the aggregated results need to be relativized for accurate comparison.
- Functional Unit Equalization: the functional unit is defined as 'a reference unit of study normally used for comparative purpose' [47]. It is a necessary parameter in a comparative assessment [47]. For example, when comparing two hospitals' performances in terms of reducing overcrowding, a fair comparison can be 'people density per square metre of the waiting area'; this is in contrast to the comparison of 'people density in the hospital', where area and functional unit are excluded for comparison. Only when all the factors are considered can a better design be identified.

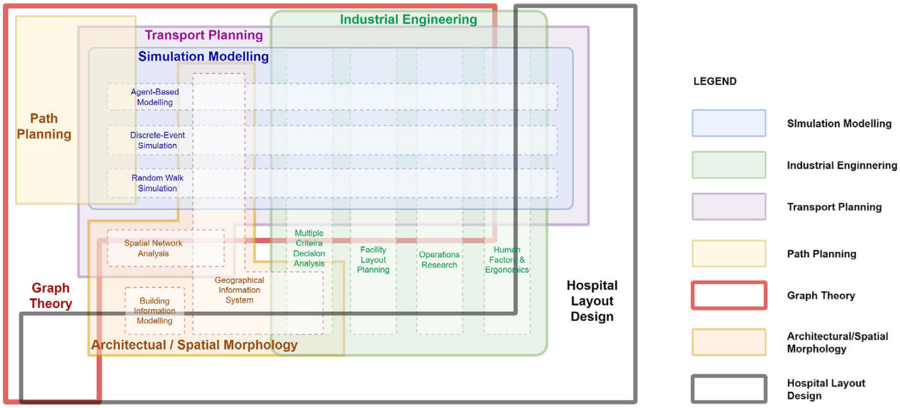

FIG. 1.9 the scope of this research, image source: author

1.4.2 Research scope

As shown in Figure 1.9, this research includes multiple interrelated disciplines. The core of this research is focused on the hospital layout design, which is supported by other main disciplines, i.e., Industrial Engineering, simulation modelling, transport planning, Indoor Navigation and Architectural/Spatial Morphology. Each main discipline has its sub-disciplines that are concerned with this research. The field of Graph Theory serves as a supporting theory which is related to most of the other disciplines. It is to be noticed that developing a Graphical User Interface (GUI) for the proposed Hospital Design Support System falls out of the scope of this research.

1.5 Research Design

This research aims to develop a Hospital Design Support System (HDSS) for assessing hospital layout performance in terms of crowdedness, patient waiting time, patient walking distance, and difficulty in wayfinding. The HDSS take inputs and provides outputs for supporting stakeholders to make informed decisions on identifying better hospital layout designs according to certain quality criteria. As illustrated in Figure 1.10, the inputs of the SDSS include hospital BIM models (representing hospital design solutions). The outputs of the HDSS include four quality criteria, namely, pedestrian density, walking distance, extra walking distance, and waiting time, which enable architects and hospital directors to make well-informed decisions in selecting the optimal hospital layout design. The

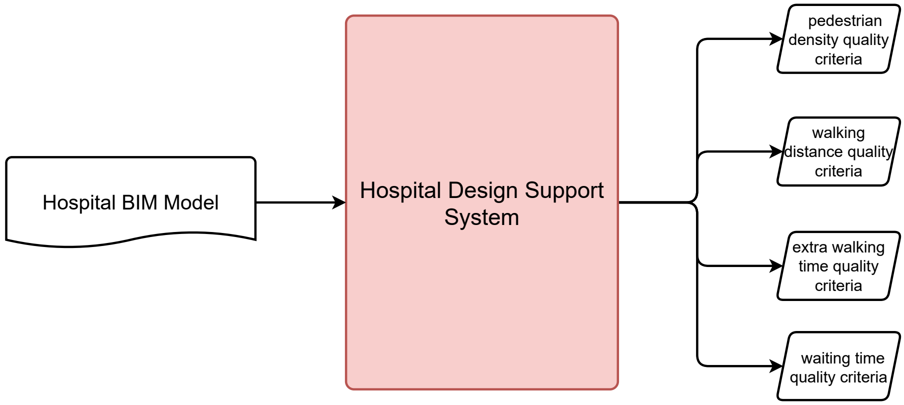

FIG. 1.10 A Hospital Design Support System Architecture, image source: author

development of the HDSS is staged into two separate but interrelated work packages. Work Package 1 focuses on developing a Hospital Configuration Model, which is a prerequisite for the operation of the HDSS, and Work Package 2 focuses on developing the HDSS. Each work package will be introduced in the following sections.

1.5.1 WP0 - A Systematic Literature Review

Before developing the HDSS, an initial Work Package including a systematic literature review on Spatial Decision Support Systems in hospital layout design was conducted to discover the existing related research and publications. The results of Work Package 0 lead to chapter 2.

1.5.2 WP1 - Hospital Configuration Model

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. To fulfil this requirement, a Hospital Configuration Model (HCM) is needed. The HCM is a layout representation model of the hospital system that incorporates four key types of information: geometric, topological, semantic, and operational. The results of Work Package 1 lead to Chapter 3, which is divided into two sub-chapters. Sub-chapter 3.1 provides a comprehensive discussion of the theoretical framework underlying the HCM. It addresses the necessity of HCMs, provides a detailed technical exposition of the four types of data an HCM incorporates, the sources from which relevant information can be extracted, and a systematic approach to the HCM's development. Sub-chapter 3.2 introduces the developed software designed to facilitate the semi-automated generation of HCMs from Building Information Modelling (BIM) data.

1.5.3 WP2 - Hospital Design Support System

Work Package 2 focuses on developing the HDSS, which consists of a Four-Step Transportation Model, a Discrete-Event Simulation model, and an exploratory network analysis model for simulating hospital operations and assessing hospital layout performances. The Four-Step Transportation Model will be applied to simulate the city-like character of hospitals and model the patient movement patterns in hospitals. These outputs of patient movement patterns can facilitate achieving the HDSS functionalities of assessing hospital spatial crowdedness, patient walking distance, and difficulty in wayfinding. However, the Four-Step Transportation Model is not suitable for evaluating 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 (DES) emerges as an optimal solution, as it explicitly models time-dependent processes and can effectively capture patient waiting times. Hence, the HDSS framework will have a DES model for simulating the factory-like character of the hospital and address the limitation of the Four-Step Transportation Model, particularly in assessing patient waiting times.

For the Four-Step Transportation Model and Discrete Event Simulation to function effectively, they require specific spatial attributes, such as room names and functions. However, to gain a broader understanding of the inherent logic of hospital space independent of these specific attributes, an alternative approach is needed. Exploratory Network Analysis serves as an ideal method for this purpose. In other words, the Four-Step Transportation Model and the DES model provide the apparatus for the science of engineering in dealing with the rational and predictable aspects of the building operations, while the exploratory network analysis model provides the mechanisms in support of the art of engineering in dealing with the irrational and the unpredictable aspects of building operations. Accordingly, our Hospital Design Support System (HDSS) integrates three primary models: the Four-Step Transportation Model, the Discrete Event Simulation model, and the Exploratory Network Analysis model.

In addition to these models, the HDSS incorporates evaluation mechanisms to interpret its outputs and support informed decision-making. Specifically, for the simulation results from the Four-Step Transportation Model and the Discrete Event Simulation model, we first aggregate the disaggregated results, then normalize them, and finally assign functional units to ensure fair comparisons across different hospital cases. For the outputs generated by the exploratory network analysis model, we visualize the centrality measures of the hospital graph and analyze their implications.

We identify functions that are best suited for spatial units with high centrality values and suggest appropriate uses for rooms with low centrality measurements.

The results of Work Package 2 lead to chapter 4, which presents a detailed technical exposition of the HDSS's Four-Step Transportation model, Discrete-Event Simulation model, Exploratory Network Analysis model, as well as the evaluation mechanisms for the simulation results.

2 Literature Review

This chapter has been published by Jia, Z., Nourian, P., Luscuere, P., & Wagenaar, C. (2023). Spatial decision support systems for hospital layout design: A review. Journal of Building Engineering, 67, 106042. [48]. The layout and content have been adjusted to fit the structure of this thesis.

ABSTRACT

This study presents a systematic review of the literature on decision support for designing hospital layouts using spatial network analysis and/or simulation modelling. The review includes 102 articles, which are classified into five different categories concerning their layout-related challenges. Specifically, the categories include overcrowding, patient waiting times, visibility & staff interaction, wayfinding & walkability, and other issues such as hospital-acquired infections. The main finding is the cross-referenced table of different performance issues related to the hospital layout to different assessment methods, indicators, and quality criteria. The review suggests prospects for associating hospital design problems/challenges with spatial layout, as well as a framework for developing methods for layout representation, aggregation and relativization borrowing from the fields of transport planning and operations research. The main focus of this study lies in the spatial layout. Viewing the spatial complexity of a hospital as an indoor spatial environment is at least as complex as an urban environment, thus justifying a geographical approach; hence, we expand the scope of the literature review to papers that may not directly address hospital design but have relations to spatial decision support systems.

2.1 Introduciton

Hospitals have multiple functions, including clinical, nursing, administration, services etc. These functions have various kinds of aspects, such as crowdedness, wayfinding, the efficiency of service, etc. Studies have shown that these aspects are determined by the layout of the hospital. According to the literature, over 67% of employees are unable to perform their jobs efficiently due to inappropriate layouts of the working environment [49]. Moreover, in hospitals, nurses were found to spend more time walking than on their caregiving activities because of the problems related to hospital layouts [50]. One study found that 28.9% of nurses' time was wasted on walking [51]. In another study, Peponis et al. [13]found that the extra expenditure caused by difficulty in wayfinding is $ 220,000 per year in 1990 in the USA. The reason is that staff are interrupted by patients to give them directions.

The reasons why the layout of a hospital has a great impact on various aspects of functions are twofold. Firstly, from a functional point of view, hospitals are complex as a 'healing factory' in which services are produced. The patient enters the hospital with a condition, a series of services are provided around the patient, and the patient leaves the hospital (ideally) healed. Secondly, from a formal/configurational point of view, hospitals are complex as small indoor cities, where corridors in hospitals can be compared to streets in a city, and different spatial units that serve different functions in hospitals can be compared to land uses in a city. Hospitals are complex from both points of view, and when we combine these two perspectives, it indicates that the layout of a hospital affects the visibility and walkability of two types of users in the hospital, namely, the people being served and the people serving others. Spatial Network Analysis is a popular method for assessing the visibility and accessibility of a layout design, and Simulation Modelling can provide quantitative measurements related to aspects of hospital functions, such as the number of patients and distance etc. This paper aims to review studies applying Spatial Network Analysis and Simulation Modelling for decision support in hospital layout design.

The importance of layout problems in hospitals can be understood by investigating inefficiencies as mentioned above, however, there are also critical issues related to the main function of a hospital, such as increased chances of transmission of Hospital-Acquired Infections (e.g. for airborne diseases such as COVID-19) with overcrowding ([52, 53, 54, 55, 56]) or long patient waiting time issues that pertain to layout problems ([57, 58, 59, 60]).

The contribution and novelty of this paper are the following:

- We propose a comprehensive engineering approach for the formulation of problems related to human movements in hospitals, spatial representation of hospital layouts, and quantification of issues such as over crowdedness. This approach borrows from Operations Research and builds on analogies between hospital layout design with Transport Planning, particularly utilizing the 4-Step Transport Modelling approach, with an explicit link made to Spatial Network Analysis.
- We demonstrate gaps in the literature for adequately quantifying several performance issues of hospitals that can be traced back to their layouts and argue for the use of simulation modelling such as ABM and DES for ex-ante assessment of hospital layouts and propose the outline of envisaged Hospital Design Support Systems (HDSS) as information systems featuring such assessment models in conjunction with Multi-Criteria Decision Analysis (MCDA) tools.

- We articulate the main components and procedural steps for making such ex-ante assessment models to operate on Building Information Models (BIM) of hospitals, namely, a spatial network representation of hospital layouts, alternative simulation modelling methods, spatial aggregation methods, and relativization methods based on standardized functional units.

2.1.1 Objectives of the review

The main focus of this review lies in the spatial layout of hospitals. A clear-cut data model or mathematical representation of a layout configuration is necessary for any kind of assessment. Spatial layout is relevant to identifying feasible locations and dimensions for a group of interrelated elements that satisfy design goals and maximize design performance according to certain preferences [14]. This study aims to review publications that apply the assessment approach of Spatial Network Analysis (SNA) and Simulation Modelling, such as Agent-Based Modelling (ABM), Discrete-Event Simulation (DES) and Random Walk Simulation (RWS) for assessing hospital layouts.

2.1.2 Questions of the review

The following thematic questions have formed the rationale of the review and underpinned the search methods and search criteria:

- **What would be the desired/required features of a hospital design support system (a spatial decision support system for informing the design of a hospital)?**

  The kind of aspects of the function include crowdedness, wayfinding, the efficiency of the service, etc., we have a strong intuition that these aspects are determined by the layout of the building, not the materiality/systems inside the building.
- **What are the effects of the layout of a hospital on its functionality?**

  As mentioned in section 2.1, Hospitals are complex as a ‘healing machine’ from a functional point of view and as small indoor cities from a formal point of view. The layout of a hospital has a great impact on the visibility and walkability for the users in the hospital. Hence, we are looking at the walkable space as a 2-manifold space and the visible space as a 3-manifold space.
- **How is Spatial Network Analysis applied in the field of Hospital Layout Design?**

  We are missing two things in Spatial Network Analysis, even though it is intuitive and useful; Spatial Network Analysis cannot give us quantities of a physical dimension (e.g., the number of people, distance, etc.). The other issue is that time is usually not in the picture of Spatial Analysis, and yet time is very important in the way a hospital functions. Hence, another concept of Simulation Modelling needs to be considered.

- **How is Simulation Modelling (e.g., Agent-Based Modelling, Discrete-Event Simulation, Random Walk Simulation, Transport Models, etc.) applied in the field of Hospital Layout Design?**

2.1.3 Previous reviews

Some other reviews share similar topics to this review. However, they do not include studies in recent years and/or their focus is on other factors such as management policies instead of spatial layout. In a recent study, Halawa et al. [61] presented a review of hospital designs that apply methodologies from Operations Research and healthcare engineering to enhance design performance. The methodologies include mathematical models, simulation modelling, statistical analysis, Space Syntax Analysis (SSA), Heuristics, Lean Six Sigma, reviews, machine learning, fuzzy logic, Markov chain, as well as observation and surveys. This review illustrates the application of Operations Research methods in healthcare facility design and its potential for further investigation. However, it does not include a cross-reference between hospital design challenges and those methodologies. Rashid [62] reviewed studies on nursing unit layout design using simulation modelling and Spatial Network Analysis (SNA) until 2014. The author only focused on one type of spatial unit of the hospital, namely the nursing unit, and did not include studies on other spatial units. Other reviews have focused only on either the methods of SNA or the methods of simulation modelling. Concerning the spatial network analysis, Haq and Luo [63] explained a methodology of SNA, namely Space Syntax Analysis (SSA), and an overview of its application in healthcare facility design until 2011. Sadek and Shepley [64] reviewed basic and newly developed SSA tools used in the field of healthcare design until 2014. Reviews on simulation modelling in healthcare research mainly focus on operational and management perspectives instead of spatial layout perspectives. For example, in an early study in 1988, Smith-Daniels et al. [65] reviewed literature applying methods such as simulation, queueing theory, Markov chains and heuristics for management decision support such as facility sizing and patient admission scheduling. Jun et al. [66] surveyed literature applying discrete event simulation in hospitals, outpatient clinics and emergency departments until 1997. Fone et al. [67] reviewed studies applying simulation modelling in population health and health care delivery. Sobolev et al. [68] overviewed studies using simulation modelling in surgical care until 2007. Brailsford et al. [69] reviewed studies applying simulation and modelling in healthcare until 2007. In a recent study, Al-Kaf [70] reviewed studies applying Discrete-Event Simulation (DES) for improving resource utilization and patient experience in outpatient clinics.

2.1.4 Paper structure

The computational assessment of layouts requires specific data structures and algorithms. The data structures, as explained further, must be compatible or related to BIM and GIS structures due to the scale and complexity of hospitals. The algorithms required for the assessment of hospitals must be capable of analysing their network models and also running simulations on top of such network-space models. Thus, the paper has sections dedicated to discussing the specifics of such algorithms and their application for layout assessment in hospital design. The paper is structured as follows: Section 2.1, an introduction including the focus of this review and relevant previous reviews. Section 2.2, the methodology used in this review. Section 2.3, brief introductions of the terminologies pertained to this study. Section 2.4, reviews taxonomies that categorize the reviewed papers into five groups. Section 2.5, review results and Section 2.6, conclusion.

2.2 Research methodology

This review follows PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) guidelines. It considers conference papers, peer-reviewed articles and PhD theses published between 1965 and 2022. The databases used in this review include Scopus and Google Scholar. The keywords used for literature searching include “hospital design”, “healthcare facility design”, “healthcare architecture”, “healthcare design”, “hospital setting”, “outpatient clinic” and “inpatient ward” in combination with “spatial network”, “space syntax”, “spatial analysis”, “layout analysis”, “decision support system”, “random walk”, “Markov chain”, “Markov model”, “queueing theory”, “simulation model”, “agent-based”, “discrete event simulation”, “simulation model”, “multiagent”, and “pre-occupancy”. A search filter was used for identifying literatures that contain these keywords in the title, abstract and keywords of the paper and was written in English. Figure 2.1 illustrates the search strategy and the number of identified literatures. The total number of identified studies includes 315 from Scopus and 109 from Google Scholar. After duplicate removal, the results are 421 unique literatures. A detailed title and abstracted review according to specific inclusion criteria left 71 studies. The inclusion criteria are as follows:

- **Inclusion criteria 1**: publications explicitly mentioned what design challenges they attempted to address or what useful facts they discovered.
- **Inclusion criteria 2**: studies that are explainable and reproducible, i.e., a clear description of the methodology in terms of mathematical formulation and/or suede

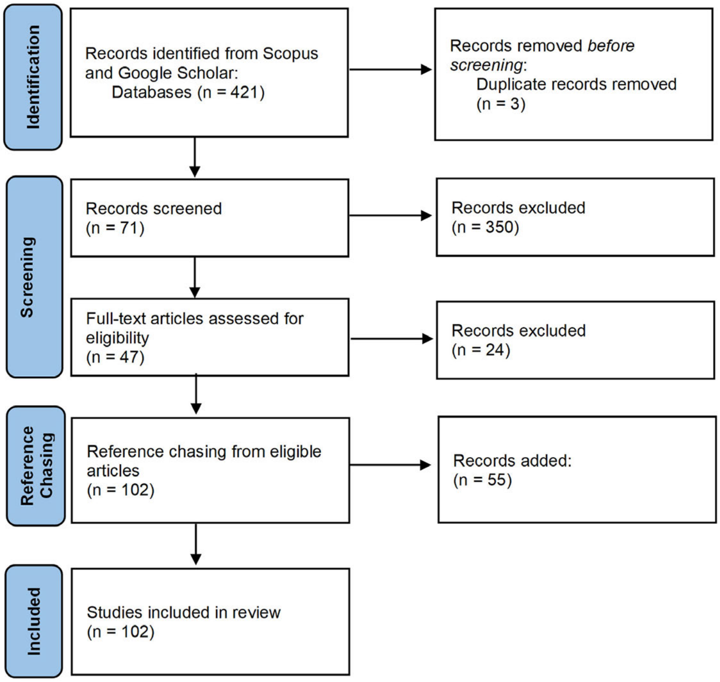

FIG. 2.1 Search strategy diagram based on PRISMA, image source [71]

codes

After a full-text review according to the inclusion criteria, there were 51 publications left. Reference chasing from the included literature was then conducted to find more related studies. Lastly, there were 102 studies included in this review.

2.3 Terminology

This section introduces the relevant terminologies of this study. The terminologies include hospital types, hospital building types, Geographical Information Systems, Building Information modelling, Operations Research and its interrelated disciplines (i.e., Industrial Engineering and Facility Planning), Graph Theory and Network Analysis, transportation planning, definition of a layout configuration model, simulation modelling, and from analysis to evaluation and decision support. Figure 2.2 shows the interrelationships between these terminologies. For specific

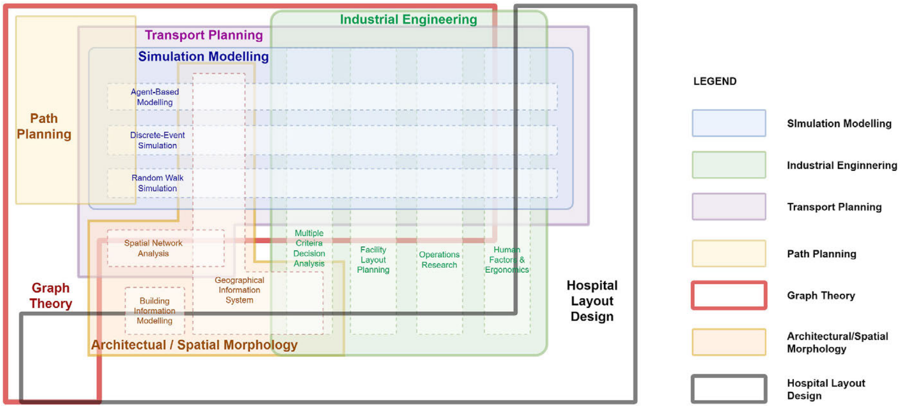

FIG. 2.2 An Euler diagram illustrating the intersections/overlaps between the fields that pertain to hospital layout design and assessment, image source: author.

introduction of each of the terminology, please refer to section 1.4.1 in chapter 1.

2.4 Review taxonomy

This section presents the five categories of the reviewed studies. The categories include overcrowding, patient waiting times, visibility and staff interaction, wayfinding and walkability, and other issues (i.e., patient/visitor interruption on staff and hospital-acquired infections). Specifically, the section is structured as follows:

- Inappropriate layout designs can lead to overcrowding, and Simulation Modelling can be used to assess the overcrowding potential.
- Overcrowding relates to another problem of long patient waiting times, which can be evaluated by simulating patient flows using ABM or DES.
- Another layout-related issue that causes multiple sub-problems in hospitals is visibility, e.g., low visibility hinders staff interactions. SNA can be utilized for assessing visibility
- Low visibility is also related to patients/visitors' difficulty in wayfinding, and difficulty in wayfinding is one of the reasons causing long patient/nurse walking distances, which can be measured using SNA or Simulation Modelling
- Other layout-related problems include patient/visitor interruption of staff and hospital-acquired infections.

2.4.1 Overcrowding

It is not easy to put a number into this intuitive notion of over crowdedness in hospitals because we do not have a very clear notion of two types of spaces (i.e., spaces to go to such as examination rooms and spaces to go through such as corridors), however, there have been attempts to measure, predict and curb/mitigate overcrowding in hospital design. For example, Schaumann et al. [72] reduced corridor overcrowding and patient interruption on staff in an internal medicine ward using the ABM approach, and the mean patient and visitor density was reduced from 0.16 patient/m^2 to 0.09 patient/m^2 after improving the layout of the ward (i.e., introducing a dayroom in the ward). In another study [57], the authors applied the ABM method for comparing two layout design alternatives for an ophthalmology outpatient clinic in terms of people density and achieved a graphical result of aggregate people density. Tang and Chen [55] reduced the overcrowding in the corridors of a hospital by improving the hospital layout design and gained quantitative measurements of the improvement by applying the ABM method. The ABM result shows that the overall patient density in the corridor has decreased from 0.719 patients/m^2 to 0.431 patients/m^2 [55]. Iskander and Carter [73] proposed a DES model to evaluate the overcrowding in a hospital care unit. The authors discovered that at least 160% more waiting spaces are needed to resolve the overcrowding in the care unit [73]. Jones and Evans [74] utilized the ABM method for reducing overcrowding in the emergency department of a hospital. Taboada et al. [75] used the ABM approach to assess the patient length of stay and overcrowding potential in a hospital emergency department. In this study, the overcrowding issue in the emergency department was mitigated by the derivation of non-urgent patients to other departments. As a result, the patient's throughput has increased by 20%–100%, and the patient's length of stay has decreased by 5%–14% [75]. In another two studies [76, 77], the authors developed an Agent-Based Model for reducing overcrowding and patient waiting times in the emergency department of a hospital. Overcrowding in the emergency department was reduced by increasing the number of staff. As a result of reduced overcrowding, the number of treated patients has increased by 100% and the average time of stay was reduced by 51% [77]. Valipoor et al. [78] utilized the DES method for reducing overcrowding in the emergency department of a hospital. In this study, overcrowding was reduced by providing care services in the hallway and introducing a dedicated triage space to improve patient flow. The resulting statistics show a significant reduction in patient length of stay (10%–16% reduction) and patient times spent in the exam room (10% reduction) [78]. In another study, Hancock and Walter [79] used the DES method to model the patient flow for assessing overcrowding potential in outpatient and inpatient departments. Badri and Hollingsworth [80] implemented a DES model intending to assess the number of patients, overcrowding potential and patient waiting time in the emergency department. The author decreased overcrowding in the emergency department of a hospital by not serving patients with less urgent conditions. Statistically, the patient mean length of stay was decreased by 8% [80]. Lopez-Valcarcel and Perez [81] utilized the DES method for assessing crowdedness and patient waiting times in the emergency department. Viana et al. [82] applied both approaches of DES and ABM for assessing the number of patients and patient length of stay in the obstetrics department of a hospital. In their experiment, the number of patients and patient length of stay increased by 18% and 200% respectively, by increasing the arrival rate of patients by 25% [82]. Lin et al. [83] utilized the DES method for reducing overcrowding in waiting areas and reducing patient waiting times in outpatient clinics. By improving resource allocation and optimizing patient appointment scheduling, the congestion in the waiting area was decreased by 46%–52% [83]. Draeger [84] built a DES model for the emergency department for evaluating overcrowding and patient waiting times. By improving the nurse scheduling policy, the crowdedness in the emergency department was down by 19%–23%, and the average patient waiting time was reduced by 51%–57% [84]. Vasilakis et al. [85] used the DES approach to identify the number of patients waiting for appointments and patient waiting time in surgical care. By altering the method of scheduling patient appointments, the number of patients was reduced by 30% [85].

2.4.2 Patients waiting times

Cubukcuoglu et al. [58] implemented a DES model and found the interrelationship between hospital layout and patient waiting time. By enlarging the area of the outpatient department of a hospital and adding one extra doctor, the patient waiting time was reduced by 86 minutes. McGuire [59] built a DES model for reducing patients' length of stay in emergency departments. The study showed that if the layout of the emergency department was changed by adding a holding area, each patient's waiting time would be reduced by 22 min [59]. Baril et al. [60] modelled outpatient flows in an orthopaedic clinic using the DES method for reducing patient waiting times. The authors discovered that patient length of stay can be reduced by up to 67% by improving the layout of the outpatient department (i.e., changing the number of consulting rooms) and improving the patient appointment scheduling policy [60]. Morrice et al. [86] utilized the DES approach for improving patient throughput and reducing patient waiting times in hospitals. The authors found that changing the layout of the care unit by adding an extra room does not affect patient waiting times; however, increasing the patient schedule time slot from 12 min to 15 min would decrease the patient waiting time by 50% [86].

Rahmat et al. [87] implemented an Agent-Based Model for reducing patient waiting times in the emergency department. By improving the triage policy, average patient waiting times in the emergency department were decreased by 17%–32% [87]. Viana et al. [88] combined the methods of ABM and DES and developed a tool for reducing patient waiting times and patient lengths of stay in post-term pregnancy outpatient clinics; the patient waiting time for staff and equipment was reduced by 51.12% and 73.06% respectively. In an early study, Fetter and Thompson [89] applied the DES method for assessing patient waiting time in the maternity suite, outpatient clinic, and surgical pavilion. The authors found that by forcing every patient to arrive on time, each patient's waiting time would be saved by 8 min, which leads to a total saving of 280 h in a period of 50 days [89]. Smith and Warner [90] used the DES approach for reducing the patient length of stay in hospitals, by changing the patient's arrival rate, and patient waiting time decreased by 40%–50%. Kho and Johnson [91] used the DES approach for assessing patient waiting time in a radiology department. Kachhal et al. [92] applied the DES approach for evaluating patient waiting times in ear, nose and throat clinics. The patient average waiting time has decreased by 44.7% by improving patient appointment scheduling policy [92]. Bailey [93] implemented a DES model for evaluating patient waiting times in the outpatient department. By improving the department's patient appointment scheduling policy, patients' average waiting time was decreased by approximately 42% [93]. Smith et al. [94] built a DES model for improving patient throughput and reducing patient waiting time in the outpatient clinic, the mean patient waiting time was decreased by 17%–33% by improving the patient appointment scheduling policy. Fitzpatrick et al. [95] applied the DES method for assessing patient throughput and patient waiting times in a hospital operating room. The average patient waiting times were reduced by 11% by improving the patient appointment scheduling procedure [95]. Klassen and Rohleder [96] utilized DES for reducing patient waiting times in the outpatient department. The authors found that by changing patient appointment scheduling rules, more than 19% of patient waiting times can be saved [96]. Hancock and Walter [79] used the DES method for increasing patients' throughput in the inpatient department. Walter [97] used the DES method for assessing patient waiting time and doctor waiting times for patients' arrival in the radiology departments. Garcia et al. [98] modelled the patient flow in the emergency department of a hospital using DES for reducing patient waiting times. By introducing a fast track lane dedicated to non-urgent patients, their waiting times were reduced by almost 25% without increasing the waiting times for urgent patients [98]. Kirtland et al. [99] built a DES model for increasing patient throughput and reducing patient waiting times in emergency departments. Enhancing the utilization of medical resources leads to a reduction of 24% in patient waiting times [99]. Blake et al. [100] utilized the DES method for investigating patient waiting times in emergency rooms. The authors found that by implementing a fast track for non-urgent patients, a 10% decrease in patient mean waiting time could be realized [100]. Edwards et al. [101] modelled patient flows in outpatient clinics using DES for reducing patient waiting times. By improving the patient appointment scheduling system, the average patient waiting times were decreased by 27% [101]. Alessandra and Grazman [102] utilized the DES method for improving patient throughput and reducing patient waiting times in hospital clinics. By improving the staff scheduling policy, the patient waiting time was reduced by 37% [102]. Mukherjee [103] applied the DES approach for reducing patient waiting time and improving patient throughput in a hospital pharmacy. By improving the staff scheduling policy in the pharmacy, the patient waiting time could be reduced by 8% [103]. Evans et al. [104] utilized the DES method for reducing patients' length of stay in an emergency room. Patient length of stay was decreased by 4% by improving the staff scheduling policy [104]. Mahachek and Knabe [105] utilized DES for evaluating patient waiting times in obstetrical and gynaecology clinics of a hospital. Liyanage and Gale [106] utilized the DES approach for reducing patient waiting times in the emergency department. O'Kane [107] implemented a DES model for assessing the number of patients and patient waiting time in the radiology department. Klafehn [108] modelled the patient flow in the radiology department using DES to assess the patient waiting time and patient length of stay. The author found that by adding one more radiologist, the patient's mean waiting time would be reduced by 25% [108]. Vemuri [109] utilized the DES method to evaluate patient waiting times in an outpatient pharmacy. The patient mean waiting time could be decreased by 49% if an additional technician is added to the pharmacy [109]. Ishimoto et al. [110] applied the DES approach for assessing patient waiting time in a hospital pharmacy. By adding another pharmacist in the pharmacy, approximately 50% of patient waiting times can be saved [110]. Hashimoto and Bell [111] studied patient flows in outpatient clinics using DES to reduce patient length of stay. The average patient length of stay was reduced from 75.4 min to 57.1 min by optimizing staffing levels [111]. Lim et al. [112] implemented a DES model to represent patient flow in emergency departments with the aim of assessing patient waiting times and lengths of stay. Patient waiting times were down by 1%–4% and patient length of stay was down by 61%–136% by improving the staff interactions [112]. Denton et al. [113] applied DES to model outpatient surgery scheduling in a hospital for assessing patient waiting time. The authors achieved a 50% improvement in patient waiting times by optimizing the patient appointment scheduling policy [113]. Kuzdrall et al. [114] built a DES model for assessing patient waiting time in a hospital surgical suite, the results show that by improving the patient appointment scheduling policy, 30% of the patient mean waiting time can be saved. Lim et al. [115] used the DES method to model patient flows in the hospital and assessed patient length of stay and patient waiting times. The patient waiting times were reduced by 28% by improving the patient appointment scheduling policy [115]. Marcon et al. [116] used the DES model to evaluate the patient waiting time and throughput in the Post-anesthesia Care Unit. Stahl et al. [117] built a DES model for assessing patient throughput and patient waiting time in the surgical and anaesthesia care units, 4% of the patient waiting times can be reduced by applying different staff scheduling policies. Testi et al. [118] developed a DES approach for reducing patient waiting time and improving patient throughput in operating rooms. According to their results, patient waiting times could be reduced by 23/24% if a different patient appointment scheduling policy was utilized [118]. VanBerkel and Blake [119] used DES for reducing patient waiting times in the General Surgery Department of a hospital; the patient throughput has increased by 3.4% by adding four extra beds in the general surgery department. Marmor et al. [120] modelled patient flow in the emergency departments using DES for assessing the patient's length of stay and waiting times. Zhang et al. [121] developed a DES model for reducing patient waiting times in a hospital. The patient waiting time can be decreased by 29% by applying different patient appointment scheduling policies [121]. Pan et al. [122] modelled patient and information flow in specialist outpatient clinics using DES for reducing patients' length of stay. The simulation results show that the average patient waiting time can be reduced by 59% by enhancing the patient appointment scheduling policy [122]. Min and Yih [123] applied the DES approach for assessing patient waiting times in an outpatient clinic. By improving the patient registration and queuing policy, each patient's waiting time can be reduced by up to 4 min [123]. Ramirez Valdivia and Crowe [124] implemented a DES model for reducing patient waiting times in hospitals. The authors conducted patient interviews and surveys and concluded that patient waiting times in the outpatient department should be less than 30 minutes they achieved the goal by improving the patient administration policies [124]. Bowers et al. [125]

applied the DES method for reducing patient waiting times and improving patient throughput in the emergency department of a hospital, and the patient length of stay has decreased by 10% by increasing bed capacity. Chu et al. [126] utilized simulation modelling for assessing patient waiting times for lifts and the number of patients waiting for lifts in two hospitals. The average patient waiting times for lifts can be reduced by up to 26% by applying a lift zoning policy (i.e., different lifts are designated with different floors) [126]. Niu et al. [127] applied the DES method for reducing patient waiting times and improving patient throughput in the operating room. According to their study, 17% of patient waiting time can be saved by optimizing the resource utilization [127]. Su and Shih [128] proposed a DES model for reducing patient waiting times in outpatient clinics. By improving the patient appointment scheduling policy, patient waiting times can be reduced by up to 59% [128]. Zonderland et al. [129] implemented a queuing model for reducing patient waiting times and patient length of stay in a university hospital. By changing the patient appointment scheduling policy, the patient throughput over one year has increased by 16% [129]. Ortiz et al. [130] proposed a DES model for reducing patient waiting times in the outpatient department of a hospital. Patient waiting times can be saved up to 13% by improving staff scheduling policy [130]. Norouzzadeh et al. [131] developed a DES model for decreasing patient waiting times by almost 20% in the outpatient clinic. Edward et al. [132] built a DES model for reducing patient waiting times in the preoperative assessment clinic of a hospital. By optimizing the patient appointment scheduling system, 95% of the patients' waiting times were reduced to less than 10 min [132]. Berg et al. [133] used the DES approach for reducing patient waiting times in a multidisciplinary outpatient clinic. The authors found that patient waiting time could be reduced by up to 17% by implementing different resource assignment strategies [133]. Demirli et al. [134] applied the DES method to decrease patient waiting times in an outpatient clinic. Patient waiting times were decreased by 86% by enhancing the cooperation between doctors and nurses [134]. Patel et al. [135] developed a DES model for assessing patient waiting times in outpatient clinics. Patient waiting times could be reduced by up to 23% by applying different resource allocation policies [135].

Creemers et al. [136] developed a Markov process model for reducing patient waiting times in hospitals. The patient waiting time can be reduced by up to 80% by applying different resource allocation policies [136]. Liao et al. [137] modelled patient arrival schedules in a hospital using the Markov chain for reducing patient waiting times. Pegden et al. [138] developed a Markov process model to evaluate patient arrival scheduling in hospitals and reduce patient waiting times. Akkerman and Knip [139] implemented a Markov process model for reducing patient waiting time in hospital wards.

2.4.3 Visibility & staff interaction

Schaumann et al. [72] reduced patient interruption on staff in an internal medicine ward by improving the layout of the ward (i.e., adding an extra day room). The result of the Agent-Based Simulation shows that visitor interruption was reduced by 35% [72]. Lu et al. [140] applied SSA to find the correlation between the visibility and density of people and their interactions in an intensive care unit (ICU). The authors found that the layout influences the visibility in the ICU and hence influences the people density in the ICU, i.e., there is more staff in the places with higher visibility (correlation coefficient $r = 0.786$) [140]. Hadi and Zimring [141] applied SSA for improving visibility in intensive care units. The authors discovered that an ICU with a less discretised layout and wider corridors will improve visibility [141]. Ossmann [142] applied SSA to find the impact of visibility on mortality rates in ICUs. By analysing the layout of the ICU rooms in terms of visibility, patients' odds of death are 42% lower in the rooms with high visibility than in the rooms with low visibility [142]. Alalouch and Aspinall [143] used the SSA method to find the correlation between visibility and privacy in hospital wards. According to their results, the ward layouts with high visibility are less preferred by the patients; in other words, there is a strong negative relationship ($r = -0.957$) between the visibility of the ward and the level of preference for the ward in terms of privacy [143]. Lu et al. [144] identified the relationship between patient mortality and room visibility using SSA. Their study shows that visibility accounts for 35% of the variance in ICU mortality [144]. Kim and Lee [145] used SSA to evaluate users' movement patterns and visibility in hospitals. Three different types of hospital ward layouts were evaluated, and the visibility difference can be up to 32% between different layouts [145]. Trzpuc et al. [146] applied SSA to assess how the layout design can influence nurse interactions in medical-surgical nursing units. Gharaveis et al. [147] used SSA for evaluating the correlation between visibility and staff communication in the emergency department. The authors found that a change in the layout design of the emergency department can lead to a 52% improvement in visibility and a 45% improvement in staff communications [147]. In a similar study, the authors used SSA to evaluate the influence of visibility on teamwork, collaborative communication and security issues in the emergency department [148]. Similarly, O'Hara et al. [149] used SSA to find the correlation between visibility and team interactions and observation of patients. Xuan et al. [150] used SSA to evaluate the influence of visibility and accessibility on nurse communication, perception of privacy, and efficiency in a nursing unit. Pachilova and Sailer [151] used SSA to investigate the influence of an inpatient ward's spatial configuration on staff communication and care quality. Three different hospital ward layouts were analysed, and the difference in visibilities can be up to 32%, which leads to a difference of 4% in staff interaction [151]. Cai and Zimring [152] used SSA to examine the nurses' interaction patterns in hospitals. By improving the layout design of the ICU, the overall visibility in the ICU was increased by 3%, and consequently, the nurse's communication rate was raised by 7% [152]. Rashid et al. [153] used SSA to find the correlation between staff communication patterns and visibility and accessibility in ICUs. The results show a positive correlation (correlation coefficient r = 0.387) between visibility and staff interaction, which indicates that staff interaction tends to happen in places with higher visibility

[153]. Similarly, in other studies, the authors used SSA to compare two hospital layout designs and evaluated the association between visibility and staff interaction [154, 155]. In Ref. [154], Rashid et al. discovered that different types of ICU layouts could lead to a 13% difference in visibility. In Ref. [155], the authors found that by improving the layout design of the ICU, the visibility can be improved by 4%–5%. Lim et al. [156] applied SSA to find the impact of visibility on staff interaction and team collaboration. Cai and Spreckelmeyer [157] applied SSA for improving visibility in a hospital's nurse working area. By improving the layout design of the nursing unit, the visibility was increased by approximately 10% [157].

2.4.4 Wayfinding & walkability

Kim and Lee [145] used SSA to evaluate users' movement patterns and visibility in different hospital wards layouts and found that the deep-plan layout can be 22% more navigable than the courtyard-plan layout [145]. Haq [158] applied the method of SSA for assessing visitors' environmental cognition and wayfinding behaviour in a hospital. The author found that the accessibility analysis of the layout can predict 56% of the variation in wayfinding difficulty [158]. Lu and Bozovic-Stamenovic [35] utilized SSA for evaluating patients' wayfinding behaviour in three hospitals. Haq et al. [159, 160] applied the SSA theory for evaluating patient/visitors' wayfinding behaviour in different hospitals. Tzeng and Huang [161] reduced patients' difficulty in wayfinding in the outpatient department of a hospital using SSA. Pouyan et al. [162] used SSA for assessing first-time users' wayfinding behaviours in a hospital. Lacanna [163] utilized SSA for assessing patient wayfinding behaviour in hospitals. Zwart and Voordt [164] applied SSA for evaluating the difficulty of wayfinding for patients and visitors in a hospital ward. Zamani [165] combined the methods of ABM and SSA for evaluating the visibility and difficulty of wayfinding in hospitals. Gath-Morad et al. [166] implemented an Agent-Based Model for assessing users' wayfinding performance in complex buildings such as hospitals.

Schaumann et al. [72] reduced staff walking distance in an internal medicine ward by improving the ward layout design (i.e., adding an extra day room). The result of the Agent-Based Simulation shows that the staff's mean walking distance was decreased by 5% [72]. In another study [167], the authors developed an Agent-Based model for evaluating nurse walking distance, patient waiting times and visitor disruption on staff in a general hospital. In Ref. [57], Schaumann et al. applied the ABM method for comparing two layout design alternatives for an ophthalmology outpatient clinic in terms of people's walking distance. The simulation results show that one design alternative outperforms another by 20% and 6% in patient walking distance and nurse walking distance, respectively [57]. Vahdatzad [168] reduced the patient walking distance in a hospital by optimizing the hospital layout (i.e., locating the waiting area in the centre of the layout and locating service areas closer to the entrance and elevator). With the application of the DES method for measuring the performances, the mean patient walking distance was reduced by approximately

33% and the average patient length of stay was decreased by 6% [168]. Nanda et al. [169] applied SSA for assessing staff travelling distance in a surgical unit of a hospital. Lee et al. [170] implemented an Agent-Based model for reducing nurse walking distance in hospital nursing units. Cai and Jia [171] applied the DES method for reducing surgeon walking distance in a surgical suite. Vahdat et al. [172] implemented a DES model for reducing patient walking distance and patient length of stay in the outpatient clinic of a hospital. O'Hara [173] proposed a DES model for assessing nurse walking distance in the Intensive Care Unit of a hospital.

2.4.5 Other issues

Other categories include the following:

- Patients/visitors' interruptions on staff

  In [57], Schaumann et al. applied the ABM method for comparing two layout design alternatives for an ophthalmology outpatient clinic in terms of patient interruptions to staff. The simulation results show that there is a 22% difference between the two designs' performances in reducing patients' interruptions on staff [57]. Hendrich et al. [174] used SSA to evaluate the influence of the nursing unit's layout on nurse movement patterns and time spent on staff-patient interactions. Sagha Zadeh [175] developed a design tool using SSA for reducing staff fatigue and interruptions in acute care units. Setola et al. [176] utilized SSA for assessing the frequencies and locations of patient-staff interaction in public spaces in the hospital. Huynh et al. [177] developed an Agent-Based Model for assessing the nurse's time spent on interpretation in a hospital. By redesigning the medical administration process, the time nurses spent on interruptions was reduced 100% [177].

- Hospital-Acquired Infections

  Wang et al. [52] developed an ABM model for testing the impact of a clinic layout design on the infection risk of COVID-19. Their findings suggest that overcrowded areas (e.g., waiting areas) have a higher infection risk (the cumulative exposure dose in the waiting areas constitutes 66.5% of the total) [52]. Tahir et al. [53] applied both methods of SNA and ABM to find the correlations between hospital layouts and the risk of hospital-acquired infections (HAIs). The authors discovered a strong positive correlation (correlation coefficient $r = 0.8$) between department prevalence and the degree centrality of the department (i.e., the higher prevalence was found in the departments with higher centrality values). Mustafa and Ahmed [54] used SSA for assessing the effects of different types of outpatient layouts on limiting the spread of COVID-19. The authors found that the integration value in a decentralized layout is 23% lower than the integration value in a centralized layout, which means that a decentralized layout has fewer overcrowded areas and thus more advantage in providing social distancing [54]. Tang and Chen [55] improved a hospital layout design for reducing the risk of the spread of COVID-19. The Agent-Based simulation results show that the overall patient density in the corridor has decreased from

0.719 patients/m2 to 0.431 patients/m2 after improvement, which enhances the control of the spread of COVID-19 because reduced congestion in the hospital helps to keep social distancing [55]. Esposito et al. [56] simulated the HAIs propagation dynamics in the hospital using the ABM method with the aim of reducing HAIs. Schaumann et al. [178] developed an Agent-Based Model for simulating and investigating HAIs in the hospital. Hotchkiss et al. [179] simulated the spread of the pathogen in an ICU using ABM with the aim of reducing HAIs. Ong et al. [180] developed an Agent-Based Model for investigating HAIs in the hospital. Meng et al. [181] applied the ABM approach for reducing HAIs in a hospital ward. Ferrer et al. [182] proposed an Agent-Based Model to simulate pathogen transmission in the ICU with the aim of controlling HAIs. Milazzo et al. [183] utilized the ABM approach for reducing HAIs in a hospital ward. Pelupessy et al. [184] developed a Markov chain model to simulate the transmission dynamics in a hospital and aimed at controlling HAIs. Lopez-Garcia and Kypraios [185] developed a Markov chain model for analysing the spread of nosocomial infections in hospitals.

2.5 Review results

The hospital design challenges, the approaches for assessing these challenges and the corresponding indicators and quality criteria were summarized in tables 2.1 and 2.2. In this table, problems related to hospital layout designs are presented in the first column which is named ‘challenges’, the disaggregated form of measurements of these problems are presented in the second column (named ‘indicators’), and the aggregated measurements are shown in the last column which is named ‘quality criteria’. It is to be noticed that indicators are the disaggregate results from assessment approaches of SNA or Simulation Modelling. The quality criteria are an aggregate form of indicators (i.e., average, maximum or minimum values, etc.). Both indicators and quality criteria indicate how to measure the challenges. Among the total 102 reviewed papers, they all investigated one or several of the seven challenges of overcrowding, long patient waiting time, patient/visitors’ difficulties in wayfinding, low visibility and less staff interaction, hospital-acquired infections, long patient/nurse travelling distance and patients’ interruptions on staff. Although these issues are related to layout, many of the reviewed studies do not associate them with the layout. Only 34% of them (35 out of 102 papers) studied the effects of layout on hospitals, and most of them applied SSA ([54, 140, 141, 142, 143, 144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 156, 157, 158, 35, 159, 160, 161, 162, 163, 164, 165, 176, 176]), others used ABM approach ([52, 55, 56, 57, 72, 178]). One study combined SSA with ABM [165]. There is a clear research gap indicating that although these studies associate the hospital problems and challenges with layout, they did not mention the representation of layout, or they do not mention what a layout representation or how to model the layout. However, a layout

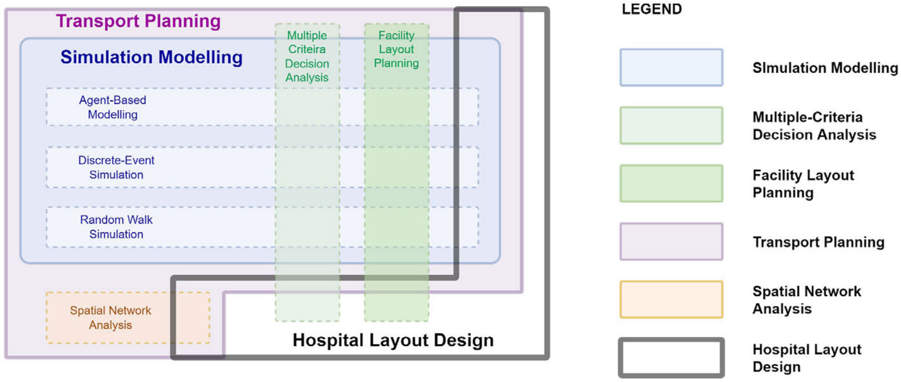

FIG. 2.3 Disciplines that will be focused on and studied together for our future research, image source: author.

representation is necessary and critical for evaluation. From the review results, the following can be summarised:

- Although all reviewed publications investigated hospital problems and challenges that are related to layout, few of them associated the problems/challenges with the layout. Especially, studies that apply simulation modelling approaches rarely associate the problems with hospital layout. This suggests a potential research direction of utilizing Simulation Modelling to study the impact of layouts on hospitals.
- As for the few studies that investigated the effects of layout on hospitals, they did not mention the representation of the layout. However, a clear representation of the layout is needed for assessments. Hence, another potential research direction is to develop methods of modelling and representing the layout.
- None of the reviewed publications introduced the method for relativizing/normalizing the quality criteria for a fair comparison between different hospitals. It is inappropriate and inaccurate to directly compare the quality criteria of a small hospital with a large hospital. Hence, methods for relativization or normalization are necessary.
- None of the reviewed studies introduced the method for defining functional units for a fair comparison. The functional unit quantifies the performance of the system and serves as a reference unit. It is necessary to have a functional unit for comparing two different hospitals' quality criteria. Hence, methods for defining functional units for comparative assessments of different hospitals are needed.
- As illustrated in Figure 2.2, some of the disciplines discussed in this review have been separated, though they have the potential to be combined and studied, which points out our future research direction of combining certain disciplines/terminologies for the study of hospital layout design (as shown in Figure 2.3).

TABLE 2.1 Problems & Challenges with hospital layout design and how to measure them.

Challenges	Indicators (disaggregate indications of how to measure)	Approaches	Quality criteria (aggregate indications of how to measure)
Overcrowding[3, 4]	Number of patients in public spaces (e.g., waiting areas, corridors, etc.) of different functional areas/departments [57, 72, 75, 76, 77, 78, 80, 81, 82]	ABM + aggregation [74, 75, 76, 77]; DES + aggregation [79, 80, 81, 82, 83]; RWS + aggregation [168]	The average people density over time in the public spaces (e.g., waiting area, corridor, etc.) of each functional area/department & Their weighted average [57, 72, 78, 186]
long patient's waiting time and/or long patient length of stay and/or low patient throughput [57, 58]	Each patient's time spent on waiting for different procedures (e.g., diagnosis, clinical checkup, ultrasound test, etc.) [58, 122, 87, 132, 187, 188, 10, 189, 190, 191]	ABM + aggregation [57, 72, 77, 76, 87, 88]; DES + aggregation [78, 187, 58, 122, 188, 10, 59, 60, 113, 73, 80, 81, 84, 86, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 100, 101, 103, 104, 105, 106, 107, 108, 109, 110, 111, 112, 115, 117, 119, 124, 125, 127, 128, 130, 131, 132, 133, 134, 135, 190, 191, 192]; RWS + aggregation [136, 137, 138, 139, 186, 189]; SNA + aggregation [140]	Average agent waiting time for each procedure (e.g., diagnosis, clinical check-up, ultrasound test, etc.) & A typical agent's average total waiting time (e.g., outpatient [58, 122, 88, 123, 125, 128, 130, 131, 132, 133, 134, 135, 187, 188, 10, 189, 190, 191]
Low visibility [140, 141, 142, 144] and Less staff interaction [146, 148]	Degree and closeness centrality value of the spatial units [140, 148, 149]; Degree and closeness centrality value of the spatial units [146, 147]	the visual outputs depicting the distribution of centrality values in the area [140, 145]; The intelligibility (i.e., a correlation coefficient between degree and closeness centrality values) of the whole layout [151]; average closeness centrality of different spaces [153]	

TABLE 2.2 Problems & Challenges with hospital layout design and how to measure them. (Continued)

Challenges	Indicators (disaggregate indications of how to measure)	Approaches	Quality criteria (aggregate indications of how to measure)
Difficulty in wayfinding [3]	Each spatial unit's centrality value. i.e., How many spatial units is one connected to and how close are these connections [13, 158, 35, 159, 160, 161, 165]; Each agent's travel path [57]	ABM + aggregation [57, 165, 166]	The intelligibility (i.e., a correlation coefficient between degree and closeness centrality values) of the whole layout and/or the visual outputs depicting the distribution of centrality values in the area [13, 158, 35, 159, 160, 161, 165]
long patient/nurse travelling distance between processes [3]	Each patient/nurse's time spent on travel [193] or each patient/nurse's travel distance [169, 170]	ABM + aggregation [167, 170]; DES + aggregation [172, 173]; SNA + aggregation [193, 169]	A typical agent's average travel time [193] or travel distance [169, 170]
Patient Interruption on staff [175]	Each spatial unit's closeness centrality value. [174, 175]; the number of staff-patient interactions and location of each interaction [57]	SNA + aggregation [57, 174, 175, 176]	Aggregate location with higher closeness centrality values [175]; Aggregate location of staff-patient interactions [57]
Hospital-acquired infection [184]	location of each actor and the location of each interaction between actors [56]	ABM + aggregation [52, 55, 56, 178, 179, 180, 181, 182, 183]; RWS + aggregation [184, 185]	Aggregate propagation areas due to the actor's interaction with the environment and other actors [56]

2.6 Conclusion and future research

The conclusion of this review paper is summarised below:

1. We have established the importance of adequate hospital layouts/by summarising problems caused by inadequate layouts (see tables 2.1 and 2.2)
2. We have summarised the gaps in the literature, especially in the proper mathematical treatment of spatial representation issues and quantification of such problems as overcrowding and risk of cross-contamination (see section 2.5)
3. We have illustrated the parallels and analogies between hospital layout problems and well-known problems in transport planning, especially in conjunction with land-use planning in cities. In other words, the paper has shown by examples that there is a lack of comprehensive frameworks for the quantification of such issues. The hospital-city analogy and the transport planning approach can lead to the

establishment of adequate methodologies capable of properly quantifying these issues for hospital layout assessment.

4 Providing any kind of reliable decision support mechanism is first and foremost about the provision of reliable and transparent assessment mechanisms for predicting the impact of design choices. Therefore, we conclude with some priorities for future research into the quantification and assessment of hospital layouts:

- Devising a mathematical framework for spatial representation and measurements in a clearly defined analogy of a hospital with a city, and borrowing the terminology and methodological practices of transport planning and land-use transport interaction models (LUTI).
- Developing a standardized hospital/building layout representation model only containing information relevant for ex-ante assessment of the effects of layout on human movement inside the hospital.
- Developing a standardized hospital layout assessment framework based on well-defined functional units, relativized formulations of quantities of interest, estimation methods driven by standardized simulation procedures, and possibly additional tools for integration/aggregation of multiple criteria in a comprehensive assessment of design choices.

The nature of the proposed Hospital Design Support System should be similar to a Transport Planning Support System because designing a hospital is similar to designing a small town, which is even folded in 3D. From both formal and functional points of view, it is similar to designing a city. However, in a city, roads can be widened, and bridges and tunnels can be built to suit the traffic demand. A city can grow, and it is elastic, while a hospital is plastic. Hence, designing a hospital is similar to but more difficult than designing a small city. The analogues of the streets of a city (or its Transport Network) will be the corridors in the hospital, and the analogues of the land uses in a city will be the different spatial units serving different functions in the hospital. This study provides a systematic review of the application of SNA and Simulation Modelling on hospital layout designs. The main focus of this study lies in the spatial layout.

To demonstrate the function of the proposed Hospital Design Support System, four use cases are described by answering the following questions: who would be the user of this system? What questions can this system answer? And at what stage of a project can these questions be answered?

- Use Case 1: The hospital director can use this system to check the crowdedness of a hospital project during the layout design stage.
- use case 2: The architect can use this system to check how difficult it will be for the first-time visitor to find their way in a hospital project during the layout design stage.
- Use Case 3: The head nurse can use this system to check if their walking distance will be too long in a new hospital project during the layout design stage.

- Use Case 4: The hospital director can use this system to check if the patient waiting time or walking distance will be too long in a new hospital project during the layout design stage.

In short, the proposed Hospital Design Support System is envisaged to be a Multi-Criteria Decision Analysis toolkit for the integral evaluation of design alternatives.

3 Hospital Configuration Model

3.1 A Configuration Model for Hospital Design Support Systems

This sub-chapter has been published by Jia, Z., Nourian, P., Luscuere, P., & Wagenaar, C. (2024). A Configuration Model for Hospital Design Support Systems. Buildings, 15(2), 163. [38] The layout has been adjusted to fit the template of this thesis.

ABSTRACT Hospital layout significantly influences hospital service quality, demanding robust tools for informed decision-making during the layout design stage. This study presents a novel Hospital Configuration Model as the foundational component of a Hospital Design Support System, which utilizes simulation modelling to provide evaluation mechanisms on hospital efficiencies and functionalities. The Hospital Configuration Model integrates four critical data types—geometric, topological, semantic, and operational—into a machine-readable digital twin, enabling comprehensive spatial and procedural analyses. The Hospital Configuration Model facilitates simulation modelling to optimize hospital layouts and predict performance metrics such as crowdingness, patient waiting times, patient walking distance, and difficulty in wayfinding. In conclusion, the Hospital Configuration Model is the core and foundation of developing the Hospital Design Support System for evaluating hospital functionalities and efficiencies, and the potential applications of the model include digital twin development, facility management, and safety enhancement. Future research directions should, in particular, include developing the proposed Hospital Design Support System and establishing a standard way of extracting hospital operational information into an industry-standard data model.

3.1.1 Introduction

Studies have shown that the layout of a hospital has great impacts on its functionality. For instance, Jia et al. [48] summarized the problems and challenges caused by inappropriate hospital layout designs. Chraibi et al. [49] investigated how the layout of the operating theatres affects staff travel distance. Ulrich et al. [50] discussed how the physical layout affects patient outcomes and operational efficiency in healthcare settings. Burgio et al. [51] analyzed nursing staff behaviors in healthcare facilities, showing the influence of environmental layouts on staff interactions. Peponis et al. [13] investigated wayfinding within hospital environments, emphasizing the importance of spatial configuration in user navigation. The reasons why hospital layout has such a big influence on its functionality are twofold. Firstly, from the functionality aspect, the medical procedures inside hospitals are complex. Secondly, from the aspect of configuration, hospitals are as complex as small cities, where corridors are similar to streets and functional units are similar to different land uses in cities [48]. Hence, combining these two aspects indicates that the layout of a hospital significantly affects users' visibility and walkability inside the hospital. When architects design a hospital, they are not merely making a building, but a system that can have many risks and problems if not treated carefully [48].

To improve the design of the system of hospital, we propose to introduce an early operational insight into the hospital design process through the development of a decision support system, namely, the Hospital Design Support System (HDSS). The HDSS is intended to provide reliable and transparent assessment mechanisms for predicting the performance of different hospital layout designs. To be able to provide such assessment mechanisms, we need a configuration model, which is a layout representation model of the hospital system containing four types of information, i.e., geometric information, topological information, semantic information, and operational information. Table 3.1 provides a detailed explanation and examples for each type of information. The "Explanation" column describes the specific data contained within each information type, while the "Example" column illustrates this data using a Python 3.11 dictionary format.

TABLE 3.1 Examples of four types of information in a Hospital Configuration Model.

Information Type	Explanation	Example
Geometric Information	Room boundary consisting of a series of 3D points	{'central_waiting': ['−20, 34, 4', '−20, 29, 4', '−19, 29, 4', '−19, 39, 4', ' −20, 34, 4']}
Topological Information	A network graph consisting of nodes and edges	{'Graph1': [{"node1": {"id": "R1"}, "node2": {"id": "R3"}, "edge1":{"id": "e1"}}]}
Semantic Information	Room name	{'Department$Imaging': ['Central_waiting']}
Operational Information	A patient journey through the hospital (a series of rooms that the patient needs to attend)	{'patient_journey_1': ['Entrance/Exit', 'Registration', 'consulting', 'Entrance/Exit']}

3.1.1.1 Research Problem and Questions

The **research problem** of this paper can be stated as follows:

- Despite the hospital layout having significant influences on hospital functionalities and operational efficiencies, there is a lack of robust tools for systematically assessing hospital layout designs in terms of operational efficiencies and functionalities at the layout design stage. To enable a robust tool to assess and predict hospital layout performance using simulation modelling, a Hospital Configuration Model integrating geometric, topological, semantic, and operational information is essential. This research addresses the need for a Hospital Configuration Model to serve as the core of the proposed tool, enabling evaluations of hospital layout designs to improve operational efficiency.

The research problem leads to the following **research questions**:

- Why do we need a Hospital Configuration Model?
- What information do we need in the Hospital Configuration Model?
- How to extract such information into the Hospital Configuration Model?

3.1.1.2 Related Works

Currently, there are several publications in the scientific literature devoted to the issue of extracting layout representation models from digital building models such as Building Information Models (BIM), Industry Foundation Classes (IFC) models, and Computer-Aided Design (CAD) models, etc. In particular, Diakite et al. [194] developed a tool for automatically generating IndoorGML models from the IFC model using C++20. The IndoorGML model is an industry-standard model that incorporates geometric, topological, and semantic information, it is a specialized layout representation model designed for indoor spatial analysis and navigation [194]. However, the IndoorGML files generated by this tool do not include any semantic information, which is inadequate for our research. Similarly, Intratech [195] developed a plugin for AutoCAD 2020 and Revit 2020 for extracting IndoorGML. The IndoorGML files generated by this plugin also lack semantic information, and this plugin relies on proprietary formats. Tong and Zheng [196] developed a tool for transforming IFC models to IndoorGML files using Autodesk's Revit 2020 and Dynamo 2.1.0, McNeel's Rhino 7 and Grasshopper 2.0, and Python 3.11. The IndoorGML files generated by this tool have semantic information. However, the tool only works for modularized buildings with simple geometries (i.e., rectangular-shaped rooms with four sides). Since hospitals are complex buildings with rooms and corridors of all kinds of irregular shapes, this tool is not suitable for our research. Jeong et al. [197] developed a tool for manually creating and editing IndoorGML files; however, this tool does not support generating IndoorGMLs from other existing sources. Similarly, Brincovean and Butean [198] created software for editing IndoorGML's topological data, which also lacks functionality for generating IndoorGML from other sources. Taehoon [199] developed a Java-based graphical editor for manually drawing IndoorGML's geometric and topological information; however, this tool cannot extract IndoorGML from other sources. Claridades et al. [200] developed a methodology for integrating the IndoorGML model with other 3D geometric information for supporting indoor navigation; however, the proposed methodology does not support the generation of IndoorGML files. Yuan and Schneider [201] constructed an indoor network model integrating geometric information for supporting indoor navigation; however, the model is not built in the industry-standard IndoorGML format, which reduces the data interoperability. Teo and Cho [202] developed a methodology for extracting geometric network models from BIM models for various indoor and outdoor route planning applications; however, their output also lacks compatibility with IndoorGML standards, which reduces the data interoperability. Khan et al. [203] developed an approach for transforming IFC files into CityGMLs (i.e., an Open Geospatial Consortium (OGC) standard designed for the representation, storage, and exchange of 3D urban spatial data [204]) and subsequently to transform CityGMLs into IndoorGML files. This approach cannot generate IndoorGMLs directly from IFC files; it can only generate CityGMLs from IFC files and then convert CityGMLs into IndoorGMLs, which is a cumbersome and complicated process. Srivastava et al. [205] developed a methodology for extracting IndoorGMLs from CAD drawings. While this methodology works for CAD models, it does not work for BIM/IFC models. CAD models are primarily 2D geometric drawings and often lack semantic information. Generating IndoorGML from CAD requires manual mapping to infer relationships and semantics, which can be error-prone and incomplete. Hashim et al. [206] developed a workflow for converting point cloud data into the Sketchup model and extracting IndoorGMLs from the Sketchup model. Unlike BIM models, SketchUp models do not inherently include rich semantic information; hence, the extracted IndoorGML files also lack semantic information. To summarize, the current gap in the literature lies in the absence of a tool capable of handling complex buildings with irregular shapes while generating IndoorGML files enriched with semantic information. Additionally, no existing tool can convert IndoorGML files into Hospital Configuration Models (HCMs) that integrate operational data and evaluate the alignment between operational needs and the spatial configuration of hospitals. This study addresses these gaps by proposing a novel methodology for the semi-automatic generation of IndoorGML models from BIM/IFC models and the subsequent conversion of these IndoorGML models into Hospital Configuration Models (HCMs).

3.1.1.3 Contributions and Novelties

This research introduces a novel framework for supporting hospital design by proposing the Hospital Configuration Model (HCM) as the foundational component of a Hospital Design Support System (HDSS). The contributions and novelties of this research can be summarized as follows:

- **Generation of IndoorGMLs:**

  Our proposed methodology incorporates a tool for the semi-automatic generation of IndoorGML files from widely used BIM/IFC models and the automated conversion of these IndoorGML files into Hospital Configuration Models (HCMs). Our tool is specifically designed to handle complex buildings with irregular shapes, ensuring that the resulting IndoorGML files contain accurate and comprehensive semantic information.

- **Development of the Hospital Configuration Model (HCM):**

  The HCM integrates four critical data types—geometric, topological, semantic, and operational—into a comprehensive, machine-readable digital twin model. By bridging spatial information with operational workflows, the HCM ensures that hospital layouts are evaluated not only for spatial efficiency but also for their alignment with medical procedures and operational needs.

- **Construction of Activity Relations Chart (ARC) Models:**

  This study proposes a method for systematically building Activity Relations Chart (ARC) models, which can be used for modelling and optimizing hospital layouts. The ARC model is a tool for representing relationships between different spatial units within a building [207] and can be thought of as the simplified graph-theoretical equivalent of the HCMs.

The goal of the paper can be summarized as making a machine-readable model/digital twin of a hospital that can bring the operations of a hospital into a spatial information model as attributes. The rest of the paper is structured as follows: The following Section 3.1.2 called Background answers research question 1: Why a Hospital Configuration Model (HCM) is essential to have as the core of an HDSS as an information system? Then, Section 3.1.3, called Research Methodology, answers the research question 2: What specific pieces of information content are needed in an HCM, based on the arguments and reflections provided in the background? Afterwards, Section 3.1.4 answers the research question 3 of how to extract such information into the Hospital Configuration Model. We dive deeper into extracting the proposed pieces of essentially required information from what is typically available as data and information models on hospitals, both the Building Information Models or BIM data models and hospital Business Process Model and Notation, or BPMN, data models. In Section 3.1.5, called Discussion, we talk about key findings, novelties, and limitations of this research. Finally, in Section 3.1.6, called Conclusion, we introduce the implications of the HCM and propose potential future research directions.

3.1.2 Background

This section explains the necessity of developing an HCM as the core of HDSS. One of the major functions of the proposed HDSS is to run simulation modelling to simulate complex dynamic situations in a hospital environment. The simulation modelling requires a configuration model as the base on which simulation can be implemented. Furthermore, another major functionality of HDSS is to ensure that the configuration of a hospital fits how the hospital is operated. In other words, the space of the hospital should be laid out in a way that serves the purpose of improving hospital operations. An HCM is therefore essential to check this fit between the hospital space and medical procedures (hospital operations).

3.1.2.1 Simulation Modelling for Ex Ante Assessment

The primary objective of developing an HDSS is to provide robust mechanisms for evaluating the potential impact of hospital configuration decisions on various quality indicators or quantitative outcomes. These outcomes may include measures of functional efficiency, levels of crowding, and other relevant performance metrics. The basic idea for devising such assessment mechanisms is to develop spatial analysis procedures based on spatial queries, which tend to be about spatial networks and traversals on their graph models. However, in the bigger scheme of configurational assessment, some inherently dynamic phenomena can only be properly understood through simulation modelling. There are multiple paradigms and at least two simulation modelling approaches that are commonly used for the study of complex systems. Complex system modelling is the bigger picture in which the whole case of making an HDSS is considered because hospitals are obviously complex socio-technical organizations that are not only complex from a spatial point of view but also from an organizational and operational point of view. It is non-trivial to understand how they work, let alone to be able to come up with recommendations as to how their functionality or operational efficiency can be improved. Thus, we must look into the bigger picture of simulation modelling for understanding hospitals as complex systems to approach the daunting task of HDSS development. To keep the scope of the paper manageable, however, here we only look at the necessity of having a hospital configuration model from the point of view of simulation modelling paradigms and approaches (which are not all necessarily relevant to the case of HDSS development, but for the sake of generality, we mention them all). There are four **simulation modelling paradigms** [208]:

1. **Discrete Event Simulation (DES)**: A Discrete-Event Simulation (DES) model is a model of a system in which events occur at specific points in time, causing changes in the system state [46]. A DES model consists of:

   – Discrete event: The discrete event is the cause of the system state change. The state of the system in the DES model only changes due to the occurrence of events [41]. For example, in a hospital DES model, the patient's walking distance in the hospital only changes if the patient moves to the next room.

- Clock: The clock records the duration of the simulation. The DES model is dynamic as time is a critical variable, i.e., the state variables of the system change over simulation time [41]. For example, in a hospital DES model, the walking distance of the patient increases as the simulation time increases.
- Random number generators: A random number generator can generate random variables for the DES [41], e.g., medical service time or patient inter-arrival rate.
- Statistics: This summarizes the results of the simulation, such as patient waiting times or patient walking distances [41].
- Ending condition: The DES ends when the ending condition is met [41], e.g., a hospital DES model is set to end when a certain number of patients are discharged.

The proposed HDSS can use DES to simulate patients' medical procedures in hospitals and predict hospital performance by calculating performance indicators, such as people density, patient waiting time, patient walking distance, etc.

2 **Agent-Based modelling (ABM)**: An Agent-Based Model comprises individual agents, their interactions with one another, and their interactions with the surrounding environment [44]. Agents are small computer programs that represent various types of entities [44]. For example, in a hospital ABM model, agents can be patients, nurses, doctors, etc. The environment in the ABM model can be a network graph where agents can interact [44]. The agents have several characteristics, which are summarized as follows:

- Autonomy: Agents are autonomous entities that behave without guidance from central controllers; they are capable of making independent decisions [45].
- Heterogeneity: Agents can have various features, such as ages, jobs, genders, etc. [45]. For example, in a hospital ABM model, agents can have different roles, such as patients, medical staff, technical staff, etc.
- Active: Agents are active in an ABM model because they are goal-directed; they are assigned to different goals and they need to achieve them [45]. To achieve their goals, agents are equipped with the capacity to perceive their environment and interact with other agents. Additionally, they are enabled to make logical decisions that facilitate goal attainment [45].
- [-25]Interactive: Agents can interact with other agents and also with the environment [45].
- Mobility: Agents can move in the ABM environment [45]. For instance, the patient or the staff agent of a hospital ABM model can move in the environment (i.e., a graph) to achieve their goals.
- Adaptation/Learning: Agents can be designed to be adaptive; they can alter their states based on previous states [45]. For instance, in a hospital agent-based model, a doctor agent becomes available for new patients once they have completed the treatment of the current patient.

ABM can also be applied in the proposed HDSS for studying individual behaviors, interactions between patients and staff, or patient flows in the hospital.

3 **Continuous Simulation**: Continuous simulations are designed to model systems in which the system states change continuously over time. For example, in a hospital continuous simulation model, the patient's length of stay increases continuously over simulation time. Continuous simulation models use differential equations or other mathematical models for defining the changing rate of the system states over time [209].

Continuous simulations can be compared with DES, where state variables in continuous simulation models change continuously over time, while in DES models they change at distinct points in time. Continuous simulations can be used for studying the spread of a contagious airborne disease (e.g., influenza or COVID-19) throughout a hospital to understand infection risk in different areas.

4 **System Dynamics**: System dynamics is a type of continuous simulation that is developed for supporting policy making in complex and dynamic systems [209]. In system dynamics models, the behavior of the system is created by the interactions between different components over time. The key components of a system dynamics model are introduced in the following:

- Stocks: Stocks are accumulations of resources in a system; they represent the state of the system [209], e.g., the number of patients in a hospital.
- Flows: Flows represent the changing rates of stocks over time [209]. In a hospital, for example, the flow could be the rate at which new patients are admitted or discharged.
- Information links: In a system dynamics model, information links connect stocks with flows and transfer information from a stock to the flow; they define how a stock influences the values of the flow [209]. For example, in a hospital system dynamics model, by linking stock (i.e., number of patients in the hospital) to the flow (i.e., patient inter-arrival rate), the patient inter-arrival rate can be influenced by the current number of patients in the hospital.

System dynamics can be applied in hospital management in terms of understanding patient flow, resource allocation, the spread of disease, etc.

And there are mainly two **simulation approaches** [210]:

1 **Causal or signal-flow-based modelling as in Simulink** [211].

2 **Acausal or equation-based modelling as in Modelica** [212].

Both of these simulation modelling approaches result in the construction of network models to be used in running the simulation model. However, the first type of network produced in signal flow-based simulation modelling is a Directed Acyclic Graph (DAG) that is used almost directly as a computational network model, whereas the second type of network model produced in equation-based modelling is closer to our configuration model. It is a network model that closely resembles the physical interconnections of elements in the system. It does not, however, readily represent a computational network model. Such a model still needs to be coupled with mathematical models to be converted into a simulation model. In an equation-based simulation modelling language like Modelica, this step happens thanks to the computational engine of the language, but in our workflow, we have to consider this as a secondary step of modelling to be performed by the modeler for the domain-specific simulation tasks. However, discussing these details is beyond the scope of this paper. Instead, here, we reflect on the requirements of an HCM for being applicable and useful for building various simulation models, such as the four types of simulation models mentioned previously.

Reflecting on the properties of the HCM from the point of view of simulation modelling, what should the properties of an HCM be to be ready for simulation models? According to the previous introduction of the four types of simulation models, DES is perhaps the most suitable simulation modelling paradigm for studying the operational efficiency of hospitals. However, ABM simulation models are also used for studying stressful, chaotic, extreme or urgent situations in which the human agents might behave like herds or flocks of animals, following and interacting with each other closely. Continuous simulation models and system dynamics models are less suitable for modelling hospital operations. Continuous simulation models are more applicable in specific contexts, such as studying the spread of contagious airborne diseases in hospitals, and system dynamics models are more suitable for supporting the design of hospital policies or management strategies. So, in short, DES and ABM models are the two simulation modelling paradigms that are most suitable for this research, with the ABM simulation models able to be used to assess the extraordinary working situations and the DES to assess the ordinary working situations of the hospitals.

Ideally, our proposed HCM can cater for the needs of both the simulation modelling approaches. This means that our HCM should have the essential spatial and operational pieces of information that can potentially be further elaborated automatically to extract higher resolution and more detailed information models as bases of such simulation models. For example, if you consider a base simple floor plate in an HCM, it can be further meshed into a high-res grid for running an ABM, but only if necessary. However, it is not necessary to store high-resolution detail information in the HCM at all times, as the high-resolution mesh can be generated on-demand using the essential boundary information already stored in the HCM.

3.1.2.2 Operational vs. Spatial Information

The most important reason to consider making an HDSS is to enhance the fit between the hospital's operational information and spatial information. A hospital's operational information pertains to the processes, workflows, and activities that occur within a hospital. It encapsulates the dynamic aspects of how the facility operates, focusing on the flow of people, materials, and resources through various functional units. Key elements include:

- Patient Journeys: A sequence of steps or locations that patients visit during their hospital stay; for an instance of the patient journey, please see ‘Operational Information’ in Table 3.1.

- Resource Utilization: Details of how hospital resources (e.g., rooms and beds) are allocated and used.

Spatial information focuses on the layout/configuration of the hospital. It provides a static framework that determines how operational activities are accommodated within the facility. Key elements include:

- Geometric Information: Details about the shapes, dimensions, and coordinates of physical spaces, such as room boundaries. For an example of a room boundary, please see ‘Geometric Information’ in Table 3.1.
- Topological Information: The connectivity between spatial units, represented as a network of nodes (e.g., rooms) and edges (e.g., connections between rooms). Table 3.1’s ‘Topological Information’ provides an example of a simple network.

While operational information captures the dynamic aspects of hospital activities, spatial information provides the static framework that houses these activities.

The purpose of enhancing the fit between a hospital’s operational information and spatial information can be expressed as ensuring that the configuration of a hospital is fit for the purpose for which it is built.

The operational steps can be related to the spatial units of a hospital—the sequences or medical procedures inevitably entail the transport of people (patients and staff), materials, and equipment inside the hospital. Therefore, the challenge of operational management of the hospital will significantly involve transport planning and operations research in a spatial sense. In conclusion, it can be said that the problem of designing an optimal hospital configuration is about the fitness of the hospital configuration for undertaking the medical procedures that are supposed to take place through the spatial layout of the hospital. Figures 3.1–3.3 illustrate some representative examples of medical procedures in real-world hospitals; Figures 3.4 and 3.5 together show the ideal configuration obtained from these medical procedures. For further explanation on how to achieve an ideal hospital configuration with regard to hospital medical procedures, please see Section 3.1.3.2.

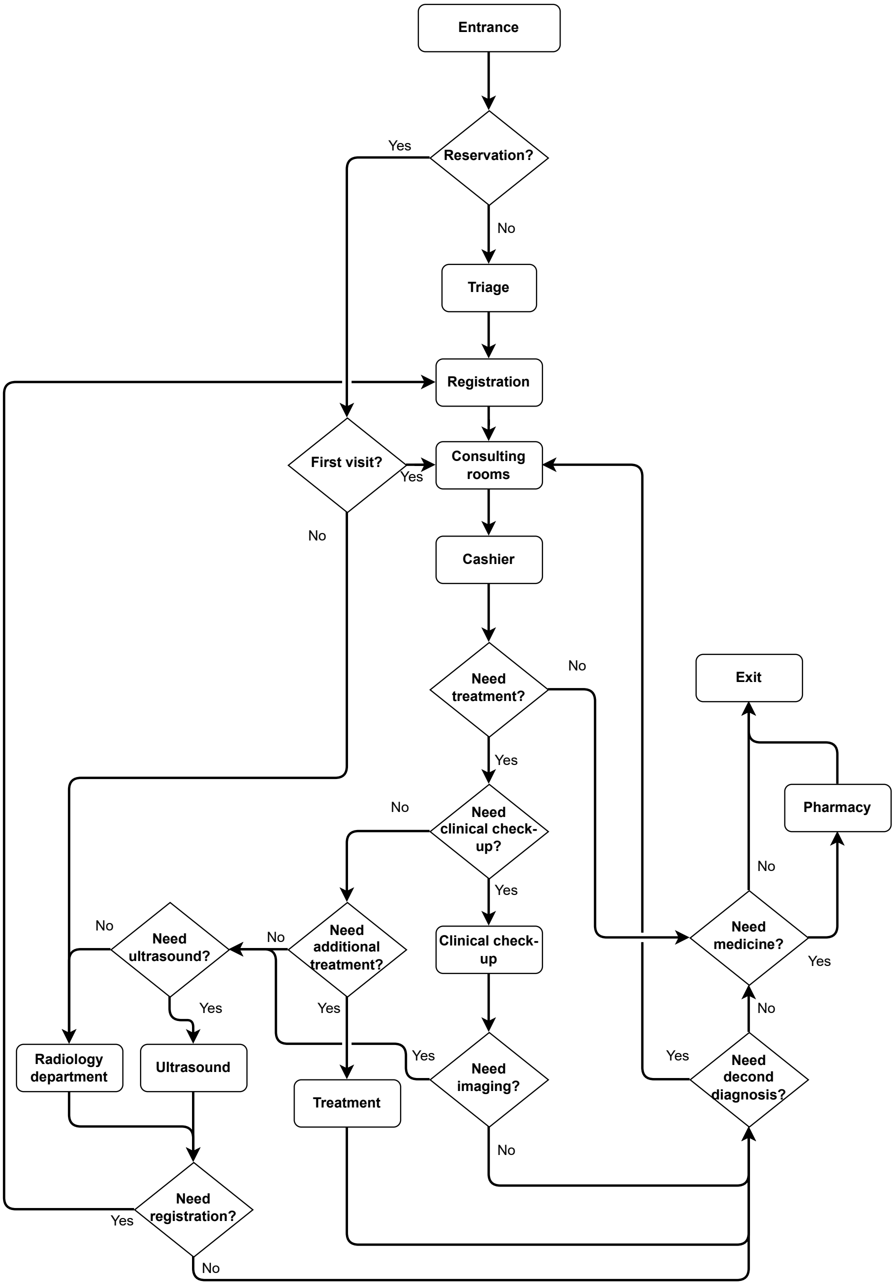

FIG. 3.1 Patients' paths in the Outpatient Department of Panyu Central Hospital, image source: [3].

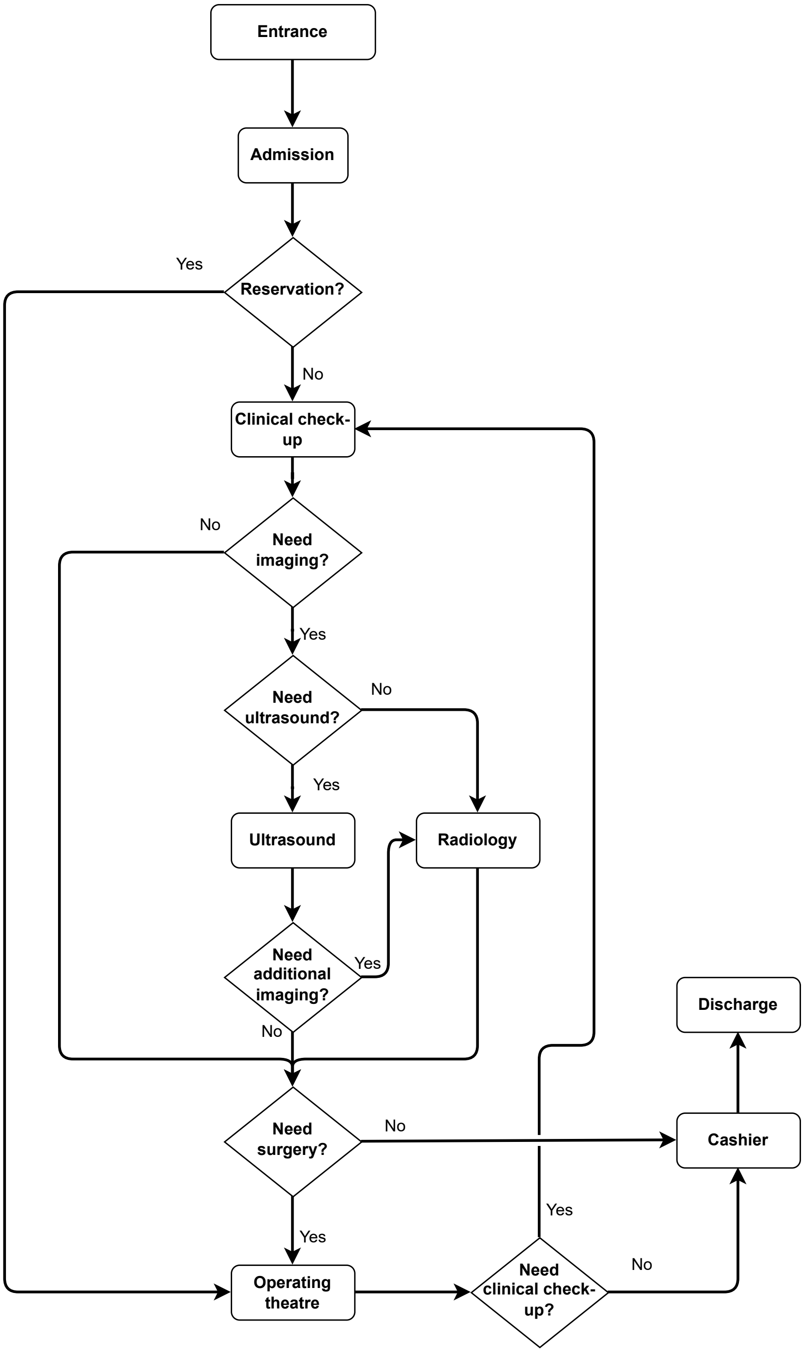

FIG. 3.2 Patients’ paths in the Inpatient Department of Panyu Central Hospital, image source: [3].

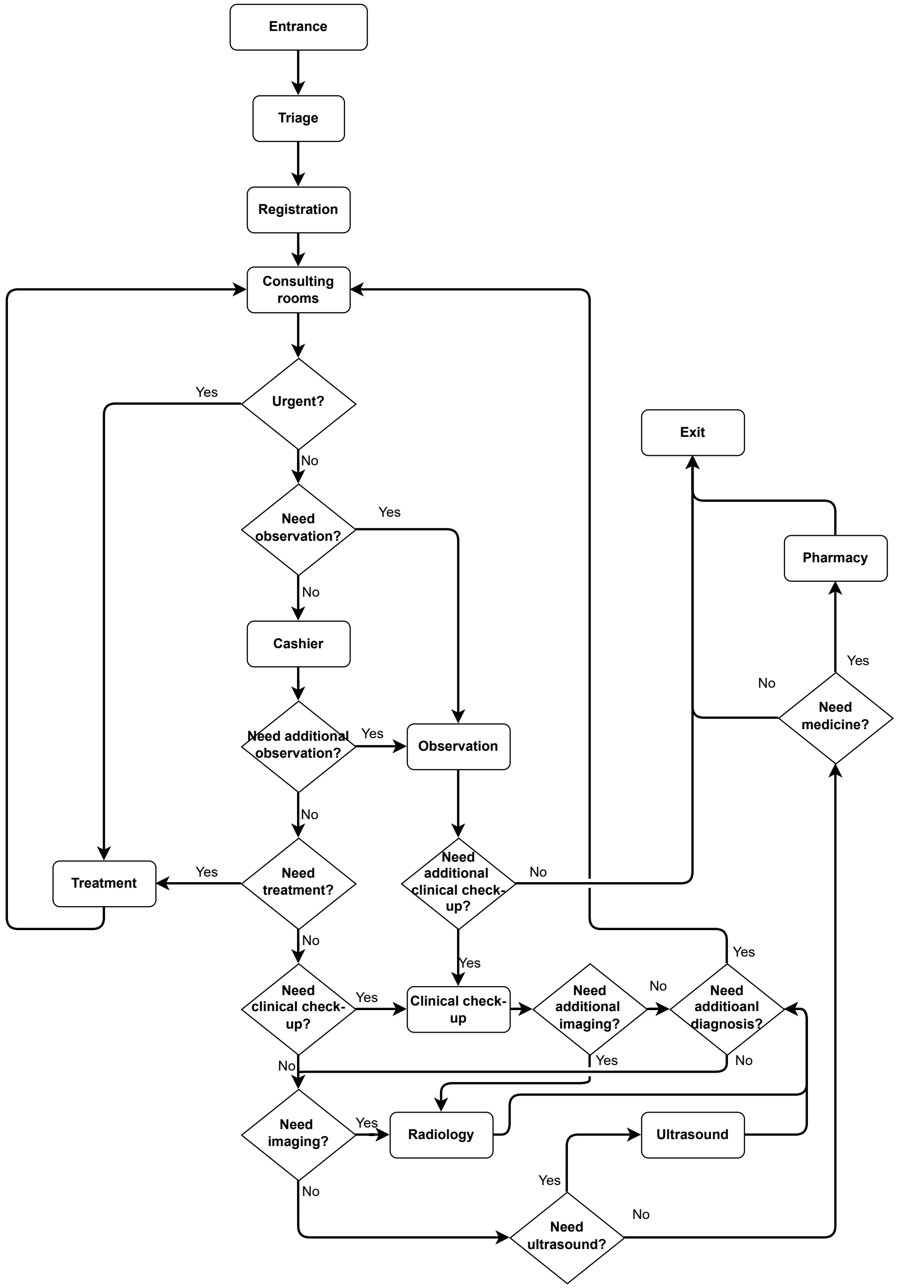

FIG. 3.3 Patients' paths in the Emergency Department of Panyu Central Hospital, image source: [3].

	Outpatient Entrance/Exit	Outpatient GPT	Outpatient Registration	Outpatient Consulting room	Outpatient Cashier	Outpatient Clinical laboratory	Outpatient Treatment	Pharmacy	Radiology	Ultrasound department	Inpatient Entrance/Exit	Inpatient admission/discharge	Inpatient ward	Operating theatre	ICU	Emergency Entrance/Exit	Emergency GPT	Emergency Registration	Emergency consulting room	Emergency treatment	Emergency cashier	Emergency observation	Emergency Laboratory
Outpatient Entrance/Exit	0.00	0.40	0.00	0.02	0.14	0.04	0.00	0.24	0.02	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Outpatient GPT	0.53	0.00	0.47	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Outpatient Registration	0.00	0.38	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Outpatient Consulting room	0.01	0.00	0.35	0.00	0.47	0.03	0.03	0.01	0.06	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Outpatient Cashier	0.11	0.00	0.00	0.50	0.00	0.13	0.03	0.11	0.06	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Outpatient Clinical laboratory	0.13	0.00	0.00	0.13	0.50	0.00	0.00	0.13	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Outpatient Treatment	0.00	0.00	0.00	0.50	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pharmacy	0.25	0.00	0.00	0.02	0.15	0.04	0.00	0.00	0.06	0.04	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.04	0.00	0.13	0.00	0.02
Radiology	0.01	0.00	0.00	0.06	0.06	0.03	0.00	0.04	0.00	0.11	0.00	0.01	0.29	0.06	0.00	0.01	0.00	0.00	0.17	0.00	0.07	0.00	0.08
Ultrasound department	0.11	0.00	0.09	0.03	0.06	0.00	0.00	0.03	0.13	0.00	0.00	0.00	0.33	0.05	0.00	0.02	0.00	0.00	0.03	0.00	0.13	0.00	0.00
Inpatient Entrance/Exit	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.93	0.02	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.02	0.00
Inpatient admission/discharge centre	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.49	0.00	0.48	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Inpatient ward	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.20	0.01	0.35	0.00	0.21	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Operating theatre	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.09	0.00	0.00	0.68	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ICU	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Emergency Entrance/Exit	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.53	0.00	0.04	0.00	0.10	0.02	0.02
Emergency GPT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.52	0.00	0.48	0.00	0.00	0.00	0.00	0.00
Emergency Registration	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.00	0.50	0.00	0.00	0.00	0.00
Emergency consulting room	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.12	0.02	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.25	0.00	0.06	0.38	0.02	0.12
Emergency treatment	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.75	0.00	0.25	0.00	0.00
Emergency cashier	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.06	0.09	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.45	0.02	0.00	0.08	0.16
Emergency observation	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.14	0.00	0.50	0.00	0.21
Emergency Laboratory	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.16	0.00	0.00	0.03	0.00	0.00	0.00	0.03	0.00	0.00	0.32	0.00	0.37	0.08	0.00

FIG. 3.4 Activity relationship chart of procedures in Panyu Central Hospital. Red cells indicate a strong connecting relationship between two procedures, blue cells indicate a weak connecting relationship. Image source: [3].

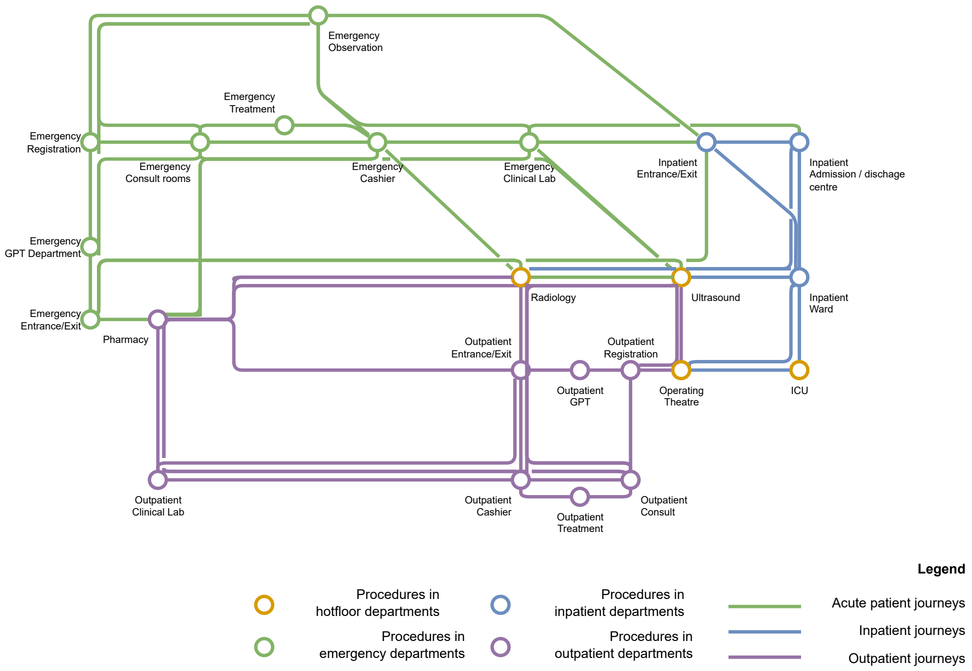

FIG. 3.5 Metro network diagram of patients' paths in Panyu Central Hospital.

3.1.3 Research Methodology

This section is about what we need to have in an HCM and why. An HDSS is essential for designing a better hospital system, as it can quantitatively and systematically evaluate the design. A configuration model is a prerequisite for developing the HDSS because it contains spatial and non-spatial information about the hospital for evaluation. This section first talks about the required information in an HCM by introducing the use cases of an HDSS. It then introduces essential data needed in hospital ARC models, which are simplified equivalents of HCM. Additionally, this section discusses the required four types of data in an HCM; each type of data is explained with a detailed example. Lastly, this section introduces the available data models from which the four types of data can be extracted. The available data and information models include two types, i.e., spatial-information-type models, such as Building Information Models (BIM), Industry Foundation Classes (IFC), and IndoorGML, and operational-information-type models in the form of Business Process Model and Notation (BPMN) data models.

3.1.3.1 Use Cases of HDSS

This section explains what we envisage to be the use cases of the HDSS and concludes the list of necessary information in an HCM based on the desired functionalities of the HDSS. The kind of information we need is not readily available in any existing file/information model. We are proposing a software application for assessing, managing or optimizing hospital configurations; the first logical step in developing such software is to have clear ideas about information processing and operations within the system.

To demonstrate the functionality and utility of the proposed HDSS, several use cases are described as examples by answering the following questions: Who would be the user of the HDSS? What questions can the HDSS answer? And at what stage of a project can these questions be answered? The required information for each use case is also summarized. However, this list is not meant to be and cannot possibly be exhaustive.

- Use case 1: The architect can use the HDSS to semi-automatically create a hospital layout at the layout design stage of a new project or optimize the hospital layout of an existing project. For this use case, the operational information of patients' medical procedures in the hospital is needed for obtaining an Activity Relations Charts (ARC) model (for further explanations, please see Section 3.1.3.2). Thus, the HCM should contain the operational information on patients' medical procedures in the hospital.
- Use case 2: The architect can use this HDSS to assess the safety of the hospital environment during the layout design stage. The environment's safety can be measured by the visibility and accessibility of spatial units within the hospital. As the visibility increases, the nurse can supervise bigger areas and hence the safety of the environment can be improved. A network graph consisting of nodes and edges is needed for this function, where each node represents a spatial unit of the hospital and each edge connecting two nodes represents the adjacent relationship between the two nodes. Hence, the HCM of the HDSS should contain the topological information of a network graph.
- Use case 3: The hospital director can use the HDSS to check if the hospital will be overcrowded during the layout design stage. For this use case, we need the topological information of the network graph. We also need to incorporate semantic information into the graph by assigning the area of each spatial unit to its corresponding node, so that the average people density in the room/spatial unit can be computed to indicate the crowdedness.
- Use case 4: The hospital director can use this system to check if the patient waiting time will be too long in a new hospital project during the layout design stage. In this use case, the graph is again needed. We also need to integrate semantic information into the graph by assigning the name of each spatial unit (e.g., 'central waiting' or 'registration', etc.) to its corresponding node. The patient's waiting time will be from the time the patient enters the waiting room till the time the patient enters the diagnosis room.

- Use case 5: The head nurse can use this system to check if patients' walking distances will be too long in a new hospital project during the layout design stage. For this use case, we need the operational information of patients' medical procedures to obtain the optimal patient paths with the shortest distance. We also need the topological information of the network graph of the hospital. Furthermore, it is necessary to incorporate semantic information into the graph by assigning the name of each spatial unit to its corresponding node. This will enable the identification of specific patient paths within the graph. Finally, it is essential to integrate geometric information into the graph by assigning 3D coordinates to each node. This will allow for the calculation of the distances along the patient's path.
- Use case 6: The architect can use this system to check how difficult it will be for first-time visitors to find their way in a hospital project during the layout design stage. For this function of measuring the difficulty in wayfinding, the extra walking distance will be the criterion of measurement. Hospital space is large and complicated; when first-time visitors enter the hospital to look for their destinations, they might get lost and go to several wrong places before arriving at their destinations. Hence, their actual travel journey will be different from the optimal journey (i.e., the shortest path); the difference between the shortest path's distance and the patient's actual travel journey's distance will indicate how difficult it is for patients to find their way. This use case requires the same information as Use Case 5.
- Use case 7: The hospital director can use this system to develop a digital twin for simulating the operational management of the existing hospital during the operation and maintenance stage. A digital twin can help hospital directors assess the impact of changes on system performance and predict the result of specific medical procedures [213]. For this use case, the needed information is the topological information of the hospital graph and the operational information, such as the patient's journey.

In summary, the HCM of the HDSS requires four main types of information: operational information, such as patient paths in the hospital, topological information, such as the hospital's network graph, semantic information, such as each room's name and area, and geometric information, such as each room's location represented by a 3D coordinate. Each type of information is explained with an example in Table 3.1. Note that developing the calculation methods for the performance indicators mentioned in the use cases above, such as crowdingness, patient waiting time, patient walking distance, and difficulty in wayfinding, is beyond the scope of this research.

3.1.3.2 ARC Model

As mentioned in use case 1 of Section 3.1.3.1, Activity Relations Charts or ARC models [207] can be thought of as the simplified graph-theoretical equivalents (or excerpts) of the HCMs. These ARC models are large square matrices that denote complex directed graphs, which use numbers indicating the relative importance of links in terms of frequencies of travel/transport between spatial/operational units of a hospital. Thus, it is clear that these ARC models form the basis of configurational approaches to the design and optimization of hospital layouts in computational design [193]. However, there is little in the scientific or professional literature about how these ARC models can be made systematically. Here, we propose a conceptual process for building these ARC models in a participatory process in consultation with the directors and planners of hospitals. The idea is to construct an ARC model in multiple logical steps by collating or superimposing multiple operational “paths” consisting of nodes that represent spatial/operational stations or operational milestones and links that indicate the smallest operational/procedural actions and their temporal duration (these attributes may or may not be used later for building Discrete Event Simulation models [193, 214]). Our proposed method is based on the idea of compiling a list of operational/spatial stations (rooms) and conducting a workshop/survey with the stakeholders to collect their proposed operational paths consisting of chains/sequences of these spatial/operational units. By putting together these paths, literally by adding the graph adjacency matrices representing these paths, we can then construct the main ARC model and its directed adjacency matrix in one go. If desired, this graph can then be row-normalized to extract the relative importance of the links between 0 and 1 [215].

Figures 3.1–3.5 together provide an illustrative example of the process for building the ARC models. Specifically, Figures 3.1–3.3 are the proposed operational paths in the form of BPMN models. A BPMN model is the industry standard that uses flow charts for modeling and illustrating processes in complex systems [216]. These BPMN models (or flow charts) show all the space-related procedures included in the patient journeys in outpatient, inpatient, and emergency departments of a real-world hospital. The hospital selected for this research is Panyu Central Hospital, located in Guangzhou, China. It is selected due to its available operational data of patient journeys as well as its representative layout complexities [3]. The Panyu Central Hospital has three main departments, namely, the outpatient department, inpatient department, and emergency department. Figures 3.1–3.3 illustrate the typical patient journeys in the outpatient, inpatient, and emergency departments of Panyu Central Hospital in the form of a flow chart. Based on the flow charts, an Activity Relations Chart can be formed as illustrated in Figure 3.4, where the rows and columns are labeled by space-related procedures in the flow charts, and entries indicate the relationships between any two pairs of procedures. The relations range from 0 to 1. If there is no connection between two procedures, the relation is 0. If a connection between two procedures exists, the relation is larger than 0 and is calculated according to the frequency of transitions between procedures. The higher the number is, the more adjacent the two procedures need to be to each other.

It can be observed that the ARC model itself is a weighted graph, where each cell in the first row/column is a node, and the entries of the ARC model are the edges associated with weights ranging from 0 to 1. This graph can be represented in a more visual way, namely, a metro network diagram, as illustrated in Figure 3.5, where each procedure is represented by a circle (node) and the connections between different procedures are represented by lines (edges). Pairs of procedures with stronger connections (i.e., higher numbers in the ARC model) are put close to each other in this diagram. By indicating and visualizing which procedures need to be adjacent to each other, these ARC models and the metro network diagram can aid in use case 1 of the HDSS, where hospital layouts need to be designed or optimized.

3.1.3.3 Hospital Configuration Model

According to the HDSS's use cases and functionalities introduced in Section 3.1.3.1, we can conclude what data is needed in a Hospital Configuration Model. As illustrated in Figure 3.6, a Hospital Configuration Model contains spatial and non-spatial information. The spatial information can be further divided into two types, namely, topological information and geometric information. The non-spatial information can also be further divided into semantic information and operational information.

A detailed technical exposition of the HCM's components is summarized as follows:

1. **Geometric Information**

   The geometric data in the HCM represent the physical shapes of the hospital, encompassing the boundaries and 3D spaces of rooms and corridors. These are defined using mathematical constructs, such as:

   - **Vertices and Edges**: Each room is represented as a polygon defined by a set of vertices (3D coordinates) and edges connecting these vertices. The polygon data are extracted from BIM/IFC models using tools like Revit and Dynamo. For an example of the room polygon data, please see geometric information in Table 3.1.
   - **Mesh Representation**: The 3D space of the room is represented by the mesh geometry, and the mesh representation algorithm is developed using the COMPAS library in Python [217].

2. **Topological Information**

   Topological information encodes the spatial relationships between different functional units of the hospital, represented as a network graph. The graph consists of:

   - **Nodes**: Each spatial unit (room or corridor) is a node.
   - **Edges**: An edge between two nodes signifies the adjacency relationship.
   - **Attributes**: Each node can carry attributes such as the room name or room capacity.

   The nodes and edges are extracted from BIM/IFC models using Rhino and Grasshopper, and the network graph is built in Python using the NetworkX library [218]. For a simplified example of a hospital graph, please see the topological information in Table 3.1.

3. **Semantic Information**

   Semantic information provides meaning to the spatial units by linking them to their functional roles. Examples include:

- **Room Names**: Identifying units such as operating rooms, waiting areas, and diagnostic labs.
- **Organizational Hierarchy**: Associating rooms with departments to enable functional grouping.

The algorithm for extracting semantic information from the BIM/IFC model is implemented in Python, and the extracted data is stored in the form of a Python dictionary. For an example of extracted semantic information, please see Semantic Information in Table 3.1.

4 **Operational Information**

Operational information captures patient journeys within the hospital. A patient journey is a detailed sequence of rooms visited during a medical procedure, e.g., see Operational Information in Table 3.1.

Business Process Model and Notation (BPMN) diagrams are used to standardize and visualize the patient journey. The patient journey data is represented as a Python list, with each element of the Python list being a room the patient needs to visit during the patient journey.

Section 3.1.4.1 explains how we extract the four types of information from available sources, such as BIM/IFC models and BPMN models, to form the HCM. In the HCM, all types of information are connected logically; the dashed lines in Figure 3.6 show the relationships between different classes, e.g., the relationship named 'Person uses rooms' indicates specific rooms that a person uses. Ideally, we will achieve consistency among the spatial information, the semantic information, and the operational information, to make the operational management in a hospital straightforward. The following subsections introduce the available data models (i.e., BIM/IFC models, IndoorGML models, and BPMN models) from which the four types of data can be extracted.

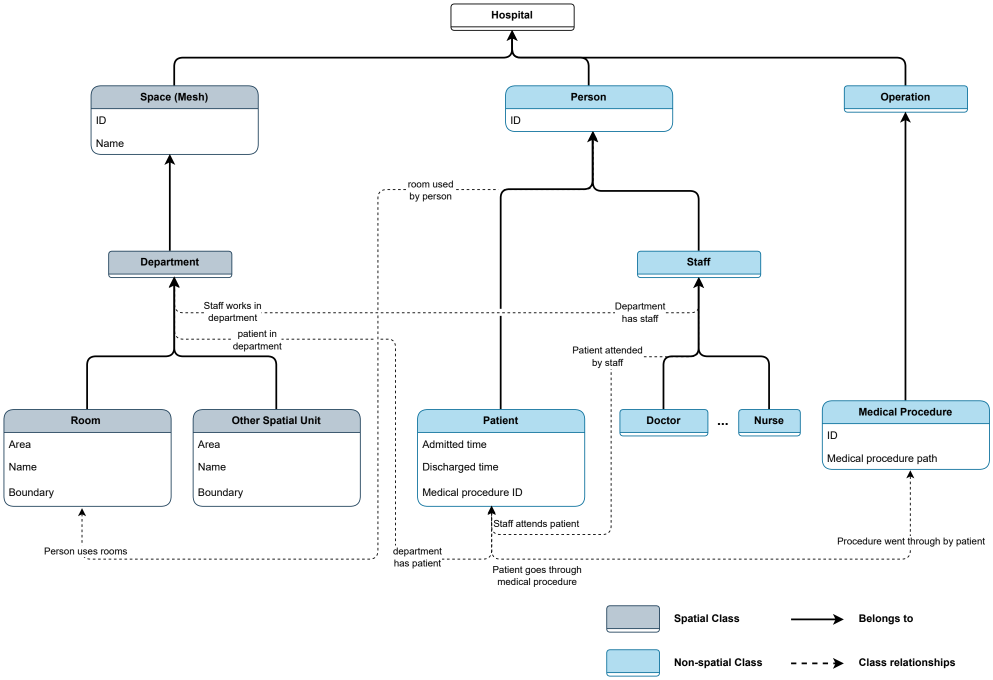

FIG. 3.6 A UML diagram illustrating data included in a Hospital Configuration Model.

3.1.3.4 Hospital BIM and IFC Models

Building Information Modeling (BIM) consists of designing and using a digital 3D model of buildings to support architectural planning, design, construction, operation, maintenance, refurbishing and demolition [219]. BIM is widely used in the Architecture Engineering and Construction (AEC) domain for aiding the design and construction stages of an architectural project [219].

One typical challenge facing BIM is that different BIM software have different file formats that do not always support one another, which causes interoperability problems when exchanging files [219]. To solve this problem, the buildingSMART consortium has invented the industry foundation classes (IFC) as a common and open format for exchanging BIM models [219].

Due to the wide application of BIM/IFC in the AEC domain, most digital 3D models of hospitals are BIM/IFC models. Hence, we will use hospital BIM/IFC files as source files for extracting geometric, topological, and semantic information for the HCM.

3.1.3.5 IndoorGML

BIM/IFC models are very complex and contain much information that is irrelevant to geospatial applications and research [194]. They integrate geometric, spatial, structural, and material information across different stages of a building's life cycle. The information we need for the use cases and functionalities of the HDSS is only a small part of the entire information in the BIM/IFC model; the rest of the information is irrelevant to our research purpose. Hence, for simplicity and convenience reasons, we only need to extract relevant information from BIM/IFC models and abandon the rest.

We can extract IndoorGML files from BIM/IFC models. IndoorGML is an Open Geospatial Consortium (OGC) standard used for the description of 3D indoor spaces and facilitating applications such as indoor navigation [194]. IndoorGML files provide geometric, topological, and semantic information about indoor spaces, which suits the aim of our research [220].

IndoorGML models have two main parts: one is the Primal Space Features and the other is the Node-Relation Graph [220]. The Primal Space Features divide the indoor space of a building into cells; cells are representations of rooms and corridors. The Node-Relation Graph describes the relations among these cells (i.e., whether two cells are adjacent). The Primal Space Features are further divided into the Cell Space and Cell Space Boundary, where the Cell Space is the smallest spatial unit of a building, such as a room, corridor and staircase, etc., and the Cell Space Boundary is the door in a building. The Node-Relation Graph is also divided into two modules, i.e., nodes and edges. A node is the dual of the corresponding Cell Space (room) or Cell Space Boundary (door), and an edge connects two nodes if the two corresponding Cell Spaces (or Cell Space Boundaries) are adjacent. Figure 3.7 gives an illustration of the four modules of the IndoorGML, and Figure 3.8 is an example of the IndoorGML model extracted from the open-source hospital IFC model used in this research [221], where the red Node-Relation Graph is embedded in the transparent Primal Space Features.

Although IndoorGMLs seem suitable for our research, they present several challenges and drawbacks that are not conducive to this research as follows:

- There is a lack of available IndoorGML files in the industry because, according to the literature study conducted in Section 3.1.1.2, there are no appropriate tools for generating correct IndoorGML files. Furthermore, IndoorGMLs are encoded in XML (eXtensible Markup Language) format [222], which is complex, highly hierarchical, cumbersome to manage, and unpopular for web applications [219].
- While IndoorGML is designed to support applications in indoor navigation and facility management, effective execution of these tasks typically requires integration with additional data, such as operational information and enriched semantic information. However, IndoorGML files currently face the challenge of lacking this critical supplementary information.

Hence, IndoorGML itself cannot meet our research requirements. To deal with the above challenges, we first developed our tool for semi-automatically generating correct IndoorGML files from BIM/IFC models. The generated IndoorGML files are further parsed into JSON (JavaScript Object Notation) format [223], which is a more popular format due to its readability and editability. Our tool can also integrate operational and semantic information into IndoorGML's spatial information to make the later simulation modeling feasible [224].

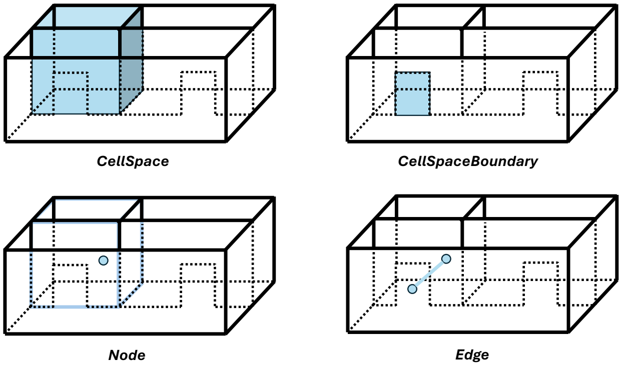

FIG. 3.7 An illustration of IndoorGML's data structure.

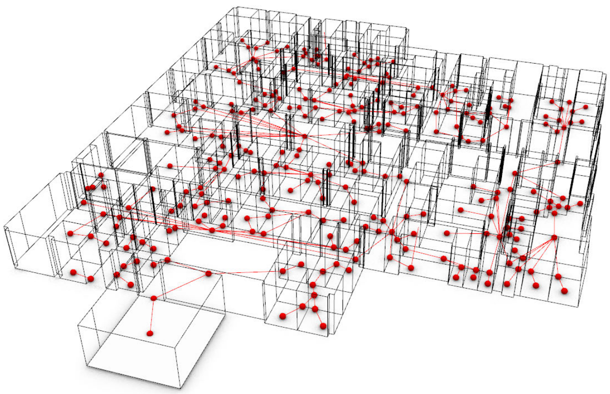

FIG. 3.8 An example of a hospital IndoorGML model, image source: [224].

3.1.3.6 Hospital BPMN Models

Since hospital BIM/IFC and IndoorGML models do not contain operational information, such as medical processes or patient journeys, we need to collect this information from other sources. In this research, we extract the operational information for the HCM from business process model notation (BPMN) models.

BPMN is an industrial standard for modeling business processes; it uses flow charts to visualize the steps included in the business process [216]. It is a common approach to model hospitals' medical processes [216, 225]. Hospitals, as complex systems, have very complicated processes involving different users and multiple steps taking place in different places. Hence, BPMN is a perfect method to model these processes. We will use BPMN models as our source files for extracting operational information into the HCM.

In this research, we selected representative hospital operational information about patient journeys from Peng's study [3] and manually modeled this information into BPMN models. The automatic generation of BPMN models is beyond the scope of this paper. However, we propose that an expert (such as an industrial engineer or someone familiar with operations research) should systematically extract such information from textual and visual documents concerning the operational management and service design of a hospital to construct multiple BPMN models to describe the main procedural workflows in a hospital. Figures 3.1–3.3 show BPMN models that we built for modeling the medical processes in outpatient, inpatient, and emergency departments in a real-world hospital. We used these three BPMN models as our source files for extracting the operational information into the HCM. Section 3.1.4.1 explains how we extract operational information from these BPMN models.

3.1.4 Research Results

In this section, we discuss how we extract the required information about our HCM from what is typically available as data and information models.

We introduce the main results of this research, which are our methodologies of extracting data from BIM/IFC models to build the HCM.

3.1.4.1 From Hospital IFC Model to HCM

This research developed software to automatically generate a configuration model from an IFC model for the evaluation of the hospital's functionality and efficiency. The generation workflow includes two main steps. The first step is converting the hospital IFC model to the IndoorGML model. The second step is to build the HCM from the IndoorGML file. Figure 3.9 depicts the workflow of converting the Hospital IFC Model to the HCM.

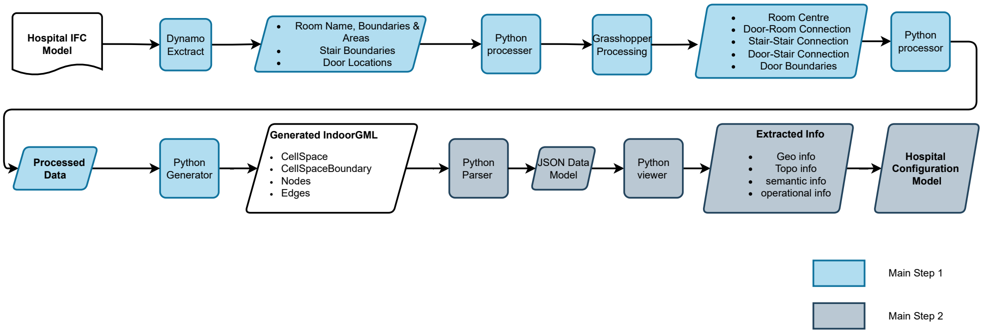

FIG. 3.9 The workflow from Hospital IFC Model to Hospital Configuration Model, source: [224].

Our software for generating IndoorGML is inspired by Tong and Zheng's work, but is more generalized and works for more complex buildings with rooms of irregular shapes. As illustrated in Figure 3.9, the workflow of generating IndoorGML files starts with extracting relevant information from the IFC model using Autodesk's Revit and Dynamo. Three groups of data (i.e., room names, boundaries and areas, stair boundaries, and door locations) are taken out of the IFC model for building IndoorGML's geometric and semantic information. The extracted data can be further used to generate IndoorGML's topological information (i.e., Node-Relation Graph), but because Dynamo and Grasshopper use different data structures to store data, the data from Dynamo needs to be first processed in Python so it is readable by Grasshopper. Once the data is imported into Grasshopper, the scripts in Grasshopper read the data and generate a Node-Relation Graph of the IndoorGML model. The data exported from Grasshopper again needs to be processed in Python so that they can be read by other Python libraries to write an IndoorGML file. Since the IndoorGML file has an XML-based exchange format [226], we use etree [227], an XML library for Python, to write the IndoorGML file. The processed geometric, topological, and semantic information is read by the Python generator and turned into XML-formatted output (i.e., IndoorGML). For more implementation details about the software, such as the scripts in Dynamo, Grasshopper, and Python, please refer to the study by Jia et al. [224].

The development of the HCM follows the design pattern of model-view-controller (MVC). MVC is the most common design pattern for developing software or user interfaces [228]. This pattern divides the program logic into three separate yet interconnected parts, i.e., data model, view, and controller [229]. Figure 3.10 presents the interrelationships among the three parts of the MVC. The **data model** component of the MVC is a data structure which contains all the raw data of the project [230]. In the case of the HCM, the data model is derived from the IndoorGML file and carries all the geometric, topological, semantic and operational information of a hospital system. The **view** component of MVC presents the model's information to the users [230]. It contains functions to access the data model and organize the data more logically so that humans can easily read it. We have developed view functions of our HCM according to the use cases introduced in Section 3.1.3.1 for users to easily query relevant information. The **controller** component of MVC serves as an intermediary between the model and the view. It listens to the event triggered by the view and makes a response to the model (e.g., adding or changing information to the data model) [230]. In the following text, we demonstrate how we obtain the data model of the HCM, develop view codes to extract information from the data model and present them in a human-readable manner, and develop controller codes to add or edit contents in the data model.

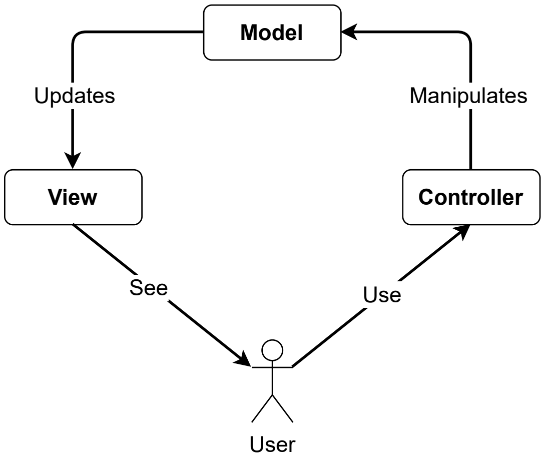

FIG. 3.10 The basic architecture of MVC, image source [231].

- **Obtaining the Model part of the HCM**

  Figure 3.9 shows that the development of the data model for the HCM includes parsing the IndoorGML file into a JavaScript Object Notation (JSON) file [223]. The parser for IndoorGML used in this study was developed by Ledoux [232]. With this parser, all the information in the IndoorGML (e.g., cell spaces, cell space boundaries, nodes and edges) is parsed into a JSON file as the data model.

- **Developing the View part of the HCM**

  The information presented by the view codes should be a mathematical construct about sets and relations. These relations are graphs, so most of our view functions should output sets and graphs or hypergraphs (a mesh is a hypergraph, and the edge in a face is considered to be a hyperedge). According to the use cases demonstrated in Section 3.1.3.1, we developed view codes to extract the following information: a mesh (hyper-graph) describing the geometrical information (i.e., the Primal Space Features) in the IndoorGML model, a graph showing the topological information (i.e., the Node-Relation Graph) in the IndoorGML model, a set of room names and room areas showing the semantic information of the hospital in the IndoorGML model, another set of hospital departments and all the rooms within their respective departments, which shows the semantic information of the hospital's organizational structure, and lastly, a set of lists demonstrating the operational information of patient journeys in the hospital.

The mesh output is obtained using the COMPAS library in Python. COMPAS is an open-source framework designed for computational research in the fields of architecture, engineering, digital fabrication and construction [217]. Users can use the view code to generate and visualize the mesh geometry to obtain a view of what the IndoorGML model of the building looks like. The graph output is obtained by developing Python scripts using the NetworkX library, a Python package made for creating, manipulating, and analysing complex networks [218]. Users can use the view code to obtain the network graph, which will be the base for running the simulation modeling. The simulation modeling is one of the core functionalities of HDSS, as mentioned in use cases 4, 5, and 6. Figure 3.8 is a visualization of the mesh output and graph output generated from the open-source hospital IFC model [221], where the red graph is embedded in the transparent mesh. The set output of room names and room areas is a Python dictionary. A Python dictionary is a data structure in Python that stores data in key-value pairs (e.g., {key: value}) [233]. In the Python dictionary of room names and areas, the room name is the key and the room area is the value. Users can use the view code to obtain all the room areas, which can aid in addressing use case 3 of assessing crowdingness in hospitals. Specifically, in the later simulation modeling step, once the room area and the number of people in the room are known, it is straightforward to assess the room's crowdingness by calculating the people's density in the room. The set output of departments and rooms is also a Python dictionary. In this dictionary, each department is represented as a key, and its associated rooms are grouped as the corresponding values.

Figure 3.11 shows the Python code to implement this function of organizing all rooms in the hospital into their respective departments, and Table 3.3 shows the resulting Python dictionary of hospital departments and rooms. The extracted operational information related to patient journeys in the hospital is in the form of Python lists. For extracting this information, we first turned the BPMN models (Figures 3.1–3.3) into multiple lists (e.g., see Input data list in Table 3.2), where each element in the list is a space-related procedure in the BPMN (i.e., rounded-corner rectangle in the flow Figures 3.1–3.3), and the entire list is a complete medical procedure in the BPMN flow chart (i.e., the procedure starts with patient entering the hospital and ends with patient leaving hospital). Subsequently, we developed view codes to identify the corresponding room names of list elements based on the extracted semantic information of hospital departments and rooms (Table 3.3). For example, the corresponding room name for the element 'registration' in the semantic information dictionary is 'RECEPTION1B13'. The view codes find the corresponding room names for each element in the list and put all corresponding room names into a new list (e.g., see Output data list in Table 3.2). The new lists contain extracted operational data on patient journeys, which can serve as input for HDSS simulation modeling, e.g., these data enable determining the shortest path for patients/agents in DES or ABM simulations. Table 3.2 provides an example of the input data list generated from the BPMN model and an example of the output data list of operational information generated from the input data list. It should be noted that one element in the input data list might have multiple corresponding room names in the output data list. This is because in a hospital, there can be multiple rooms for the same function. For example, the element 'diagnosis' in the input list has twelve corresponding room names ('INTERACTIONSTATION1D07', 'INTERACTIONSTATION1D08', etc.) in the output data list because, in the selected hospital BIM model, there are twelve rooms all serving the same function of diagnosis. Hence, the patient can have twelve options when choosing the diagnosis room, and there will be twelve different potential paths for the patient to complete the same patient journey. For more implementation details of the view codes' Python scripts, please refer to [224] or the repository (`https://github.com/ZhuoranJia/IFC2BCM`, accessed on 25 November 2024).

TABLE 3.2 Source data and output data of HCM's operational information, source: [224].

Input Data List	Output Data List
origianl_medical_path_1 = ['registration', 'triage', 'waiting', 'diagnosis', 'medicine']	medical_path_1 = ['RECEPTION1B13', 'WTSandMEAS.ROOM1D15', 'WTSandMEAS.ROOM1D30', 'WAITING/ACTIVITYAREA1DC1', 'INTERACTIONSTATION1D11', 'INTERACTIONSTATION1D07', 'INTERACTIONSTATION1D32', 'INTERACTIONSTATION1D02', 'INTERACTIONSTATION1D13', 'INTERACTIONSTATION1D36', 'INTERACTIONSTATION1D10', 'INTERACTIONSTATION1D08', 'INTERACTIONSTATION1D09', 'INTERACTIONSTATION1D28', 'INTERACTIONSTATION1D34', 'INTERACTIONSTATION1D35', 'PHARM.DISP.1A16']

FIG. 3.11 View function for extracting semantic information, source: [224].

TABLE 3.3 Extracted semantic information of the HCM. Note: for simplicity reasons, the information shown here is incomplete; for a complete version of the information please see this repository (`https://github.com/ZhuoranJia/IFC2BCM`, accessed on 25 November 2024).

Departments & Rooms
{'Department$A': ['CENTRALWAITING1AC1', 'CORRIDOR2AC3', 'PHARM.DISP.1A16', 'CORRIDOR2AC1', 'DENTALWAITING2A11', ... 'X-RAYALCOVE2A12-A']}
{'Department$B': ['CORRIDOR1BC2', 'LAB1B04', 'CORRIDOR1BC4', ... 'RECEPTION1B01', 'RECEPTION1B13', 'TECHOFFICE2B9']}
{'Department$D': ['WAITING/ACTIVITYAREA1DC1', 'MAINMECHANICALROOM2D05', ... 'INTERACTIONSTATION1D11', 'INTERACTIONSTATION1D07', 'INTERACTIONSTATION1D08', 'INTERACTIONSTATION1D09', 'INTERACTIONSTATION1D28', 'INTERACTIONSTATION1D34', 'INTERACTIONSTATION1D35', ... 'COMPUTERROOM2D04A']}
...

– **The Controller part of the HCM**

The controller codes we envisage are for updating the data model; in other words, adding/changing information to the data model. Once the simulation is complete, we need to update the data model by adding the disaggregated simulation results and aggregated evaluation results to the data model, so that users can easily view them. For example, once the simulation is finished and we know each room's people density, we need to add this attribute to the dictionary that describes the room's information. Table 3.4 provides an example for illustrating how one part of the data model has been changed before and after the controller code adds information to it. In addition to adding the disaggregated information, we also propose controller codes for adding aggregated information, such as the average people density, average patient walking distance, average patient waiting time, and average patient's extra walking distance.

Another example of the use of controller code is for updating the data model's network graph. The original network graph only contains topological information; the controller codes can integrate semantic and geometric information into the graph, for example, assigning each node its corresponding room name, area, and 3D coordinate. By adding such information to the graph, the graph can aid in the simulation modeling, such as finding the shortest path in the graph according to the patient journey data list (output data list in Table 3.2), calculating the distance along the shortest path, and calculating the people density in a room.

TABLE 3.4 An example showing how controller codes add information to the data model (please note the data for people density in this example is hypothetical).

	Room Attributes
Before	{‘CENTRALWAITING’: {‘area’: ‘127’},‘WAITING/ACTIVITYARE’: {‘area’: ‘178’}, . . . }
After	{‘CENTRALWAITING’: {‘area’: ‘127’, ‘people density’: ‘0.9’},‘WAITING/ACTIVITYARE’: {‘area’: ‘178’, ‘people density’: ‘1.0’}, . . . }

3.1.5 Discussion

This study presents a novel Hospital Configuration Model (HCM) as the foundational component for a Hospital Design Support System (HDSS). By integrating geometric, topological, semantic, and operational data, the HCM enables the HDSS to utilize simulation modeling for assessing hospital layout efficiency and functionality. In this section, we summarize the key findings, the comparison with the academic literature, and the research limitations.

This study presents several key findings that contribute to advancing the field of hospital layout design and simulation modeling. First, a robust systematic methodology was developed for the semi-automatic generation of IndoorGML files from existing Building Information Models (BIM) and Industry Foundation Classes (IFC) data. This approach helps enhance the accessibility and availability of IndoorGML data for applications such as indoor navigation and indoor location-based services. The methodology further facilitates the automatic transformation of IndoorGML files into Hospital Configuration Models (HCMs). These HCMs, integrating geometric, topological, semantic, and operational data, enable spatial analysis and simulation modeling. To validate the methodology, it was successfully applied to a real-world hospital BIM model, resulting in an HCM which allows for a quantitative evaluation of hospital layout designs, focusing on key performance indicators, such as crowdingness, patient walking distance, patient waiting time, and difficulty in wayfinding.

This research bridges the gaps of other related studies. As discussed in Section 3.1.1.2, several gaps and limitations are evident in the existing body of related studies. Firstly, certain tools, such as those developed by Diakite et al. [194] and Intratech [195], generate IndoorGMLs that lack semantic information. Our methodology can generate IndoorGMLs integrated with semantic data. Secondly, Tong and Zheng’s software [196] is incapable of dealing with complex building models with irregular shapes—our methodology overcomes this limitation. Thirdly, many existing tools do not support the generation of IndoorGML from other sources. These tools include the ones developed by Jeong et al. [197], Brincovean and Butean [198], Taehoon [199], and Claridades et al. [200]. Our methodology can generate IndoorGMLs from BIM/IFC files. Fourthly, several tools, such as those developed by Yuan and Schneider [201] and Teo and Cho [202], generate layout representation models in other formats, instead of the industry-standard IndoorGML format, which reduces data interoperability. Our methodology can generate correct

IndoorGML files, enhancing data interoperability. Additionally, the approach developed by Khan et al. [203] includes the extra step of converting IFC files into CityGMLs, and then extracting IndoorGMLs from CityGMLs, which is cumbersome. Our methodology can directly extract IndoorGMLs from IFC models. Lastly, Srivastava et al. [205]'s methodology and Hashim et al. [206]'s workflow can only generate IndoorGML files from CAD and Sketchup models instead of BIM/IFC models. The lack of 3D geometric information in CAD models and semantic information in SketchUp models makes them less suitable as source models for this research compared to BIM/IFC models. Our methodology is designed to be able to work with BIM/IFC inputs. Furthermore, none of the studies developed further steps for editing the IndoorGML files. Our methodology can subsequently convert the IndoorGML files into HCMs. The advantages of HSMs over IndoorGMLs can be found in Section 3.1.3.5.

While this research provides valuable insights, it is important to note that this research has several limitations. Firstly, the operational information discussed in this research focuses solely on the patient aspect. Specifically, when extracting operational data into the HCM, we concentrated only on the patient journey. However, operational information encompasses additional aspects, such as staff workflows, which include staff movement patterns and their interactions with both other staff and patients. This aspect is also integral to HCM's operational information and could provide further insights if considered. Secondly, the operational data integrated into the HCM were derived from pre-existing sources and may not comprehensively capture the dynamic variability of hospital workflows. The static nature of some operational inputs might limit the model's ability to simulate highly dynamic scenarios, such as those involving emergencies or sudden changes in patient flows. Incorporating real-time or stochastic operational data into the model could enhance its predictive capabilities and applicability in more complex scenarios. The third limitation of the developed methodology lies in its approach to representing spatial connections in the hospital layout graph. When generating the graph for the hospital layout, the methodology creates edges by connecting a room's node to the corresponding node of its door. Consequently, the methodology only establishes connections between two spatial units if they are linked by a door. For instance, if a room and a corridor share the same door, they will be connected through that door. However, if two corridors are directly connected without an intervening door, the methodology does not create an edge between them, leaving them unlinked. This approach introduces inaccuracies, as spatial units that are directly connected without doors should still be represented as connected by an edge in the graph. Additionally, the methodology is developed using a combination of Python scripts, Grasshopper scripts, and Dynamo scripts. While this multi-tool approach leverages the unique strengths of each platform, it also imposes significant challenges on users. Specifically, users must switch between these three tools to execute the software's functionality, resulting in a fragmented and cumbersome workflow. This lack of integration not only complicates the user experience but also introduces potential inefficiencies, such as increased learning curves, higher risks of user error, and reduced operational consistency. Lastly, the application and validation of the methodology were conducted on a single real-world hospital BIM model. While this case study demonstrates the feasibility and effectiveness of the proposed approach, the generalizability of the findings to other hospital layouts with varying levels of complexity and functional requirements remains to be further investigated.

3.1.6 Conclusions

The aim of this study was to develop a methodology for building a Hospital Configuration Model as the foundational component of a Hospital Design Support that applies simulation modeling for providing evaluation mechanisms on hospital layout performances in terms of operational efficiencies and functionalities. In practical application, the methodology can be used at the layout design stage of a new building project; it can also be used at the operation and maintenance stage of an existing hospital. The research results include the methodology of semi-automatically generating configuration models for hospitals from BIM/IFC models. The methodology has two parts: the first part includes the conversion of hospital BIM/IFC models to IndoorGML models, and the second part pertains to the automatic generation of HCM from the IndoorGML model. The following sub-sections discuss the future research directions and implications of this study.

3.1.6.1 Future Research

Our future research and development should, in particular, focus on the development of HDSS prototypes, which use an HCM as input and implement operational simulation models for assessing the accessibility of services and the efficiency of mobility. The HDSS development process further involves establishing methodologies for calculating key performance indicators, including average people density, average patient waiting time, average patient walking distance, and average difficulty in wayfinding. Another potential direction for future research is to establish a standard way of extracting hospital operational information (e.g., medical procedures) into a data model using the methods of BPMN.

3.1.6.2 Implications

The HCM's implications for policy, industry, and economy are summarized as follows:

- The HCM can help policymakers in establishing guidelines that ensure new hospital layout designs prioritize patient outcomes and operational efficiency. By mandating early-stage evaluations of layout designs against operational requirements, regulatory bodies can minimize hospital inefficiencies and operational expenditures.

- An HCM can aid in the application of **space optimization** by providing the basis to study relationships and flows between different spatial units.
- Together with the operational information, an HCM can be used as a digital twin for simulating and monitoring the daily operations of a hospital, e.g., in **operational management** and in **facility management**
- An HCM can help improve the safety of a building by optimizing the placement of guards or cameras to ensure maximum coverage while keeping the lowest number of guards/cameras within the building.
- An HCM can be augmented with 3D information (after the hospital is realized) to help build a model for indoor navigation and way-finding.
- By optimizing hospital layouts and operational flows, the HCM can help reduce costs related to inefficiencies, such as prolonged patient waiting times and excessive patient walking distances. For hospitals, these improvements can translate into lower operational costs, and enhanced capacity to serve more patients without increasing physical space or workforce.
- For the construction and architecture sectors, the integration of HCM into hospital design processes promotes cost-effective planning, reducing redesign expenses and construction overruns.

We can conclude that a specific type of information model, dubbed a Hospital Configuration Model (HCM) is needed to collate spatial and operational information concerning the planned procedures in a hospital as a core of a class of information systems called Hospital Design Support Systems (HDSSs). In this paper, we introduced and proposed some constructs that need to be embodied into an HCM with an outlook towards the envisaged use cases for an HDSS. It is only natural that when prototyping an HDSS, we might realize that we need to revise our HCM, but such revisions are quite common and necessary in design science research [234, 235]. For now, given the outlook of usage of the HDSS, the most essential types of information to be squeezed into an HCM are the spatial, configuration, semantic, and operational pieces of information as introduced in the paper.

3.2 IFC2BCM: A Tool for Generating IndoorGML and Building Configuration Model from IFC

This sub-chapter has been published by Jia, Z., Nourian, P., Luscuere, P., & Wagenaar, C. (2025). IFC2BCM: A Tool for Generating IndoorGML and Building Configuration

Model from IFC. SoftwareX, 29, 101975. [224] The layout has been adjusted to fit the template of this thesis.

ABSTRACT

IFC2BCM is a novel software tool designed to generate IndoorGML and Building Configuration Models (BCM) from IFC/BIM models. The primary motivation behind IFC2BCM is to develop a tool for generating BCM as the core foundation of a Spatial Design Support System that will evaluate layout designs of complex buildings such as hospitals regarding operational efficiency. The software addresses the need for detailed spatial network analysis and simulation modelling in complex environments, offering a semi-automatic process to convert IFC data into IndoorGML, and subsequently into a comprehensive BCM. The BCM generated by this tool consists of geometric, topological, semantic, and operational information, it supports applications such as space optimization, facility management, ensuring safety, and indoor navigation. More generally, the results are relevant to the study of complex buildings such as airports, transport hubs, public buildings, etc.

Metadata

The ancillary data table 3.5 gives information about the codes of software.

TABLE 3.5 Code metadata

Code metadata description	Information
Current code version	v1.1.0
Permanent link to code/repository used for this code version	`https://github.com/ZhuoranJia/IFC2BCM`
Permanent link to Reproducible Capsule	`https://codeocean.com/capsule/8363427/tree`
Legal Code License	MIT License
Code versioning system used	git
Software code languages, tools, and services used	Python, Jupyter Notebook, Autodesk's Revit and Dynamo, McNeel's Rhino and Grasshopper
Compilation requirements, operating environments & dependencies	dependencies for python: pandas, NumPy, COMPAS, Matplotlib, NetworkX, LXML. dependencies for Grasshopper: Human, LunchBox, LunchBoxML.
If available Link to developer documentation/manual	None
Support email for questions	Z.Jia@tudelft.nl

3.2.1 **Introduction**

3.2.1.1 Motivation and significance

The spatial configuration of complex buildings significantly impacts their functionality, creating varying distances and connections. Unlike traditional architectural analysis, configurational design focuses on the spaces within a building rather than its physical boundaries. It is challenging to obtain an explicit model of these internal spaces using standard Building Information Models (BIM). This paper introduces a digital workflow to extract a Building Configuration Information Model (BCM) from BIM models in Industry Foundation Classes (IFC) file formats. We designed this workflow for general use in supporting the design and analysis of different types of complex buildings such as airports, transport hubs, museums, hospitals, etc. In this study, among all types of complex buildings, we chose hospitals as the case, because the hospital is a very representative type of complex buildings. Its complexities are twofold, firstly, the spatial complexity of a hospital can be compared to small cities, where corridors in hospitals are similar to roads in a city and different rooms with various functions in a hospital are similar to different land uses in a city [48]. Secondly, the procedural/operational complexity in a hospital is significant. Hospitals function as a 'healing factory' where multiple procedures (e.g., diagnostic procedures, surgical procedures, emergency and critical care procedures, etc.) take place simultaneously [48]. Hence in this paper, our attention is focused on hospitals.

Our research is part of a project developing Hospital Design Support Systems (HDSS), which incorporates early operational insights to improve hospital layouts. The HDSS uses spatial analysis and simulation modelling to evaluate hospital efficiency, requiring a Hospital Configuration Model (HCM) that includes spatial and non-spatial information. Spatial information encompasses geometric and topological data, while non-spatial information includes semantic and operational details. For instance, geometric data can be room boundaries defined by lists of vertices with 3D coordinates, and topological data can be a graph that illustrates relationships between spatial units. Semantic information might include room names and areas, while operational information covers medical processes in hospitals such as patient journeys (see figure 3.17). Figure 3.12 illustrates the spatial and non-spatial information in an HCM and the relationship between different types of information. Consistency among these data types ensures effective operational management in hospitals.

According to our literature study (see section 3.2.1.4), there is no available tool that can generate hospital configuration models or building configuration models. To address the lack of tools for generating building configuration models, we developed IFC2BCM [236], a tool for semi-automatically creating BCM/HCM from BIM/IFC models. This tool forms the core of the HDSS, enabling the evaluation of hospital layout designs in terms of functionality and efficiency.

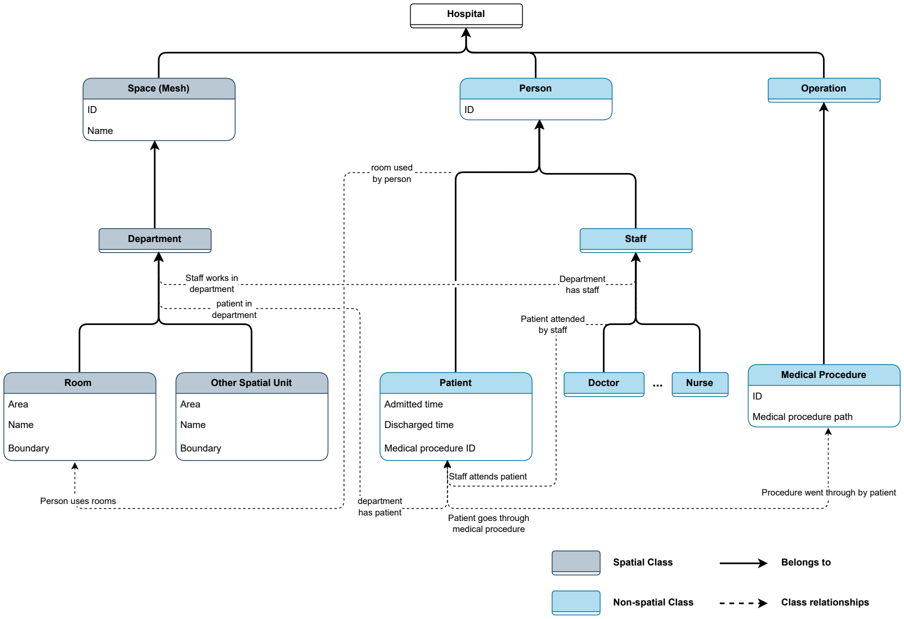

FIG. 3.12 A UML diagram illustrating data included in a Hospital Configuration Model [38]

3.2.1.2 Contribution

The contributions of this software are summarized as follows:

- IFC2BCM can semi-automatically generate a correct IndoorGML file, which is an Open Geospatial Consortium (OGC) standard for representing and exchanging indoor spatial information [220]. IndoorGML consists of four groups of spatial data, namely, CellSpace, CellSpaceBoundary, Node, and Edge. The term 'CellSpace' refers to the room or corridor in a building, 'CellSpaceBoundary' refers to the door, 'Node' is a point representation of the room, and an 'Edge' connects two nodes if the two corresponding rooms of the nodes are adjacent. IndoorGML files can facilitate applications in indoor navigation and facility management [194]. However, there is a lack of available IndoorGML files, and also a lack of appropriate tools for correctly generating IndoorGML files. Our model resolves these limitations, as it contributes to providing more IndoorGML files with correct structures and necessary information. It also works for any type of building input (e.g., buildings with regular/irregular shapes, or buildings with simple/complex indoor space, etc.).
- Although IndoorGML is designed to support applications in indoor navigation and facility management, to be able to accomplish such tasks, IndoorGML models often need to be equipped with other data, such as operational information and meaningful semantic information. For instance, if we want to simulate the operations in a hospital using a hospital IndoorGML model, besides the geometric and topological

information that the hospital IndoorGML has, we also need to acquire the operational information of the hospital (e.g., the patient journey in the hospital) and semantic information related to hospital organizations. IndoorGML files are facing the challenge of missing such information. The HCM generated by our software addresses this challenge. In this study, we developed software functions for extracting hierarchical semantic information according to hospital organizational structures into HCM. We also developed functions for extracting operational information (i.e., patient journey in the form of Python lists) from available data (figure 3.17) into HCM.

- Another challenge that IndoorGML faces is that it is encoded in XML (eXtensible Markup Language) format [222], which is tedious, deeply hierarchical, complicated and not well-suited for the web [219]. These features of XML encoding make IndoorGML files very hard to parse and collect information from. As a result, there is a limited number of software packages supporting IndoorGML, and a limited number of available IndoorGML files [219]. By contrast, our BCM/HCM files are encoded in JSON (JavaScript Object Notation) format [223], which is a more popular exchange format with more available libraries and users. We use JSON format to encode BCM/HCM in a more 'flattened out' structure [219], which makes the BCM/HCM more editable and easier to understand by humans compared to IndoorGML.
- The BCM generated by IFC2BCM can support multiple research applications such as space optimization, facility management, indoor navigation, wayfinding, etc.

Jia et al. [38] used this software to develop an HCM as the core of HDSS for assessing hospital layouts' efficiencies and efficacy in terms of four performance indicators, i.e., crowdedness in hospital space, patient waiting time, patient walking distance, and difficulty in way-finding).

3.2.1.3 Experimental setting

IFC2BCM is designed for semi-automatically converting BIM/IFC files into IndoorGML and generating BCM/HCM from IndoorGML. The software used for developing IFC2BCM includes Autodesk's Revit and Dynamo, McNeel's Rhino and Grasshopper, and Python. Dependencies are also needed for this tool. The dependencies for Grasshopper include Human, LunchBox, and LunchBoxML. The libraries for Python are pandas, NumPy, COMPAS, Matplotlib, NetworkX, and LXML. The data used for this experiment is an open-source hospital IFC file [221].

The experimental procedure includes three main steps, which are summarised as follows:

- **Step 1, Importing IFC.** Open the open-source IFC file with Autodesk's Revit. In Revit, open the Dynamo file 'Home.dyn' which is located in 'geometry_software' directory of the repository. This step will produce two output files, one for the building's room boundaries and another for the building's door locations.

– **Step 2, Generating IndoorGML.** This step can be subdivided into five sub-steps.

  Sub-step 1, **generating CellSpace for IndoorGML**. Put the room boundary output file from step 1 into the 'edit_csv.ipynb' file located in the 'notes/csv processor' directory of the repository, and process the boundary file, the processed boundary here is the room lower boundary (i.e., floor boundary), then put the processed file into the 'add_storey.ipynb' file to get room storeys. The functions in the 'add_storey.ipynb' file assign each room a storey. Each room's Z coordinate was checked; if it is zero, the functions assign level 0 to this room, if it is 4.57, the functions assign level 1 to this room, and if the Z coordinate is 9.25, the functions assign level 2 to this room. Next, put the room lower boundary file into the 'create_upper_boundary.ipynb' file to get the room upper boundary (ceiling boundary) file, here room boundaries' Z coordinates were changed according to the storey. Then put both the room lower boundary and upper boundary files into 'create_wall_boundary.ipynb' to get the wall boundary file. Lastly, put the room lower boundary, upper boundary, and wall boundary files into 'add_all_csBoundary_together.ipynb' to create the CellSpace data.

  Sub-step 2, **generating CellSpaceBoundary for IndoorGML**. Put the door location output file from step 1 into 'edit_door_csv.ipynb' located in the 'notes/csv processor' directory of the repository for processing the data and make it readable by Grasshopper, then put the processed data into the Grasshopper file named 'create_graph.gh' in 'geometry_software' directory of the repository, and create door boundaries. The Grasshopper scripts treat the door's location as a lower centre point and draw the door boundary upwards. Next, put the door boundaries file into 'edit_door_boundaries.ipynb' to get the final CellSpaceBoundary data.

  Sub-step 3, **generating nodes for IndoorGML**. In the room boundary file generated by step 1, select only corridor boundaries to obtain a corridor boundary file, and select only stair boundaries to obtain a stair boundary file. Then put the room boundary file, corridor boundary file, and stair boundary file into the 'edit_csv.ipynb' file to process them and make them readable by Grasshopper. Then, put the processed files into the Grasshopper file 'create_graph.gh' to get the nodes and edges data. The nodes were created by finding each room boundary's centre point, and the edges were created by connecting the room boundary's centre point to its corresponding door location point. Specifically, the algorithms in the Grasshopper check if the door location point is on the room boundary; if yes, connect the door location point to this room boundary's centre point, if not, skip. Subsequently, put the nodes and edges data into the 'add_edges_to_nodes.ipynb' located in the 'notes/csv processor' directory of the repository to add both groups of data together to obtain the final nodes file.

  Sub-step 4, **generating edges for IndoorGML**. In the last sub-step, from the Grasshopper file 'create_graph.gh', export all edges' start and end points to a csv file, and then put this output file together with the final nodes file from the last sub-step into 'create_transitions.ipynb' in 'notes/csv processor' directory of the repository to generate final edge data.

  Sub-step 5, **generating IndoorGML**. Put all four final output files from previous sub-steps into 'etree_to_gml.ipynb' in the 'IndoorGML Generator' directory of the repository to obtain the IndoorGML file. This Python generator uses LXML's etree modeule [227] for encoding XML files. The functions were designed according to the XML's structure for creating properly structured IndoorGML files.

- **Step 3, Generating HCM.** Import the IndoorGML file from step 2 into the IndoorGML parser named 'ig2ij.ipynb' in the 'HCM generator' in the 'notes/HCM generator' directory of the repository to get a JSON [223] file, which is encoded in a more 'flattened out' and editable structure [219]. Then put the JSON file into 'ij2cp_and_nx.ipynb' for extracting geometric and topological information for the HCM. The geometric information was extracted into COMPAS mesh and visualized using COMPAS library [217], and the topological information was extracted into a network graph using NetworkX [218]. The JSON file can also be put into the 'ij2semantic_and_operational_info.ipynb' file for extracting semantic and operational information. The semantic information was extracted into a Python dictionary, demonstrating hospital departments and all the rooms within their respective departments. The operational information is extracted into Python lists, indicating patient journeys in the hospital. All these four types of information constitute the HCM.

3.2.1.4 Related works

Our work is inspired by Tong and Zheng's work [196]. They developed a tool for transforming IFC models to IndoorGML files using Autodesk Revit and Dynamo, McNeel Rhino and Grasshopper, and Python. However, the generated IndoorGML files are not equivalent to configuration models, and this tool is limited to modular buildings with simple geometries, such as rectangular rooms with four sides. It does not work for buildings with complex shapes. Our software is built on Tong and Zheng's tool, and is equipped with the function of generating HCM from an IndoorGML file, it also offers a more generalized solution that works for buildings with rooms of irregular shapes. Other software used in our study includes an IndoorGML parser developed by Ledoux [232].

Another related work is a tool developed by Diakite et al. [194], they created a C++ tool that automatically generates IndoorGML models from IFC models, but the resulting IndoorGML files lack semantic information.

Intratech [195] developed a plugin for AutoCAD and Revit to extract IndoorGML. However, this plugin also generates IndoorGMLs that lack semantic information, and this plugin relies on exclusive formats.

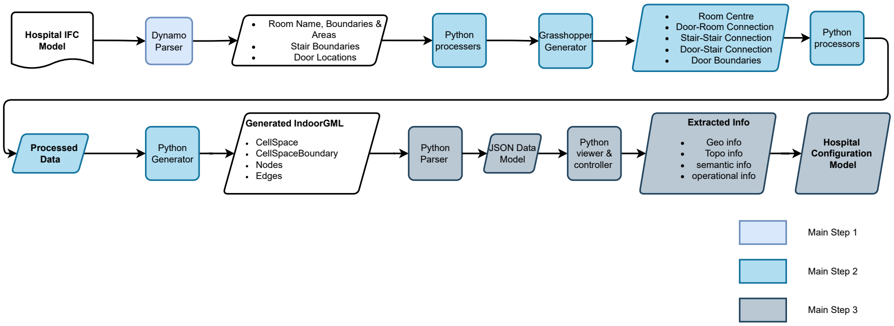

FIG. 3.13 The workflow of the software system [38]

3.2.2 Software description

3.2.2.1 Software architecture

Figure 3.13 illustrates the detailed workflow of the software system. As described in section 3.2.1.3, the workflow includes three main steps. The first step is to import the IFC file into the Dynamo parser to extract relevant information.

The second step is to put the extracted data into Python processors as well as Grasshopper and Python generators for generating IndoorGML files. Because Dynamo and Grasshopper utilize different data structures, the data exported from Dynamo in Step 1 needs to be first processed in Python processors to be compatible with Grasshopper generators. Once the data is processed and imported into the Grasshopper generator, the scripts inside the Grasshopper generator read the data and generate the necessary components for the IndoorGML model. The data made by the Grasshopper generator again needs to be processed in Python processors to become compatible with the Python generator that will write the final IndoorGML file. Given that the IndoorGML file uses an XML-based exchange format [226], we use etree [227], an XML library for Python, for scripting our Python generator.

The last step of the workflow is to create an HCM file from the IndoorGML file. The IndoorGML model was first parsed into a JSON file by the Python parser that was developed by Ledoux [232]. The JSON file was then processed by the Python viewer and controller for extracting semantic and operational information and integrating them with geometric and topological information to form the HCM. Libraries used for scripting the Python viewer and controller include COMPAS [217], NetworkX [218], and matplotlib [237].

3.2.2.2 Software functionalities

The major functionalities of the software are summarised as follows:

- Major function 1, Semi-automatically producing IndoorGML files with semantic information that can be applied in indoor navigation and facility management. Compared to Tong and Zheng's software [196], our software's functionality is more generalized and works for complex-shaped buildings.
- Major function 2, Automatically generating BCM/HCM containing four types of information (i.e., geometric information, topological information, semantic information, and operational information) from the IndoorGML file, which can be used for spatial network analysis and simulation modelling. This major function is composed of four minor functions. The first minor function is to extract the geometry of the interior space of the IndoorGML model and convert it into a mesh and visualize it. The second minor function is to extract the topological information of the IndoorGML model and convert it into a graph and visualize it. The third minor function is to extract the semantic information of the IndoorGML model and convert it into a Python dictionary with a hierarchical structure. The fourth minor function is to extract operational information (i.e., patient journey data) from available documents related to hospital procedures and convert such information into Python lists for further simulation uses.

3.2.3 Illustrative examples

This section shows an instance of HCM, and it shows what exactly it contains. We used a real-world hospital's IFC model [221] as our input and used our software to convert it into an HCM. Figure 3.14 illustrates the geometric and topological information of the HCM, where the red graph is embedded in the transparent building geometry. It is to be noticed that for clarity reasons, we only visualized one floor of the hospital building instead of all three floors. Figure 3.15 shows the hierarchical semantic information of the HCM as well as the function codes of how to extract such information and organize it into a hierarchical structure. Table 3.7 is the resulting Python dictionary of the extracted departments and their rooms. Table 3.6's right column shows HCM's operational information, since the hospital IFC model does not contain operational information such as medical procedures, we need to extract such information from other sources. We selected representative hospital operational information pertaining to patient journeys from Peng's study [3] and reproduced this information in the form of a BPMN flow chart (see figure 3.17). BPMN is an industry-standard using flow charts to illustrate system processes [216]. Figure 3.17 illustrates typical patient journeys in the outpatient department. We converted the patient journeys in this figure into Python lists as shown in the left column of table 3.6. In these lists, each element is a place in the hospital that the patient needs to go to, and the entire list is the patient's journey. What we did next was to use these lists as inputs for our tool to generate the operational information. Specifically, for each element (i.e., space) in the input list, we used our tool to find its corresponding room names from the HCM's semantic information which contains all the room names of the hospital, and put all corresponding room names into a new list to form the patient path data (right column of table 3.6). This patient path data is HCM's operational information and will be used for HDSS's simulation modelling process. It is to be noticed that the element in the input data list might have multiple corresponding nodes, for example, there are multiple 'registration stations' or 'waiting areas' in our hospital case, and we only chose the appropriate ones to form the output data list according to the IFC model.

TABLE 3.6 Input and Output data list of HCM's operational information (notice: for simplicity reasons, not all data are shown in this table, for complete data please go to **https://github.com/ZhuoranJia/IFC2BCM**)

Input data list	Output data list
origianl_medical_path_1 = ['registration','triage','waiting', 'diaganosis','medicine']	medical_path_1 = ['RECEPTION1B13', 'WTSandMEAS.ROOM1D15', 'WTSandMEAS.ROOM1D30', WAITING/ACTIVITYAREA1DC1', 'INTERACTIONSTATION1D11', ..., 'PHARM.DISP.1A16']
origianl_medical_path_2 = ['registration','triage','waiting', 'diaganosis','waiting', 'clinical-checkups','medicine']	medical_path_2 = ['RECEPTION1B13', 'WTSandMEAS.ROOM1D15', 'WTSandMEAS.ROOM1D30', 'WAITING/ACTIVITYAREA1DC1', 'INTERACTIONSTATION1D11', ..., 'CENTRALWAITING1AC1', 'BLOODDRAW1B03', 'PHARM.DISP.1A16']
origianl_medical_path_3 = ['registration','triage','waiting', 'diaganosis','waiting', 'imaging','medicine']	medical_path_3 = ['RECEPTION1B13', 'WTSandMEAS.ROOM1D15', 'WTSandMEAS.ROOM1D30', 'WAITING/ACTIVITYAREA1DC1', 'INTERACTIONSTATION1D11', ..., 'CENTRALWAITING1AC1', 'RADIOGRAPHICROOM1B19', 'PHARM.DISP.1A16']

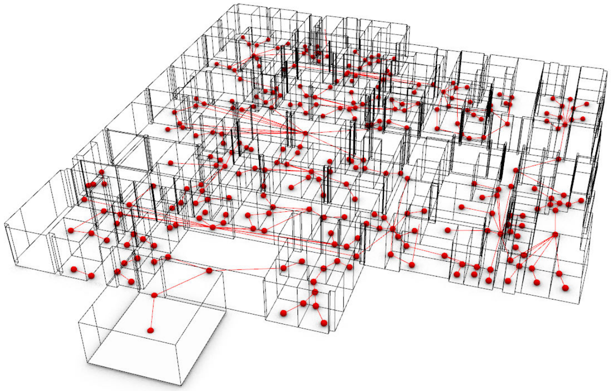

FIG. 3.14 Visualization of an HCM's geometric and topological information

Organize rooms to their deparments

```python
def get_department_of_rooms_dict(room_name_area):

    output_data = {}

    # Loop through each item in the list to organize by department
    for key in room_name_area:
        # Extract department character (the last third character of the room name)
        department = 'Department$' + key[-3]

        # Check if the department key exists in the dictionary
        if department not in output_data:
            # If not, create a new list for this department
            output_data[department] = []

        # Append the room and area tuple to the appropriate department list
        output_data[department].append(key)

    return output_data

new_output_data = get_department_of_rooms_dict(dict_room_Name_and_area)
new_output_data
```

✓ 0.0s Python

FIG. 3.15 An HCM's semantic information

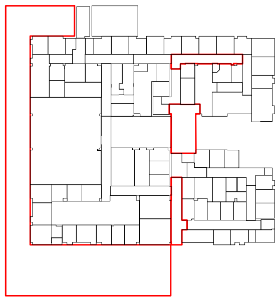

FIG. 3.16 Second Floor Plan of the selected hospital case

TABLE 3.7 Extracted semantic information of the HCM (notice: for simplicity reasons, not all data are shown in this table, for complete data please go to `https://github.com/ZhuoranJia/IFC2BCM`)

Departments & Rooms
{Department$A': ['CENTRALWAITING1AC1','CORRIDOR2AC3','PHARM.DISP.1A16', 'CORRIDOR2AC1','DENTALWAITING2A11', ... 'X-RAYALCOVE2A12-A']}
{'Department$B': ['CORRIDOR1BC2','LAB1B04','CORRIDOR1BC4', ... 'RECEPTION1B01','RECEPTION1B13','TECHOFFICE2B9']}
{'Department$D': ['WAITING/ACTIVITYAREA1DC1','MAINMECHANICALROOM2D05', ... 'INTERACTIONSTATION1D11','INTERACTIONSTATION1D07', 'INTERACTIONSTATION1D08','INTERACTIONSTATION1D09', 'INTERACTIONSTATION1D28','INTERACTIONSTATION1D34', 'INTERACTIONSTATION1D35', ... 'COMPUTERROOM2D04A']} ...

Figure 3.16 proves our software's ability to handle complex building geometries. This figure is the second-floor plan of the selected hospital case study, and it shows the geometric complexities of the hospital space. Several corridors with irregular shapes (e.g., multiple turns and corners) are highlighted in red. These irregular-shaped corridors were successfully handled by our tool for generating correct IndoorGML files. By contrast, Tong and Zheng's tool [196] failed to generate the correct IndoorGML file for this hospital case.

3.2.4 Impact

3.2.4.1 Contributions to Future Research

One of the potential Future research directions is to use the BCM as an input for developing Spatial Decision Support Systems (e.g., HDSS), which applies methods of spatial network analysis and simulation modelling for evaluating service accessibility and mobility efficiency in complex buildings such as hospitals, airports, and transport hubs etc.

Another possible direction for future research is to develop a standardized method for automatically extracting hospital operational data, such as medical procedures, into a data model utilizing business process model notation (BPMN) [216] or enterprise resource planning (ERP) system [238] techniques. BPMN is an industry standard for business process modelling, utilizing flow charts to depict the steps involved in a business process [216].

It is straightforward to understand that the necessary operational information for comprehending hospital procedures can be extracted into BPMN diagrams. Thus, creating a systematic approach for the automatic extraction of such information can be a desirable future research direction. We propose that an expert, such as an Industrial Engineer or someone knowledgeable in Operations Research, should systematically extract this information from textual and visual documents related to the operational management and service design of a hospital to build BPMN models for describing the main procedural workflows in the hospital. These models, providing operational information, can be integrated into the HCM. In Figure 3.17, we illustrate how the BPMN model of the operational information in a real-world hospital should look.

3.2.4.2 Contributions to Current Research

The ways how our software improves the pursuit of existing research are summarised as follows:

- IFC2BCM can semi-automatically generate a BCM which can facilitate space optimization by serving as a foundation to analyze the relationships and flows between various spatial units.
- With operational information, an HCM generated by IFC2BCM can serve as the basis of a digital twin for simulating and monitoring the medical processes taking place in a hospital, such as operational management and facility management.
- A BCM generated by IFC2BCM can enhance a building's safety by strategically

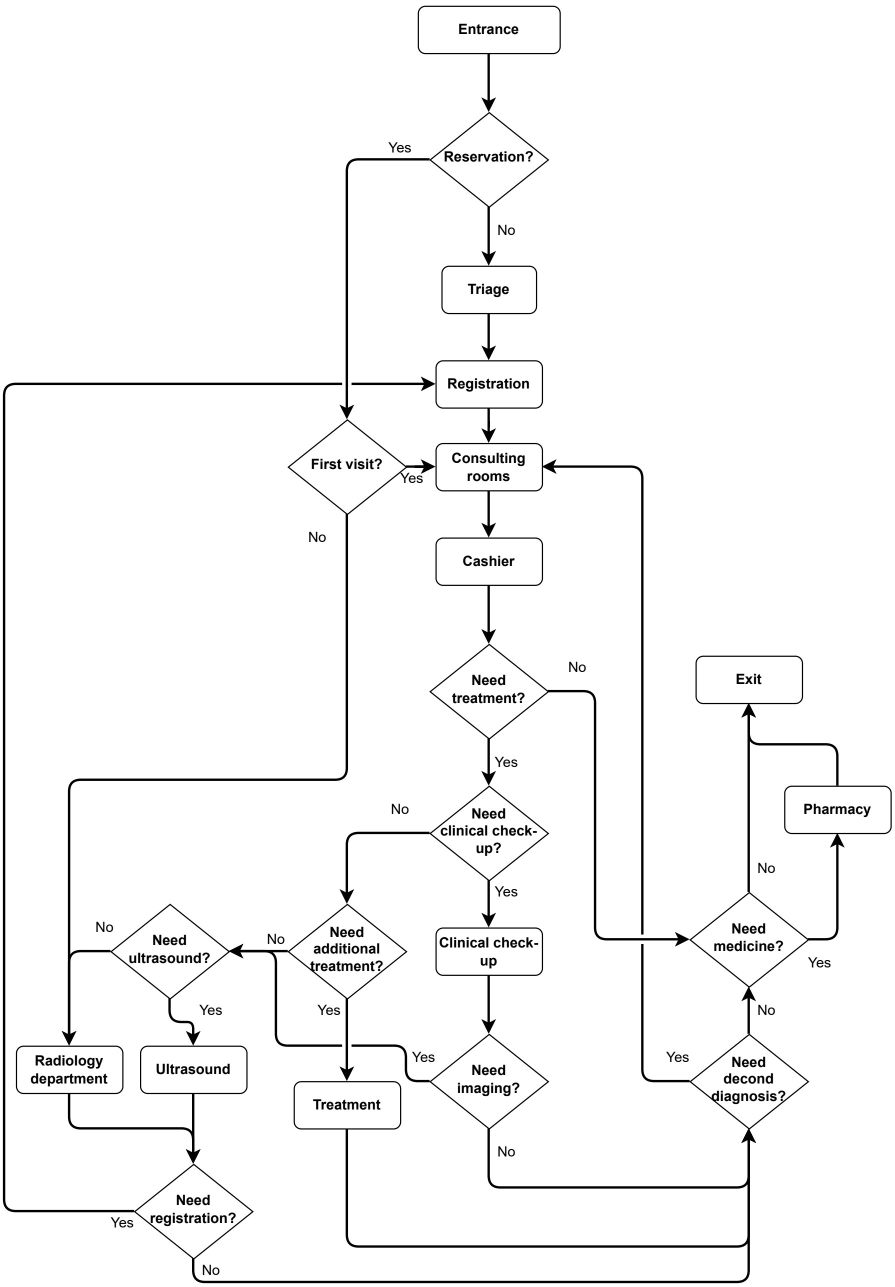

FIG. 3.17 Patients' Paths in Outpatient Department of Panyu Central Hospital, image source: [3] [38]

positioning guards or cameras to achieve optimal coverage with the minimal necessary number of guards or cameras.

- After the building is constructed, we can use IFC2BCM to generate the building's BCM and augment it with 3D information to create a model for indoor navigation and way-finding.

3.2.4.3 Impact Pathway

This subsection introduces the impact pathway of IFC2BCM. Impact pathway is a concept model proposed by the Dutch Research Council (NWO) [239]. It outlines the process through which a research project's outputs lead to intended outcomes, and result in some impacts, where outputs are direct findings of the research project, outcomes are changes in stakeholders' behaviours and activities due to the application of outputs, and impacts are changes in economic, environmental or social conditions caused by outputs [239]. Figure 3.18 illustrates the impact pathway of our software. The direct outputs of our software are generated IndoorGML and BCM/HCM models. These outputs can lead to the intermediate outcomes that more researchers will use this software to generate IndoorGMLs and BCMs for supporting applications such as space optimization, facility management, indoor safety improvement, and indoor navigation. These intermediate outcomes, together with the future work of the development of an HDSS, can further contribute to the outcomes that architects and hospital directors design better hospitals in terms of operational efficiency, which ultimately leads to the impacts of reduced hospital expenditures and improved public health.

3.2.4.4 Application

Jia et al. [38] used this software in a study for constructing a hospital configuration model as the core of a Hospital Design Support System (HDSS) for assessing the performances of hospital layout designs in terms of crowdingness in hospital spaces, patient waiting time, patient walking distance, and difficulty in way-finding. In this study, we first stated that it is beneficial to use spatial design support systems such as HDSS for assessing hospital performances in terms of accessibility and mobility because such systems can provide intuitive and explainable assessment mechanisms for design decision support. We then argued that the HCM is the core of HDSS because it will be what we evaluate. Specifically, the HCM contains four types of information, i.e., geometric information, topological information, semantic information, and operational information. These types of information will be the inputs for running the assessments.

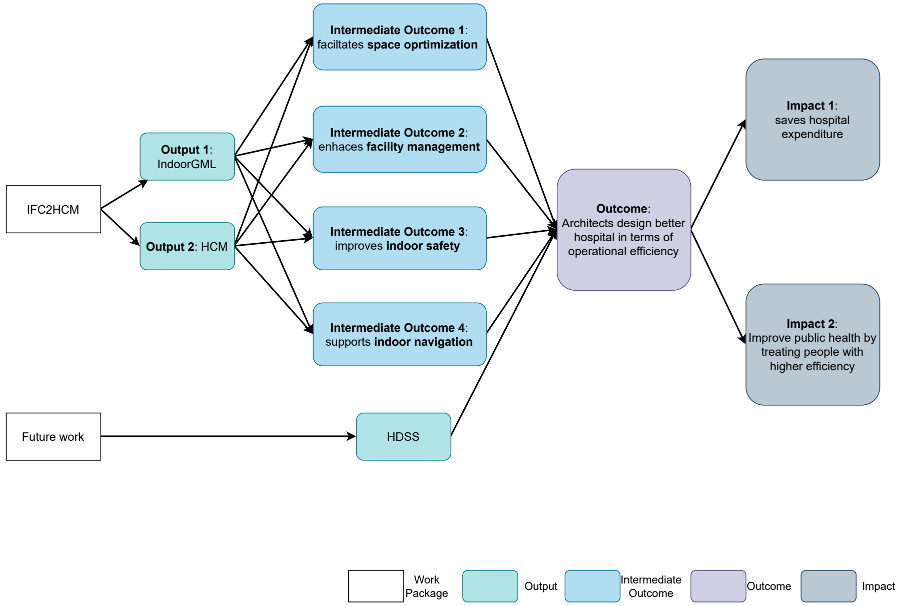

FIG. 3.18 Impact pathway of IFC2BCM

To determine what specific data of each type is needed in the HCM, we first envisaged the use cases for the HDSS, then based on the use cases, we decided what specific data we want in the HCM. For example, one of the use cases is that the architect can use this HDSS to check how long a patient needs to walk in the hospital to complete the patient's medical procedure. In this use case, the operational information of the patient's medical procedure is needed because from the patient medical procedure, we can extract the patient's path, which shows all the rooms the patient needs to go to in order to complete the medical procedure. The topological information needed in this use case is a network graph of the hospital layout. The network graph contains nodes and edges where nodes represent spatial units in the hospital and edges show their relationships. We also need to add semantic information to the graph, i.e., we need to add each spatial unit's name to its corresponding node, so that we can find the specific patient path in the graph. Lastly, we need to add geometric information to the graph, in other words, we need to add each node's 3D coordinates so that we will be able to calculate the distance of this patient's path. For other use cases and other specific data needed in the HCM, please refer to [38].

3.2.5 Conclusions

We developed a tool for converting IFC/BIM models into IndoorGML and subsequently into Building Configuration Models (BCMs), this tool provides the basis for developing the Spatial Design Support System, which uses methods of spatial analysis and simulation modelling for evaluating service accessibility and mobility efficiency in complex buildings. Addressing the lack of tools for generating IndoorGMLs and enhancing IndoorGML files with operational and semantic data, IFC2BCM uses JSON encoding to improve accessibility and usability. Table 3.8 summarises the differences between IndoorGML files and BCMs. This software's robustness and flexibility make it applicable to various building types, including hospitals, airports, and transport hubs, highlighting its broader relevance and potential impact on the design and operational efficiency of complex environments. However, this software still has several limitations which are summarised as follows:

- **User Experience:** This software is written in Python scripts, Grasshopper scripts, and Dynamo scripts. Users are required to switch between these three tools to operate the software, which significantly complicates the user experience.
- **Software's Accuracy:** When creating the graph for the hospital layout, this software generates edges by connecting the room's node to its corresponding door's node. This means the software will only connect two spatial units if they are connected by a door. For example, if a room and a corridor are connected to the same door, then this room and this corridor will be connected through that door. If one corridor is directly connected to another corridor and there is no door connecting them, the software will not link these two corridors and leave them disconnected, which is inaccurate because if two spatial units are directly connected without doors, they should be linked by an edge in the graph.
- Time Efficiency: The software's overall time efficiency performance is adequate. However, the scripts for visualizing the mesh geometry of the HCM are time-consuming. As the input IFC model gets bigger, more time will be taken to visualize the model's geometry.

These limitations lead to the future works:

- Integrating the scripts in different tools into one for a simpler user experience.
- Improving software's accuracy in terms of generating edges of the hospital's layout graph.
- Improving software's function of visualizing geometric information of the HCM so it can be less time-consuming.

Other future works will include developing the Hospital Design Support System and enhancing operational data extraction.

TABLE 3.8 Differences between IndoorGML and BCM

	IndoorGML	BCM
Information Content	- Geometric Info - Topological Info - Some IndoorGML files contain unstructured semantic info, while others do not	- Geometric Info - Topological Info - Hierarchical semantic info which facilitates simulation modelling - Operational Info which facilitates simulation modelling
Encoding	XML	JSON
edit-ability	Low edit-ability: difficult to add/remove contents to/from IndoorGML	High edit-ability: easy to add/remove contents to/from BCM

4 Hospital Design Support System

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, relativization, 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.

4.1 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, we propose 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", we naturally need to make simplifications, abstractions, and analogies to replicate, reveal, and simulate (model) the functioning of a hospital as a system. In this regard, it is important to note the differences of this proposed approach with the more commonly studied simulation modelling experiments, e.g. way-finding in hospitals. Even though these two types of endeavours (ours and theirs) are related, they serve completely different purposes. We are here focused on the efficacy and efficiency of the day-to-day functioning of a hospital layout configuration as a system and thus we can use macro simulation models such as Discrete Event Simulation and Four-Step Transportation Models of the system but of course when the focus is on the safety and security or the individual experiences of clients and staff in various spatial situations an Agent-Based Modelling approach (stochastic) or an alternative deterministic approach to micro-simulation of transport flows such as "social physics" (Helbing's model) can be more appropriate for the task. However, due to the reasons that we are focusing on the bigger picture of hospital operations and their effectiveness and efficiency, we explicitly exclude such micro-simulation modelling approaches from our methodology.

It is important to explicitly view and contemplate our methodological choices in the context of our purpose: Devising a spatial decision support system to help architects, building managers, and hospital planners assess (ex-ante or ex-post) the efficiency and efficacy of hospital configurations, practically in objectively comparing various alternatives about multiple operational optimal criteria. The central analogy of this system in 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 4.1.1 discusses the necessity of an HDSS in detail. Sections 4.1.2, 4.1.3, and 4.1.4 outline the key components of an HDSS., Section 4.2 describes the methodology for developing the HDSS. Finally, section 4.3 concludes our key findings, contributions, limitations and potential future research directions.

4.1.1 Hospital Design Challenges

In this section, we will explain why an HDSS is needed and what it is needed for exactly. The main design questions related to hospitals can be summarized as [48]:

- 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 minimize bottlenecks that contribute to delays in care delivery?
- Long Patient/Staff Walking Distances: Are the spatial relationships between key departments and areas optimized to minimize 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 questions 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 modeling 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 unlabeled graph structure but also how different rooms are positioned within it, according 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 organization 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 minimizes confusion. Reliance solely on intuition or experiential judgment is insufficient to ensure such spatial coherence; instead, simulation modeling is essential to quantitatively evaluate a hospital configuration's performance in terms of wayfinding efficiency. We argue that to address these questions/challenges systematically, we need to construct a Hospital Design Support System (HDSS) consisting of simulation models and an exploratory network analysis module to assess the hospital layout performances in terms of overcrowding, patient waiting time, patient walking distance, and difficulty in wayfinding.

4.1.2 Hospital Spatial Structure

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 modeling and exploratory network analysis approaches. Both approaches require a foundational dataset or structure to function properly. An HCM fulfills 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 [38] and software [224] 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 4.1 and summarized in the following text:

1 **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 [38]. This data is defined using mathematical constructs such as:

- **Vertices and Edges**: Each room is modeled as a polygon, characterized 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 4.1.
- **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 [217].

2 **Topological Information**

Topological information represents the spatial relationships among the functional units of the hospital, structured as a network graph comprising [38]:

- **Nodes**: Each spatial unit, such as a room or corridor, is represented as a node.
- **Edges**: An edge between two nodes indicates an adjacency relationship between the corresponding spatial units.
- **Attributes**: Nodes can include attributes such as room names, capacities, or other relevant metadata.

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 [218]. For a simplified illustration of a hospital network graph, refer to the topological information in Table 4.1. The topological information of the HCM explicitly represents the structure of the hospital building.

3 **Semantic Information**

Semantic information assigns meaning to spatial units by connecting them to their functional roles [38]. Examples include:

- **Room Names**: Identifying spaces such as diagnostic rooms and waiting rooms.

- **Organizational 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 organized as a Python dictionary. A Python dictionary is a data structure that organizes data as key-value pairs (e.g., key: value) [233]. For an example of the extracted semantic information, refer to the semantic information in Table 4.1.

4 **Operational Information**

Operational information encapsulates patient journeys within the hospital, detailing the sequential movement of patients through various rooms during medical procedures [38]. 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 a patient journey, please see operational information in Table 4.1.

It is to be noticed that in Jia[38]'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 [3]. 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 generalize to other hospitals. In this study, we aim to model general patient movement patterns across different hospitals rather than precisely predict specific patient journeys in a certain hospital. Our 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 [240]. To achieve this, we use the Four-Step Transportation Model, a widely used framework in transportation planning to predict travel demand and analyze traffic patterns in urban areas [36], 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, the same as the one illustrated in Table 4.1.

Figure 4.1 presents a visualization of the HCM's geometric and topological information, where the red graph is embedded within the transparent building geometry.

The structural organization of hospital buildings shares remarkable similarities with that of small cities. From a mathematical perspective, both hospitals and cities can be modeled 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.

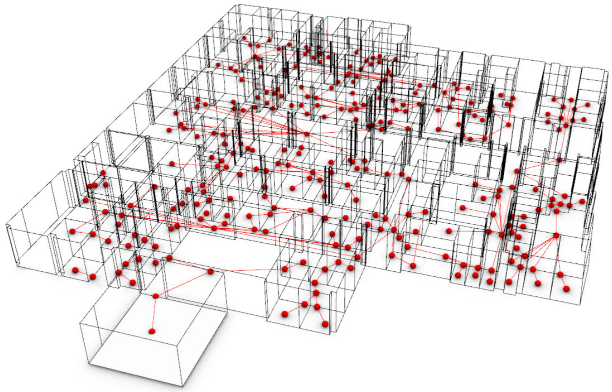

FIG. 4.1 A visualization of the HCM, image source: [224].

TABLE 4.1 Exemplified descriptions of four types of information in a Hospital Configuration Model [38]

Information Type	Explanation	Example
Geometric Information	Room boundary consisting of a series of 3D points	{'central_waiting': ['−20, 34, 4', '−20, 29, 4', '−19, 29, 4', '−19, 39, 4', ' −20, 34, 4']}
Topological Information	A network graph consisting of nodes and edges	{'Graph1': [{"node1": {"id": "R1"}, "node2": {"id": "R3"}, "edge1":{"id": "e1"}}]}
Semantic Information	Room name	{'Department$Imaging': ['Central_waiting']}
Operational Information	A patient journey through the hospital (a series of rooms that the patient needs to attend)	{'patient_journey_1': ['Entrance/Exit', 'Registration', 'consulting', 'Entrance/Exit']}

4.1.3 Hospital Operational Character

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 4.1). 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 modeling 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 [46]. Our HDSS will include a DES model for simulating the factory-like character of hospitals.

4.1.4 Optimal Adaptation vs Redundant Resilience

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 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. Long story short, these assumptions pave the way towards optimizing 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 optimized 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 reflecting on the necessity of redundancies. Instead, we reason and argue 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 visualized. 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 the 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 aggregate evaluation tools and remains only a visual inspection tool for studying patterns at a disaggregated level.

4.2 Methodology

This section introduced how we built the HDSS by developing a Four-Step Transportation Model, DES model, and exploratory network analysis model for simulating hospital operations and assessing performance metrics such as crowdedness, patient waiting times, patient walking distance, and difficulty in wayfinding.

4.2.1 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. In this section, we first provide a brief introduction to the Four-Step Transportation Model, then explain in detail how our framework utilizes 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 [36]. 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 modeling 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" [37]. 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 [36]:

$$\sum_{i=1}^{n} P_i = \sum_{j=1}^{n} A_j \tag{4.1}$$

where:

- P_i: Total trip productions in zone i,
- 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 traveling to and from each spatial unit. Table 4.2 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 4.1), with total trip productions balancing total trip attractions.

TABLE 4.2 Trip generation in a virtual hospital project [48]

Functional units	Production (number of patients)	Attraction (number of patients)
Reception hall	50	28
Emergency room	30	26
Diagnosis room	10	20
Imaging room	20	17
Pharmacy	5	24
Total	115	115

- Step 2: trip distribution

This step distributes the trips generated in Step 1 (trip generation) between origin and destination zones, it determines the number of people from each origin to each destination by producing an origin-destination matrix [37]. A trip distribution model (e.g., a gravity model) estimates the origin-destination matrix, which shows the number of trips traveling between each pair of origin and destination [36]. In the context of hospital design, this step calculates the number of patients moving between each origin and destination. Table 4.3 presents an example illustrating the computed number of patients traveling 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 [36]. This relationship is termed “zonal constraints" and can be formulated as [36]:

$$\sum_{j=1}^{n} T_{ij} = P_i \quad \forall i \in \{1, 2, \ldots, n\} \tag{4.2}$$

and

$$\sum_{i=1}^{n} T_{ij} = A_j \quad \forall j \in \{1, 2, \ldots, n\} \tag{4.3}$$

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 4.2 and 4.3, where the sum of trips originating from each spatial unit in the origin-destination matrix (table 4.3) corresponds to the trip production for each spatial unit in table 4.2. Similarly, the sum of trips arriving at each spatial unit in the origin-destination matrix (table 4.3) matches the trip attraction for each spatial unit in table 4.2.

TABLE 4.3 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

- Step 3: mode choice

  This step predicts the mode of travel for each pedestrian [37]. 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 4.3) generated in step 2 as input, and assigns each trip in the matrix a specific path [37]. 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 primary objective of developing a Hospital Decision Support System (HDSS) is to establish robust and explainable evaluation mechanisms for predicting the performance of various hospital layout designs. This is achieved by leveraging the Four-Step Transportation Model and Discrete-Event Simulation (DES). Both approaches require a layout configuration model as a foundation for their implementation. As discussed in Section 4.1.2, a Hospital Configuration Model (HCM) that integrates geometric, topological, semantic, and operational information meets this requirement and serves as the basis for the application of both the Four-Step Transportation Model and DES in the HDSS. Consequently, an HCM is essential as input for the HDSS. In this study, we utilized the HCM-generating software developed by Jia et al. [224] to obtain an HCM from an open-source hospital IFC file [221]. The obtained HCM contains the geometric information of 3D boundary of each spatial unit (e.g., room or corridor) in the hospital, the topological information of a network graph consisted of nodes and edges, where each node is a spatial unit or a door, and each edge represents the adjacency relationship between two nodes, the nodes are also assigned with semantic attributes such as room names and room areas. For generality and applicability reasons, the operational information of the HCM is not used in this research. Instead, we use the Four-Step Transportation Model to generate operational information on patient journeys. 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.

4.2.1.1 Trip Generation

This step estimates the number of trip productions and trip attractions at each node of the HCM's network graph. The number of trips for each node is calculated based on its area attribute. Specifically, we use 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:

$$P_i = A_i = \text{Room Capacity} = \frac{Area_i}{S_i} \tag{4.4}$$

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 meters),
- S_i is the space requirement per person (in this study, we define space requirement as 10 square meters per person).

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 4.4 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 this repository. 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.

TABLE 4.4 Results of trip generation

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

4.2.1.2 Trip Distribution

In this step, we distribute the trips generated in step 1. Specifically, this step estimates the number of patients traveling from each origin to each destination by producing an origin-destination matrix. In this research, we construct the origin-destination matrix using a simple gravity model, which can be formulated as follows:

$$T_{ij} \propto \frac{P_i \cdot A_j}{d_{ij}^2} \tag{4.5}$$

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,
- d_{ij}: Distance between nodes i and j.

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 repr,esenting the internal system (i.e., the hospital graph excluding entrance and exit nodes) must adhere to the principles of total trip balance (Equation 4.1) and zonal constraints (Equations 4.2 and 4.3).

However, the origin-destination matrix generated by the simple gravity model (equation 4.5) 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, we need to adjust the origin-destination matrix to make it follow the zonal constraints principle. In this study, we applied the Algebraic Iterative Proportional Fitting algorithm developed by Nourian et al. [241] for adjusting the origin-destination matrix. The Algebraic Iterative Proportional Fitting algorithm is designed for adjusting a matrix A to satisfy given target row and column sums while minimizing the squared error, It ensures that the adjusted matrix $\tilde{A}$ satisfies the constraints [241]:

- 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.

In our study, the matrix need to be adjusted is the origin-destination matrix A, the row sums of the matrix A are the actual trip productions at each spatial unit, and the target row sums $(\mathbf{r})$ are the estimated trip productions of each spatial unit obtained in the step of trip generation shown in table 4.4, the column sums of A are the actual trip attractions at each spatial unit, and the target column sums $(\mathbf{c})$ are the estimated trip attractions at each spatial unit generated in the step of trip generation. We used the Algebraic Iterative Proportional Fitting algorithm to adjust the matrix A into $\tilde{A}$ so that row sums of the $\tilde{A}$ equals $(\mathbf{r})$ and the column sums of $\tilde{A}$ equals $(\mathbf{c})$. The resulting adjusted origin-destination matrix $\tilde{A}$ is stored in the form of a 2-dimensional Numpy array. A NumPy array is a data structure provided by the NumPy library in Python, designed specifically for handling large, multi-dimensional arrays and matrices efficiently [242]. Given the large size of the resulting matrix ($\tilde{A} \in \mathbb{R}^{502\times502}$), table 4.5 only presents a subset of $\tilde{A}$, the element $\tilde{A}_{ij}$ indicates the number of trips between the two nodes, i.e., if $\tilde{A}_{ij} = 0$, it indicates there is no trip between the nodes i and j, if $\tilde{A}_{ij} > 0$, it indicates there exists paths between nodes i and j. For the complete dataset of $\tilde{A}$, please refer to this repository.

TABLE 4.5 Results of trip distribution

Node ID	0	1	...	7	...	501
0	0.000e+000	0.000e+000	...	1.665e+000	...	0.000e+000
1	0.000e+000	0.000e+000	...	0.000e+000	...	0.000e+000
...	...	...	0.000e+000	...	...	...
7	1.665e+000	0.000e+000	0.000e+000	0.000e+000	...	0.000e+000
...	...	...	...	...	...	...
501	0.000e+000	...	...	...	...	0.000e+000

4.2.1.3 Mode Choice

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

4.2.1.4 Route Assignment

For this step, as introduced earlier, we assign two specific paths for each trip. One is the shortest-distance path to simulate the scenario in which patients reach their destination using the optimal route, another is the random path, modeling 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:

1 Shortest-distance path:

We assign the shortest 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), we find the shortest path between nodes i and j and assign this path to the trip that starts at node i and ends at node j. We use the NetworkX library, a Python package made for building and analysing complex networks [218], to find the shortest path between two nodes in the network graph of the HCM. The shortest path is stored in the form of a Python list, where each element of the Python list is a node ID. All paths are stored in a Python dictionary, where the keys of the dictionary are the trips consisted of origins and destinations (see “Trips" in table 4.6), and the values of the dictionary are the Python lists of the shortest paths (see “Shortest Paths" in table 4.6). Table 4.6 gives an illustration of some of the shortest paths stored in the Python dictionary. For the complete dataset of all shortest paths, please refer to this repository.

TABLE 4.6 Results of route assignment

Trips	Shortest Paths
(0, 7)	[0, 335, 7]
(0, 13)	[0, 335, 7, 347, 13]
(0, 26)	[0, 271, 26]
...	...
(10, 6)	[10, 297, 89, 266, 193, 263, 454, 51, 391, 6]
...	...
(263, 193)	[263, 193]

2 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. We use a 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 [243]. 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 behaviors. The key characters of RWS can be summarized as follows [243]:

- 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.

Here we present an illustrative example of an RWS model using the hypothetical hospital consisting of five spatial units, as introduced in Section 4.2.1. Figure 4.2 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 neighboring nodes with equal probability. For example, a possible random walk path could be as follows:

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

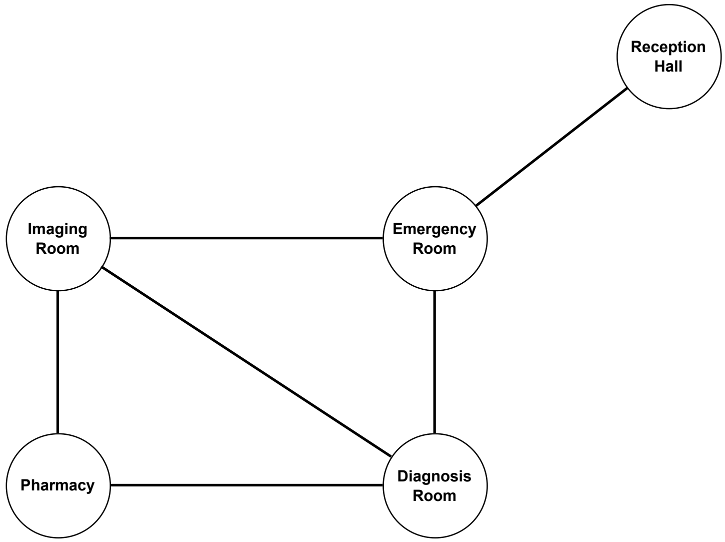

FIG. 4.2 An illustrative example of a Random Walk Simulation model

Thus, the random walk path, expressed as a Python list, is: [“Reception Hall", “Emergency room", “Diagnosis Room", “Imaging Room", “Pharmacy"]. This example demonstrates the stochastic nature of the random walk process, where agents navigate the hospital environment without prior knowledge of the optimal path.

Similar to the assignment of the shortest path, for each trip $\tilde{A}_{ij}$ in the adjusted origin-destination matrix $\tilde{A}$, if $\tilde{A}_{ij} > 0$ (i.e., if paths exist between between nodes i and j), a random path is assigned to the trip starting at node i and ending at node j. The RWS method, as introduced in the preceding example, is employed to determine a random path between two nodes in the network graph of the HCM. The assigned random path is also stored as a Python list, where each element represents a node ID. All paths are organized within a Python dictionary, consistent with the shortest path assignment. For access to the complete dataset of all random paths, please refer to this repository.

In summary, the final outputs of the Four-Step Transportation Model consist of two Python dictionaries: one representing the shortest paths and the other capturing random paths, both of which describe patient movements under different conditions within the hospital. Figure 4.3 presents a visualization 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. The trip production data estimated from the Four-Step Transportation Model’s trip generation step also supports the evaluation of overcrowding. For a detailed explanation of how the Four-Step Transportation Model’s outputs contribute to these assessments, refer to Section 4.2.4. However, the Four-Step Transportation Model is not suitable for

FIG. 4.3 Visualization of patient movement patterns (please note that for clarity reason, only one floor of the building geometry is visualized here)

evaluating 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 patient waiting times.

4.2.2 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 limitations of the Four-Step Transportation Model, particularly in assessing 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 [46]. A DES model comprises the following key components:

- Discrete Event: A discrete event catalyzes changes in the system state. In a DES model, the state transitions occur exclusively due to event occurrences [41]. For instance, in a hospital DES model, a patient's walking distance changes only when they move to another room.
- 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 [41]. 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 [41], such as patient inter-arrival rates or the duration of medical services.

- Statistics: This component aggregates and analyzes simulation results, including key performance metrics such as patient waiting times and total walking distances [41].
- Termination Condition: The simulation concludes once a predefined condition is met [41]. 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 utilize 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 4.4), 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). The architecture of the DES model adheres rigorously to the five components of DES models—discrete event, clock, random number generators, statistics, and termination condition—as outlined earlier.

The discrete event of our DES model is the patient agent moving to the next node along the respective shortest path. The clock of the DES model traces the simulation time, each patient agent's arrival time and departure time. The random number generators in our DES model simulate patient inter-arrival times and service times using an exponential distribution. Specifically, the inter-arrival time between consecutive patient agents follows an exponential distribution with a mean of 5 minutes. Similarly, the service time at each node is also modeled as an exponentially distributed variable with a mean of 5 minutes. The statistics in our DES model mainly focus on 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:

$$W_{\text{total}} = \sum_{i=1}^{N} W_i = \sum_{i=1}^{N} (T_{\text{enter},i} - T_{\text{arrive},i}) \tag{4.6}$$

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.

The termination condition of our DES model is when the simulation time reaches 1000 minutes. Our DES model's main output is each patient agent's total waiting time, plus other patient-level data such as each patient agent's unique ID, arrival time, departure time, origin, and destination. These datasets are systematically stored in a Python dictionary, facilitating efficient data organization and retrieval.

4.2.3 Exploratory Network Analysis

To adequately address concerns related to criticalities and required redundancies in the configuration design of a hospital, we propose 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 [244]. Here, 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; but rather, here we are mainly concerned with those issues that pertain to the macro-scale structure of the configuration related to its inter-accessibility network. Therefore, here we propose to include a suite of tools for performing three archetypical network analysis procedures as follows:

1. $[Local]$ 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 [25]. 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 [30]. 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 specialization 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 [30]:

$$C_C(i) = \frac{1}{\sum_{j \in P_i^R} D(i,j)} \tag{4.7}$$

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 k-th 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 normalize the centrality measures, given by the previous formula multiplied by the number of nodes within the "local neighborhood" P_i^R, resulting in [30]:

$$C'_C(i) = \frac{|P_i^R|}{\sum_{j \in P_i^R} D(i,j)} \tag{4.8}$$

This calculation ensures the resulting local closeness centrality is between 0 and 1.

2 $[Local]$ 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 [25]. 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 Betweeness Centrality is calculated as follows [30]:

$$B_C(i) = \sum_{s \neq t \in P_i^R} \frac{\sigma_{s,t}(i)}{\sigma_{s,t}}, \tag{4.9}$$

where:

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

To compare local betweenness scores across different hospital networks, one can include a normalization factor based on the size of P_i^R. For example, if P_i^R has $|P_i^R| = M$ nodes, one might normalize as follows [30]:

$$B'_C(i) = \frac{2}{(M-1)(M-2)} \sum_{s < t \in P_i^R} \frac{\sigma_{s,t}(i)}{\sigma_{s,t}}, \tag{4.10}$$

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.

3 $[Local]$ 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 [25]. 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. To compute local eigenvector centrality, we restrict the summation to a local subgraph centered around i. Let:

- $S(i)$ be the local neighborhood of i, typically defined as the k-hop neighborhood (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 [30]:

$$E_C(i) = \frac{1}{\lambda_{local}} \sum_{t \in A} a_{i,t} x_t^{(local)}, \tag{4.11}$$

The equation 4.11 can also be written in a vector form as:

$$\mathbf{E_C}^{(local)} = \frac{1}{\lambda_{local}} A^{(local)} \mathbf{E_C}^{(local)}$$

Which simplifies to the eigenvector equation:

$$A^{(local)} \mathbf{E_C}^{(local)} = \lambda_{local} \mathbf{E_C}^{(local)} \tag{4.12}$$

This shows that $\mathbf{E_C}^{(local)}$ is the eigenvector of the local adjacency matrix $A^{(local)}$ corresponding to the largest eigenvalue λ_{local}. To normalize the local eigenvector centrality for comparison across different networks, we first need to compute the normalized local adjacency matrix $N^{(local)}$ [245]:

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

Where:

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

Then the normalized local eigenvector centrality satisfies the equation:

$$\mathbf{E'_C}^{(local)} = (N^{(local)})^T \mathbf{E'_C}^{(local)} \tag{4.13}$$

4.2.4 The evaluation mechanisms

In this section, we elaborate on how we 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.

4.2.4.1 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 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 summarizing and consolidating disaggregated simulation results into higher-level statistical metrics or grouped datasets [209]. This process is used to extract meaningful insights by computing averages, totals, distributions, or other summary statistics from individual simulation outputs [209]. For example, in a hospital simulation, different individual patient waiting times can be aggregated to derive an average waiting time.
- relativization: The relativization process involves the normalization or standardization of the aggregated simulation outputs to facilitate comparison across different spatial scales [246]. This process typically transforms absolute values into relative indicators, such as ratios or percentages, allowing for meaningful comparison and analysis across different scales [246]. For instance, the average patient waiting times in different hospitals with varied scales can be relativized based on the total time spent in hospitals.
- Interpretation: Functional unit interpretation refers to the process of harmonizing relativized simulation outputs by adjusting them to a common functional unit, ensuring comparability between different datasets or scenarios [247]. This is particularly useful when results come from models with different scales, units, or baseline assumptions. In hospital simulations, for example, the relativized 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

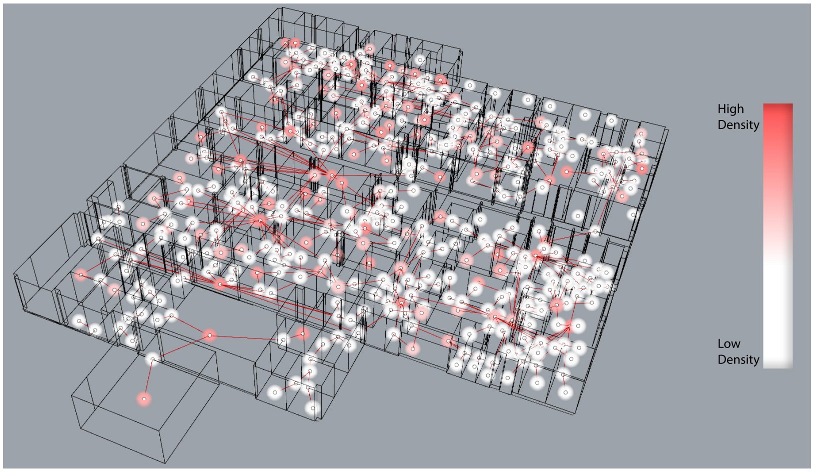

FIG. 4.4 Visualization of people density in each spatial unit

layouts by assessing four key quality criteria: public spatial crowdedness, patient waiting time, patient walking distance, and wayfinding difficulty. To be able to assess these quality criteria, we first need to identify the disaggregated indicators of the four quality criteria from the simulation results. Specifically, for assessing crowdedness in public spaces, the disaggregated indicator is the people density in each spatial unit, which can be calculated as:

$$\rho_i = \frac{C_i}{Area_i} \tag{4.14}$$

where:

- ρ_i: the people density at spatial unit i,
- C_i: the count of patients in spatial unit i,
- $Area_i$: the area of spatial unit i.

We can identify the count of patients in spatial units i (C_i) from the Four-Step Transportation Model, i.e., each spatial unit's total trip production (P_i) obtained in the trip generation step indicates the number of patients at each spatial unit. The room area data is also available from the node attributes of the HCM's graph. Hence, we can rewrite the formula 4.14 as follows:

$$\rho_i = \frac{P_i}{Area_i} \tag{4.15}$$

and directly compute each spatial unit's people density, then filter out the public spatial units' people densities. Figure 4.4 visualizes the computed people density in each spatial unit of the HCM, with higher-density spatial units shown in red and lower-density ones in white.

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. We can calculate the total distance for each path as follows:

$$D_p^{\text{shortest}} = \sum_{i=1}^{k_p-1} d(n_{p,i}, n_{p,i+1}) \tag{4.16}$$

where:

- D_p^{shortest}: the total distance of the patient p's shortest path,
- $n_{p,i}$: the i-th 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, we define 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. We can calculate the distance of the random walk paths (D_p^{random}) using formula 4.16 and compute each patient's extra walking distance as follows:

$$D_p^{\text{extra}} = D_p^{\text{random}} - D_p^{\text{shortest}} \tag{4.17}$$

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 4.6).

The following paragraphs discuss how we use the steps of aggregation, relativization, 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, we use the average to aggregate the four indicators: people density in each spatial unit, each patient's walking distance, extra walking distance, and waiting time. Specifically, the average people density in the public area is calculated as follows:

$$\bar{\rho}_{\text{public}} = \frac{\sum_{i=1}^{M} \rho_i}{M} \tag{4.18}$$

where:

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

The average patient walking distance is computed as follows:

$$\bar{D} = \frac{\sum_{p=1}^{P} D_p^{\text{shortest}}}{P} \tag{4.19}$$

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:

$$\bar{D}^{\text{extra}} = \frac{\sum_{p=1}^{P} D_p^{\text{extra}}}{P} \tag{4.20}$$

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:

$$\bar{W} = \frac{\sum_{p=1}^{P} W_p^{\text{total}}}{P} \tag{4.21}$$

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 relativization, we relativize the aggregated simulation results to enable the comparison between hospitals of different sizes and scales. We relativize the average people density in public areas by comparing it to the target people density in public areas. Specifically, the relativized people density in public areas is calculated as follows:

$$\rho_{\text{rel}} = \frac{P_{\text{total}}}{C_{\text{public}}} \tag{4.22}$$

where:

- ρ_{rel}: the relativized 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, we define the target people density in public spaces ρ_{target} as one person per square meter. However, this number can be adjusted according to different cases.

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

$$D_{\text{rel}} = \frac{\bar{D}}{D_{\text{total}}} \tag{4.23}$$

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, we can compute the relative patient extra walking distance as follows:

$$D_{\text{rel}}^{\text{extra}} = \frac{D^{\bar{\text{extra}}}}{D_{\text{total}}} \tag{4.24}$$

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.

For the relative patient waiting time, we can obtain it by comparing the average patient waiting time with the average patient total time spent in the hospital:

$$W_{\text{rel}} = \frac{\bar{W}}{\bar{W}_{\text{ts}}} \tag{4.25}$$

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 toal time spent by patient p in the hospital, and P is the total number of patients.

In the step of interpretation, we establish a functional unit for each relativized 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 meter." Under this definition, a relative people density of 10% per square meter in a hospital's public areas indicates that, on average, only 10% of the hospital's capacity is utilized per square meter. 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 4.7 summarizes the mathematical formulas used to derive the disaggregated indicator, aggregated quality criterion, and relativized quality criterion for each of the four hospital design challenges. Additionally, the table presents the functional units associated with these design challenges.

TABLE 4.7 A summary of the HDSS's evaluation mechanisms

	Disaggregated Indicator	Aggregated Quality Criterion	Relativized Quality Criterion	Functional Unit
Spatial Crowdedness	$\rho_i = \frac{P_i}{Area_i}$	$\bar{\rho}_{\text{public}} = \frac{\sum_{i=1}^{M} \rho_i}{M}$	$\rho_{\text{rel}} = \frac{P_{\text{total}}}{C_{\text{public}}}$	Occupancy percentage per square meter
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	$D_p^{\text{extra}} = D_p^{\text{random}} - D_p^{\text{shortest}}$	$\bar{D}^{\text{extra}} = \frac{\sum_{p=1}^{P} D_p^{\text{extra}}}{P}$	$D_{\text{rel}}^{\text{extra}} = \frac{D^{\text{extra}}}{D_{\text{total}}}$	Percentage of hospital size per patient
Patient Waiting Time	$W_{\text{total}} = \sum_{i=1}^{N} (T_{\text{enter},i} - T_{\text{arrive},i})$	$\bar{W} = \frac{\sum_{p=1}^{P} W_p^{\text{total}}}{P}$	$W_{\text{rel}} = \frac{\bar{W}}{W_{\text{ts}}}$	Percentage of total time spent per patient

4.2.4.2 Interpretation of exploratory network analysis results

In the exploratory network analysis, centrality measurements are inherently disaggregated and normalized, with each node in the graph assigned a unique value between 0 and 1. As a result, we do not apply the same evaluation mechanisms as those used in simulation modeling. Instead, we interpret the centrality measures to analyze their implications for hospital layout design and spatial connectivity.

Figure 4.5 illustrates the results of Local Closeness Centrality measures of the HCM's network graph. The local region is defined as the subgraph induced by all nodes reachable within a radius of five edges from the target node. The nodes colored 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

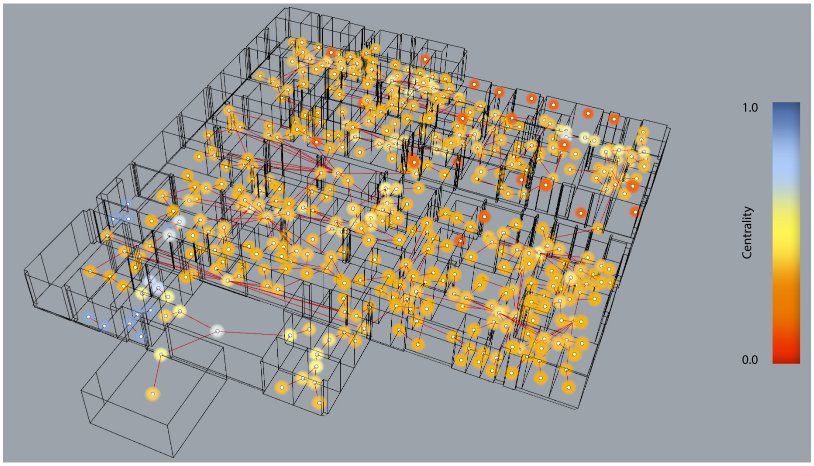

FIG. 4.5 Local Closeness Centrality ($R = 5$) measures of the HCM's graph

correspond to spatial units with lower local closeness centrality, signifying more remote or isolated locations within the network. These areas are likely to serve specialized or lower-traffic functions, such as patient rooms or recovery areas, where reduced interaction with other hospital units is appropriate.

Figure 4.6 presents a visualization 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. Hence, a consistency can be observed between Figure 4.6 and Figure 4.4, as spatial units with high betweenness centrality in Figure 4.6 also exhibit high people density in Figure 4.4. This alignment supports the effectiveness of betweenness centrality in identifying potential overcrowding areas. 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 optimize 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.

Figure 4.7 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 colored in blue represent spatial units with high local eigenvector centrality; they are connected to other highly connected rooms, making

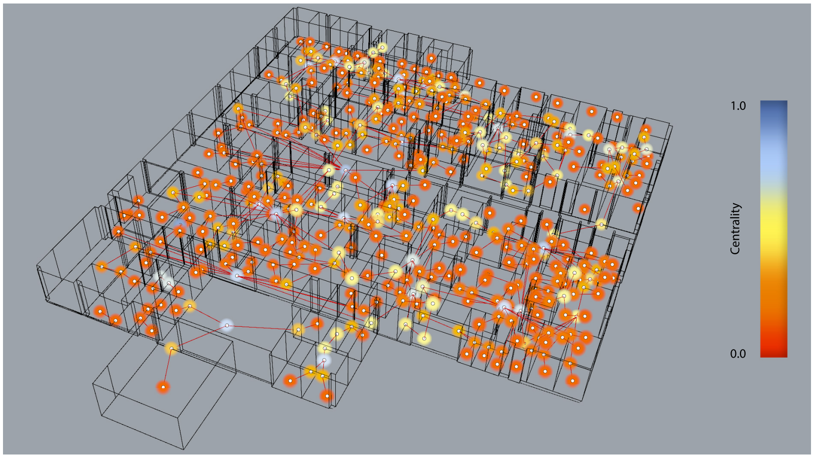

FIG. 4.6 Local Betweeness Centrality ($R = 5$) measures of the HCM's graph

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 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, specialized treatment areas, or private consultation spaces.

4.3 Conclusion

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.

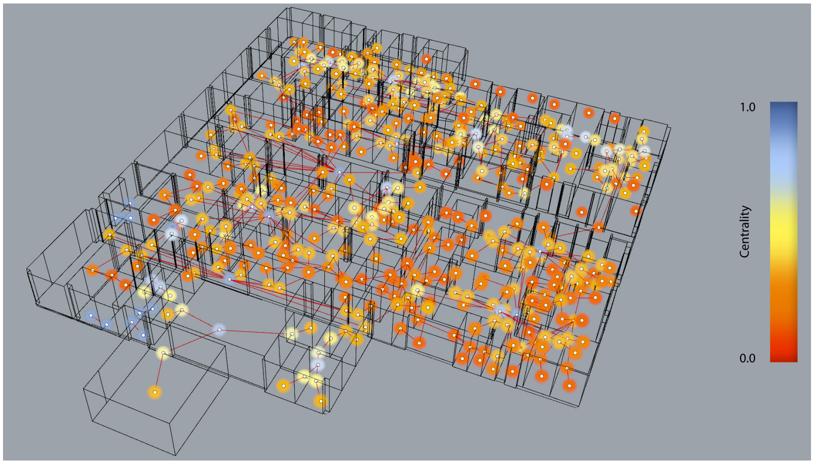

FIG. 4.7 Local Eigenvector Centrality ($R = 5$) measures of the HCM's graph

This study presents significant findings that enhance the field of hospital layout design and simulation modeling. 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 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 optimization 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, relativization, and interpretation of simulation outputs—that transform disaggregated data into actionable quality criteria. This methodological rigor 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, the Four-Step Transportation Model is based on certain simplifying assumptions—for instance, the use of a fixed space requirement per person for all spatial units—which may not fully capture the complexity and variability inherent in real-world hospitals. Second, the framework currently lacks integration of real-time operational data, relying predominantly on synthetic or modeled data. Lastly, 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 generalizability across diverse hospital layouts with varying levels of complexity and functional requirements.

Addressing these limitations offers avenues for future research. Enhancing model flexibility by incorporating stochastic variations and more nuanced behavioral parameters could further improve the fidelity of the simulations. Additionally, integrating HDSS with real-time data processing capabilities enables the development of hospital digital twins. This advancement would facilitate continuous performance assessment and enable proactive decision-making in hospital management. 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 realizing its full potential in hospital design decision-making.

5 Conclusion

In this dissertation, a spatial design decision support system, termed the Hospital Design Support System (HDSS), was developed to enhance hospital layout design performance, specifically addressing issues such as overcrowding, long patient waiting times, long patient walking distances, and difficulty in wayfinding. A systematic literature review was first conducted to identify the key design challenges associated with hospital layout planning and approaches for measuring these challenges. The HDSS is designed to provide a reliable and transparent assessment framework for evaluating the performance of various hospital layout designs through simulation modelling and exploratory network analysis. Both methods require a robust foundational dataset to function effectively. To meet this requirement, a Hospital Configuration Model (HCM) is developed, supplying essential information—including geometric, topological, semantic, and operational data—necessary for the HDSS to operate with accuracy and efficiency. A software named is also developed for semi-automatically obtaining HCMs from hospital BIM/IFC files. The HDSS comprises three core models: (1) a Four-Step Transportation Model, which simulates the city-like characteristics of hospitals and assesses layout performance in terms of overcrowding, patient walking distance, and difficulty in wayfinding; (2) a Discrete-Event Simulation Model, which captures the factory-like nature of hospital operations and evaluates layout performance based on patient waiting times; and (3) an Exploratory Network Analysis Model, which examines the inherent logic of hospital spatial structures. Additionally, an evaluation mechanism was developed to translate simulation results into actionable insights for informed decision-making. Specifically, disaggregated simulation outputs are aggregated, normalized, and defined with a functional unit to enable fair comparisons across hospitals of varying scales. The HDSS serves as a robust tool for architects, hospital directors, and head nurses during the early design stages, facilitating the identification of optimal hospital layout alternatives. This chapter addresses the research questions proposed in Chapter 1 and discusses the contributions of this study. Additionally, the research limitations are examined, and potential directions for future research are outlined.

5.1 Responses to Research Questions

This section presents the answers to the research questions:

- **Research question 1**: How to measure the accessibility and visibility of a spatial unit concerning all other spatial units in a hospital layout?

  The exploratory network analysis model within the HDSS evaluates the accessibility and visibility of all spatial units within a hospital layout. This process begins with the development of a hospital configuration model, which generates a network graph representing the spatial structure of the hospital. This network graph serves as the input for the exploratory network analysis model, producing three key metrics—closeness centrality, betweenness centrality, and Eigenvector centrality—quantifying the accessibility and visibility of each spatial unit in the hospital. To enhance interpretability, these centrality metrics are visualized, providing intuitive representations of spatial units' accessibility and visibility concerning all other spaces in the hospital.

- **Research question 2** How to measure the crowdedness in a hospital layout design?

  The Four-Step Transportation Model within the HDSS measures the level of crowdedness in a hospital layout. The process begins with the development of a Hospital Configuration Model, which serves as the input for the Four-Step Transportation Model. This model estimates the number of patients in each spatial unit based on its area, after which the crowdedness of each unit is calculated as people density—the number of patients within a spatial unit divided by its area. To assess overall crowdedness in the public areas of the hospital, the average people density across all public spatial units is computed. This average density is then normalized by comparing it to the target density for public areas. Finally, a functional unit, defined as "occupancy percentage per square meter", is introduced to facilitate fair comparisons across hospital layouts of varying scales.

- **Research question 3** How to measure the patient's walking distance in a hospital layout design?

  The Four-Step Transportation Model within the HDSS evaluates patient walking distances within a hospital layout. Utilizing the Hospital Configuration Model as input, the model estimates the total number of trips originating from and arriving at each spatial unit. It then distributes these trips and generates an origin-destination matrix to determine the number of trips between each pair of origin and destination. Subsequently, the shortest path for each trip in the origin-destination matrix is identified, and walking distances are computed based on these shortest paths. The disaggregated walking distances are then aggregated using the average walking distance per patient. To standardize comparisons across different hospital layouts, this measure is relativized by relating it to the total distance of the hospital network. Finally, a functional unit, defined as the "percentage of hospital size per patient" is introduced to ensure fair comparisons across various hospital designs.

- **Research question 4** How to measure patient/visitor's difficulty in wayfinding in a hospital layout + procedures (program of requirements) design?

  The assessment of patient difficulty in wayfinding within a hospital closely parallels the evaluation of patient walking distance. The only difference is that the Four-Step Transportation Model assigns two paths for each trip in the origin-destination matrix: the shortest path and a random path that simulates the scenario in which patients become disoriented and visit unintended locations before reaching their destination. Difficulty in Wayfinding is then quantified as the difference between the distance of the random path and that of the shortest path. The subsequent steps—aggregation, relativization, and functional unit definition for difficulty in wayfinding—mirror the methodological approach used in measuring patient walking distance.

- **Research question 5** How to measure patient waiting time in a hospital layout design?

  Patient waiting times are measured using the Discrete-Event Simulation (DES) model within the HDSS. The patient's shortest paths generated by the Four-Step Transportation Model serve as inputs for the DES model. For each patient's shortest path, a corresponding patient agent is created, and the DES model simulates the process of the patient agent geos through its corresponding patient path, recording waiting times along the path. The disaggregated waiting times are then averaged and normalized by comparing them to the total time spent for the patient to complete the path. Finally, a functional unit, defined as the "Percentage of Total Time Spent per Patient," is introduced to facilitate fair comparisons across multiple cases.

5.2 Contributions

This section summarises the main contributions of this research. The systematic literature review presented in chapter 2 summarises the main design challenges related to hospital layout design and how to assess them (see tables 2.1 and 2.2). We have identified key gaps in the literature, particularly in the rigorous mathematical treatment of spatial representation issues and the quantitative assessment of challenges such as overcrowding and the risk of cross-contamination. These identified research gaps highlight potential directions for future research.

Building on the research gap identified in Chapter 2—specifically, the lack of a mathematical representation of hospital layouts—we developed a systematic and robust methodology for hospital layout configuration modelling (see subchapter 3.1). This methodology first enables the semi-automatic generation of IndoorGML models from Building Information Models (BIM) and Industry Foundation Classes (IFC) files, improving the accessibility and usability of IndoorGML data for applications such as indoor navigation and location-based services. Furthermore, it facilitates the transformation of IndoorGML models into Hospital Configuration Models (HCMs), which employ mathematical constructs to represent hospital layouts, enabling advanced spatial analysis and simulation modelling. This methodology addresses existing limitations in the current approaches for generating IndoorGML models. For instance, conventional methods often produce IndoorGML files that lack semantic information or are restricted to input BIM models with simple, modularized shapes. Our approach overcomes these shortcomings by ensuring rich semantic representation and broader applicability to complex hospital layouts.

The methodology was further implemented as a software application, IFC2BCM, which enables the semi-automatic generation of IndoorGML and HCM models from BIM/IFC files (see subchapter 3.2). A key contribution of this software is its ability to produce HCMs, which provide several advantages over traditional IndoorGML models. A significant challenge with IndoorGML is its reliance on XML (eXtensible Markup Language) encoding, which is inherently complex, highly hierarchical, and not optimized for web-based applications [219]. These characteristics make parsing and extracting information from IndoorGML files cumbersome, leading to limited software support and a scarcity of publicly available IndoorGML datasets [219]. In contrast, our HCM models utilize JSON (JavaScript Object Notation) encoding, a widely adopted data exchange format with extensive library support and a broader user base. By structuring HCM files in a more streamlined and less hierarchical manner [219], the JSON format enhances readability, simplifies editing, and improves overall accessibility compared to IndoorGML.

The Hospital Configuration Model provides the foundational dataset required to develop the Hospital Design Support System (HDSS), a comprehensive framework designed to provide reliable and transparent assessment mechanisms for evaluating the performance of various hospital layout designs (chapter 4). It achieves this by integrating the methodologies of the Four-Step Transportation Model, Discrete-Event Simulation, and Exploratory Network Analysis. Unlike conventional methods that rely on either stand-alone simulations or qualitative assessments, the HDSS integrates multiple disciplinary approaches to create a comprehensive framework for hospital layout evaluation. This system employs an innovative hybrid simulation approach that integrates the Four-Step Transportation Model and Discrete-Event Simulation (DES). The Four-Step Transportation Model captures the city-like characteristics of hospitals, while DES simulates their factory-like operational dynamics. Both models collectively represent the rational aspects of hospital functioning. Additionally, Exploratory Network Analysis is incorporated to account for the irrational aspects of hospital environments, complementing the overall capabilities of the HDSS and providing a more comprehensive framework for hospital layout evaluation. The HDSS also provides a systematic evaluation framework incorporating aggregation, normalization, and interpretation of simulation results, enabling the transformation of raw data into meaningful performance indicators. This methodological advancement sets a new standard for assessing complex healthcare infrastructures, fostering a data-driven approach to hospital architecture and design.

5.3 Limitations

While this research offers valuable insights, it is important to acknowledge several limitations. One key constraint of the methodology for generating the Hospital Configuration Model (HCM) is its exclusive focus on patient-related operational data. Specifically, the extraction of operational information into the HCM primarily considers patient movement and pathways, while other critical aspects, such as staff workflows, remain unaddressed. Staff movement patterns, as well as their interactions with both colleagues and patients, constitute an essential component of hospital operations. Incorporating these elements into the HCM could provide a more comprehensive representation of hospital dynamics and lead to deeper insights. Additionally, the operational data integrated into the HCM are derived from pre-existing datasets, which may not fully capture the inherent variability of hospital workflows. The reliance on static input data limits the model's ability to accurately reflect highly dynamic scenarios, such as emergency situations or sudden fluctuations in patient flow. Enhancing the model with real-time or stochastic operational data could improve its predictive capabilities and broaden its applicability to complex and rapidly changing environments. Another limitation pertains to the representation of spatial connections within the hospital layout graph. The current methodology generates edges by linking a room's node to the corresponding node of its door, ensuring that only spaces connected by doors are represented as connected in the graph. While this approach works for many cases, it introduces inaccuracies when two spatial units are directly connected without an intervening door. For example, if two corridors transition seamlessly into each other without a door, the methodology fails to create an edge between them, leaving them unlinked in the spatial graph. A more refined approach to representing spatial adjacency would improve the accuracy of the hospital layout model.

The IFC2BCM software, developed for generating Hospital Configuration Models (HCMs), also has several limitations. One notable constraint is its reliance on a combination of Python scripts, Grasshopper scripts, and Dynamo scripts. Although this multi-tool approach capitalizes on the strengths of each platform, it presents challenges for users, who must navigate between these tools to access the software's full functionality. This fragmented workflow complicates the user experience and may lead to inefficiencies, such as increased learning curves, a higher likelihood of user error, and reduced operational consistency. Furthermore, the methodology was applied and validated using a single real-world hospital BIM model. While this case study demonstrates the feasibility of the approach, the applicability of the findings to other hospital layouts, particularly those with different levels of complexity and operational requirements, remains uncertain. Further exploration is needed to assess the generalizability of the methodology across a wider range of hospital environments.

While the HDSS framework offers significant advantages, it also has several inherent limitations. First, the Four-Step Transportation Model rely on certain simplifying assumptions, such as assigning a fixed space requirement per person for every spatial unit. This approach, while practical, may not fully encapsulate the dynamic and complex nature of real-world hospitals. Another limitation is the framework's reliance on synthetic or modeled data, as it does not currently integrate real-time operational inputs. Incorporating live data streams could enhance the model's adaptability and predictive accuracy in dynamically changing hospital environments. Finally, the methodology has been validated using a single real-world hospital BIM model. While this case study demonstrates the approach's feasibility and effectiveness, its applicability to a broader range of hospital layouts with differing complexities and functional demands requires further investigation. Expanding the scope of validation would strengthen the framework's robustness and generalizability.

5.4 Potential Future Research Direction

The limitations outlined in Section 5.3 suggest several promising avenues for future research. One direction involves expanding the operational data integrated into the HCM by incorporating additional variables such as staff workflows and movement patterns. Another opportunity is to enhance the IFC2BCM software by consolidating its multi-script implementation into a unified framework, thereby simplifying the user experience. Another promising direction for future research is the integration of real-time data capabilities into the IFC2BCM and HDSS frameworks, transforming them into a digital twin system for hospital management. By continuously receiving real-time patient movement data, the system could perform simulation modelling and predictive analysis to identify potential congestion points and areas at high risk of contamination. This would enable hospital administrators to take proactive measures, optimizing operational efficiency and improving patient safety. Moreover, the adaptability of this digital twin framework extends beyond hospital environments. For instance, it could be applied to intelligent transportation systems in urban settings, where real-time traffic data is used to simulate and predict congestion hotspots, allowing policymakers to implement timely interventions. Similarly, the framework could enhance crowd management in train stations by guiding passenger flow and improving transit efficiency. These applications highlight the system's versatility and potential for broader impact across various domains.

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Publications

Journal Papers

Jia, Z., Nourian, P., Luscuere, P., & Wagenaar, C. (2023). Spatial decision support systems for hospital layout design: A review. Journal of Building Engineering, 67, 106042. https://doi.org/10.1016/j.jobe.2023.106042

Jia, Z., Nourian, P., Luscuere, P., & Wagenaar, C. (2024). A Configuration Model for Hospital Design Support Systems. Buildings, 15(2), 163. https://doi.org/10.3390/buildings15020163

Jia, Z., Nourian, P., Luscuere, P., & Wagenaar, C. (2025). IFC2BCM: A Tool for Generating IndoorGML and Building Configuration Model from IFC. SoftwareX, 29, 101975. https://doi.org/10.1016/j.softx.2024.101975

Curriculum Vitae

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Summary

During my doctoral research at the Faculty of Architecture, Delft University of Technology, Netherlands, I have acquired the following core skills:

- **Intelligent Transportation Systems:** Proficient in Transportation Planning, Four-Step Transportation Model, Discrete Event Simulation, Agent-Based Modeling, and System Dynamics.
- **Advanced Technologies:** Experienced in developing and applying Digital Twin technologies, Machine Learning, and SQL databases.

Education

Ph.D. | Interdisciplinary Research: Design Informatics
Delft University of Technology, Netherlands (March 2021 – Present)
Relevant courses: Machine Learning for the Built Environment, Python Programming for Geomatics, 3D Modelling of the Built Environment, GEO Database Management

Systems.

Bachelor’s & Master’s Degree | Architecture
University of Sydney, Australia
Bachelor: March 2014 – December 2016; Master: July 2017 – December 2019

Research Experience

Project 1: A Systematic Review of Spatial Decision Support Systems for Hospital Layout Design (June 2021 – March 2022)

- Explored how spatial network analysis and simulation modeling address hospital layout challenges.
- Identified gaps in literature for quantifying hospital performance issues.
- Published in Journal of Building Engineering.

Project 2: Hospital Configuration Model for Hospital Design Support Systems (March 2022 – April 2023)

- Developed an innovative Hospital Configuration Model integrating geometric, topological, semantic, and operational data.
- Model supports performance prediction through simulation.
- Published in Buildings.

Project 3: Software Development for Automatically Generating Building Configuration Models (April 2023 – May 2024)

- Developed software to generate building configuration models from BIM data.
- Implemented using Python, Dynamo, and Grasshopper.
- Published in SoftwareX.

Project 4: Software Development for Hospital Design Support Systems (May 2024 – Present)

- Developing a spatial decision support system for hospital layout design.

- System employs Four-Step Transportation Model and Discrete Event Simulation.
- Extendable to digital twin applications.

Professional Experience

Development Assistant | Sunglow Australia (Dec 2019 – June 2020)

- Prepared project feasibility studies using Estate Master software.
- Conducted market research on real estate sectors.
- Managed contracts, purchase orders, and budgets.

Architecture Intern | Juchuan Architectural Design Office, China (May 2017 – July 2017)

- Conducted site inspections, conceptual design, and landscape design.
- Created digital models, drawings, and renderings for presentations.
- Contributed to the Liulin Theater project in Shanxi Province.

Technical Skills

- **Digital Twin:** Skilled in developing digital twin technologies.
- **Machine Learning:** Proficient in Pytorch and TensorFlow.
- **Programming Languages:** Python, C++.
- **Software and Tools:** PTV Vissim, Revit & Dynamo, Rhino & Grasshopper, Photoshop, Illustrator.
- **Simulation Methods:** Four-Step Transportation Model, Discrete Event Simulation, Agent-Based Modeling, System Dynamics.

25#21

A Hospital Design Support System

Addressing Hospital Layout Design Challenges in China

Zhuoran Jia

Hospital layout design plays a crucial role in ensuring operational efficiency. This research develops 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 layout performance in terms of operational efficiency. The HDSS evaluates four key 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, relativization, 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.

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