Chair of Computational Modeling and Simulation
TUM School of Engineering and Design
Technical University of Munich

Reasoning IFC Models for Space-level Circulation Design Rationale using Graph-based Analysis and Community Detection

Scientific work to obtain the degree

Master of Science (M.Sc.)

at the TUM School of Engineering and Design
of the Technical University of Munich.

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Submitted on December 30, 2024

Abstract

Space-level circulation design rationale refers to the underlying logic and principles that guide the arrangement of pathways, connections, and spaces within a building to facilitate movement and accessibility. Capturing and reusing this rationale is crucial for designers, as it enables the efficient adaptation of existing designs to new contexts, preserving both functionality and intent while reducing the time and effort required for rework. Traditionally, reasoning about circulation design has relied on manual interpretations, conceptual sketches, and designer intuition, often resulting in incomplete or ambiguous representations of spatial relationships. These approaches, while creative, lack the systematic rigour necessary for ensuring consistency and adaptability across diverse design scenarios.

This thesis explores the application of graph-based analysis techniques, including graph clustering algorithms and centrality-based node analyses, to reason space-level circulation design rationale. The method computes space-level topological relationships by leveraging IFC schema relationships and utilizing a voxel-grid-based approach, establishing graph-based representations of IFC models. These representations provide a systematic means of understanding space-level organization and connectivity. This research demonstrates the potential of integrating graph-based concepts into building design and verification processes, highlighting the effectiveness of graphs for the representation and analysis of circulation entities.

Keywords — Circulation Design Rationale, Voxel-based Analysis, Graph Theory, Community Detection

Zusammenfassung

Das Konzept der raumbezogenen Zirkulationsdesign-Rationalität bezieht sich auf die zugrunde liegende Logik und die Prinzipien, die die Anordnung von Wegen, Verbindungen und Räumen innerhalb eines Gebäudes leiten, um Bewegung und Zugänglichkeit zu erleichtern. Die Erfassung und Wiederverwendung dieser Rationalität ist für Planer von entscheidender Bedeutung, da sie eine effiziente Anpassung bestehender Entwürfe an neue Kontexte ermöglicht, wobei sowohl Funktionalität als auch Intention erhalten bleiben und der Zeit- und Arbeitsaufwand für Nachbearbeitungen reduziert wird. Traditionell stützte sich das Erschließen von Zirkulationsdesigns auf manuelle Interpretationen, konzeptionelle Skizzen und die Intuition der Planer, was oft zu unvollständigen oder mehrdeutigen Darstellungen räumlicher Beziehungen führte. Diese Ansätze sind zwar kreativ, es mangelt ihnen jedoch an der systematischen Strenge, die erforderlich ist, um Konsistenz und Anpassungsfähigkeit in unterschiedlichen Entwurfsszenarien zu gewährleisten.

Diese Arbeit untersucht die Anwendung graphbasierter Analysetechniken, einschließlich Graph-Cluster-Algorithmen und zentralitätsbasierter Knotenanalysen, zur Erschließung der raumbezogenen Zirkulationsdesign-Rationalität. Die Methode berechnet topologische Beziehungen auf Raumebene, indem sie IFC-Schema-Beziehungen nutzt und einen voxelgitterbasierten Ansatz anwendet, um graphbasierte Darstellungen von IFC-Modellen zu erstellen. Diese Darstellungen bieten einen systematischen Ansatz zum Verständnis der Organisation und Konnektivität auf Raumebene. Diese Forschung zeigt das Potenzial der Integration graphbasierter Konzepte in Entwurfs- und Verifizierungsprozesse der Architektur auf und unterstreicht die Wirksamkeit von Graphen für die Darstellung und Analyse von Zirkulationselementen.

Schlüsselwörter — Zirkulationsdesign-Rationalität, Voxel-basierte Analyse, Graphentheorie, Gemeinschaftserkennung

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Chapter 1

Introduction

Building design harmonizes ideas into tangible solutions, balancing creativity and precision within a dynamic and often uncertain environment (Wiggins, 1989). This process merges aesthetics, functionality, and compliance, requiring designers to navigate abstract concepts and practical constraints. A critical component of this endeavour is design rationale—the principles and intentions that guide decision-making (Horner & Atwood, 2006). Effectively articulating and preserving this rationale is essential for the immediate success of a design and also for its adaptability and reuse in future design and construction tasks (Tang et al., 2006). The evolution of architectural practices has highlighted the importance of understanding and reasoning behind design decisions (Al-Sayed et al., 2010). However, achieving clarity in design rationale faces both technical and organizational challenges. Improving the clarity of design rationale can enhance scientific understanding and communication, ultimately benefiting individual projects and the industry as a whole (Chachere & Haymaker, 2011).

Digital methods have become indispensable in contemporary architectural design workflows. Building Information Modeling (BIM) has emerged as a transformative paradigm for managing and coordinating building data throughout a project's lifecycle (Eastman et al., 2018). BIM enables multidisciplinary collaboration by integrating diverse types of information—geometric, semantic, and parametric—within a digital framework. The adoption of BIM streamlines the design, construction, and maintenance processes by promoting efficiency, reducing errors, and enhancing decision-making (Borrmann et al., 2018). The effectiveness of BIM relies on the interoperability of its tools and systems, necessitating standardized methods for data exchange and representation.

Industry Foundation Classes (IFC) is an open international standard for sharing data developed by buildingSMART International (buildingSMART International, 2024a). IFC serves as a universal schema for structuring building information, enabling data exchange between disparate BIM tools and software. As an open and neutral standard, IFC facilitates the representation of geometric, semantic, and spatial relationships within building models (buildingSMART Technical, 2024b). This interoperability is critical for fostering collaboration across disciplines and ensuring that all stakeholders have access to consistent and accurate project data. Despite its success, however, IFC models primarily focus on explicit geometric and semantic data while often neglecting the implicit reasoning and design rationale embedded in architectural decisions (Krijnen & Tamke, 2015). For instance, while an IFC model can represent the dimensions and placement of a corridor, it typically does not convey why that corridor was designed to connect specific spaces or its intended role in circulation design.

In building design practice, design exchange scenarios frequently arise, where building models are transferred between stakeholders or adapted for new contexts (EASTMAN et al., 2018). These exchanges require a clear understanding of the underlying design rationale to ensure the integrity of the design is preserved (BAYRAKTAR SARI & JABI, 2024). For example, during project modifications or extensions, the absence of rationale behind circulation layouts or structural decisions may lead to inefficiencies or errors. The current limitations in communicating design rationale during IFC-based data exchange represent a significant challenge (KRIJNEN & TAMKE, 2015; ZAHEDI et al., 2022). Addressing these challenges is essential to enable seamless design adaptation and effective reuse of building information.

Reasoning of IFC models involves employing logical and inferential techniques to extract and interpret embedded knowledge, which is vital for understanding and communicating design rationale (ZAHEDI et al., 2022). This reasoning process is particularly pertinent when addressing circulation design rationale. Circulation constitutes a fundamental aspect of spatial planning. In the context of spatial accessibility planning, the 2010 ADA Standards for Accessible Design define a "Circulation Path" as: "An exterior or interior way of passage provided for pedestrian travel, including but not limited to, walks, hallways, courtyards, elevators, platform lifts, ramps, stairways, and landings." (ADA STANDARDS, 2010). Spatial planning, including circulation design, is multifaceted and requires meticulous planning and coordination (J. K. LEE et al., 2010). Errors in this area can lead to considerable inefficiencies and potential safety hazards (NOURIAN, 2016). The necessity to reason about the underlying design rationale for circulation elements is further emphasized by the lack of explicit representations in current IFC models (J. WU et al., 2024). Therefore, developing techniques that can infer and articulate circulation design rationale from IFC models is imperative.

Architects and designers generally use hand-drawn "sketch models" as showcased in Figure 1.1 in the early stages of design. This intuitive and abstract approach to space planning underlines the challenges faced when trying to translate early-stage design concepts into detailed models that conform to parametric standards and retain the original design rationale (JABI, 2014). This thesis aims to address the challenge of reasoning IFC models to elucidate circulation design rationale. By concentrating on methodologies that enhance the interpretability and usability of IFC data, the research aims to improve design reasoning, thereby facilitating better design reuse and adaptability.

1.1 Research goal

Understanding the rationale behind circulation design in architectural spaces is essential for enhancing the overall design process. Ensuring effective and efficient circulation presents significant challenges as buildings become increasingly complex (SHIN & LEE, 2019). Current digital modelling practices, particularly those leveraging IFC standards, provide promising avenues for managing and analyzing building data. However, a notable

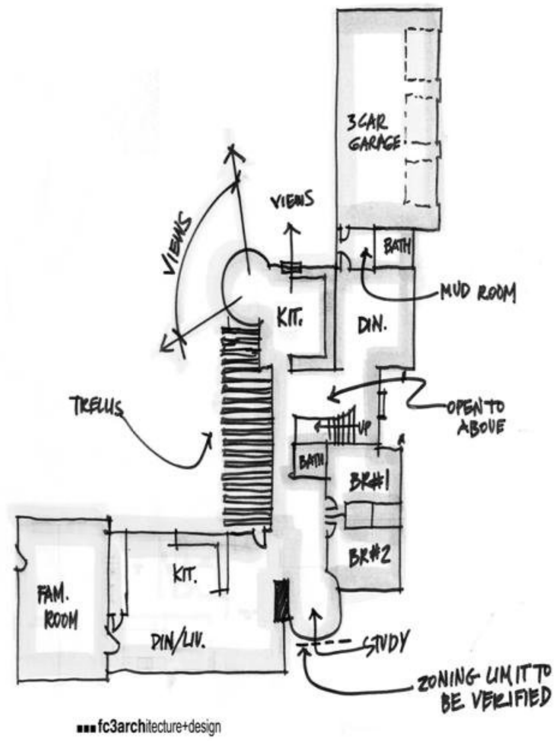


Figure 1.1: A typical architect's sketch from the early design stages (JABI, 2014)

gap remains regarding the reasoning behind the embedded design logic within these models, especially in relation to circulation design. This gap hinders the transferability and adaptability of building designs across different contexts (J. WU et al., 2024). To bridge this gap, this thesis focuses on addressing the following key research question:

> *"How can the embedded logic for circulation design in IFC data models be reasoned and represented to improve transferability in architectural building design?"*

This question emphasizes the necessity of extracting and interpreting the design rationale embedded in circulation elements, which are often represented in an abstract and implicit manner within IFC models. The main objective is to create a robust methodology that connects space-level representation with a high-level conceptual understanding of design goals, facilitating effective reasoning about design choices. To tackle the research question, this thesis proposes a comprehensive three-phase framework. Firstly, IFC processing involves processing the IFC model to identify and extract essential building elements within the context of circulation design. Utilizing IfcOpenShell[1], an open-source software library, the model is parsed to capture geometric and semantic data of key entities, which are subsequently prepared for further analysis (IFCOPENSHELL.ORG, n.d.). This preparation entails converting complex geometries into a more manageable format that establishes fundamental space-level relationships within the model. Secondly, space-level relationship reasoning concentrates on analyzing the connectivity and adjacency of various spaces

[1] https://ifcopenshell.org/

within the building. This analysis aims to reveal how spaces interconnect both horizontally and vertically, offering insights into accessibility and flow within the structure.

Finally, graph-based analysis involves translating the space-level data into a graph structure, with building spaces represented as nodes and their relationships as edges. Graph algorithms are employed to uncover patterns and communities within the building's layout, revealing the space-level organization and circulation strategies. This process aids in visualizing and interpreting the design rationale, providing a clearer understanding of how spaces are structured to facilitate movement and accessibility. In summary, this framework offers a systematic approach for analyzing and reasoning about circulation design within IFC models. By integrating space-level analysis with graph-based methods, the research presents a comprehensive means of understanding and transferring architectural circulation design rationale across diverse contexts.

1.2 Thesis structure

The thesis is organized into five chapters, each contributing to the overall objective of reasoning IFC models space-level circulation design rationale. Chapter 2 provides a comprehensive literature review, examining existing methodologies and identifying gaps that the current research aims to address. Chapter 3 details the methodology employed in the research, describing the approaches and tools used to achieve the study's objectives. Chapter 4 discusses the prototype implementation, including a case study that demonstrates the practical application of the proposed framework. Finally, Chapter 5 concludes the thesis by summarizing the findings, limitations and suggesting directions for future research.

Chapter 2

State of the art

BIM has revolutionized the AEC industry over the past two decades. By enabling efficient collaboration and streamlining workflows, BIM has significantly improved project coordination, reduced errors, and optimized construction processes. BIM-related technologies have become essential tools for stakeholders in the AEC sector, fostering innovation and driving efficiency across the industry (BORRMANN et al., 2018; EASTMAN et al., 2018). Figure 2.1 illustrates the evolution of design communication from 2D drawings to IFC models.

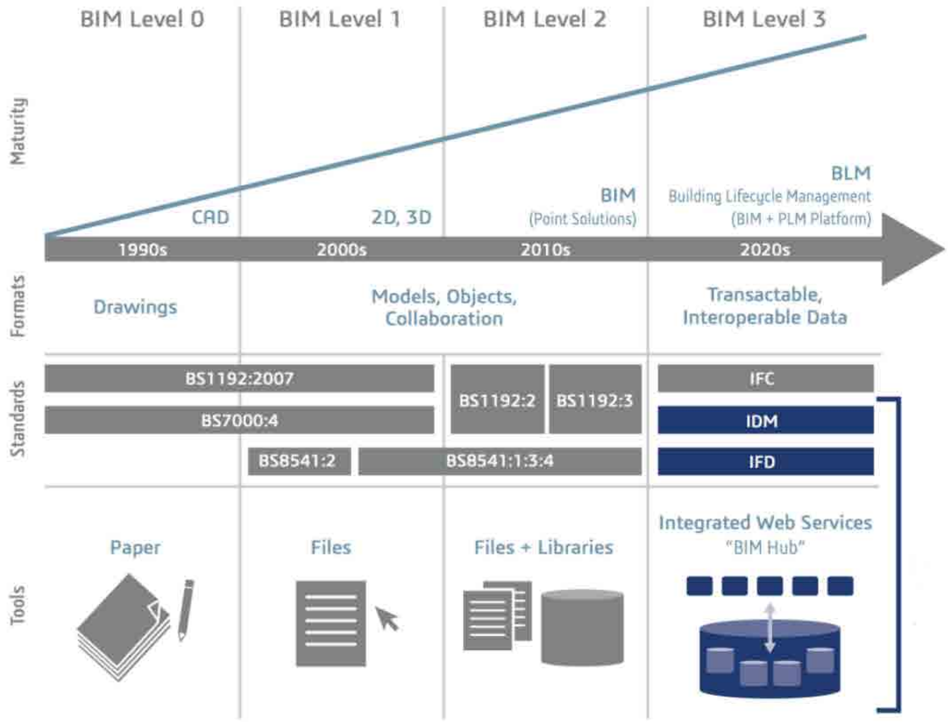


Figure 2.1: Brief timeline of BIM evolution (ROZMANITH, 2014)

A key aspect of BIM is its ability to enable model exchange using the IFC format. As an open standard, IFC facilitates seamless data interoperability between various software tools, playing a crucial role in OpenBIM (buildingSMART INTERNATIONAL, n.d.; buildingSMART TECHNICAL, 2024b). This ensures that all stakeholders can access discipline-specific data efficiently, promoting smoother project execution (GU & LONDON, 2010). However, a persistent challenge lies in capturing design intent within IFC models (ZAHEDI et al., 2022). The difficulty in representing the underlying reasoning behind design decisions within these models can hinder their effectiveness in certain complex projects, such as hospitals, where the design rationale must be meticulously defined and adhered to (BAYRAKTAR SARI & JABI, 2024). To address this, spatial reasoning plays a crucial role in understanding building geometry and layout, offering valuable insights into spatial relationships and the architectural organization of a building (BORRMANN & BEETZ, 2010). Additionally, methods such as voxelization provide a robust way to break down and analyze complex spatial layouts using a grid-based system, which aids in establishing and understanding spatial relationships (MITKO ALEKSANDROV & DIAKITE, 2024). Furthermore, graph-based representations serve as another effective tool for visualizing and interpreting spatial relationships, contributing to a more comprehensive spatial analysis to effectively capture the interactions between different spatial components in a building's design (EISENSTADT et al., 2024a). Building on these methods, community detection enhances spatial reasoning by revealing functional zones and circulation clusters within the building, exposing the implicit architectural principles that guided the original design decisions about movement through the building (EISENSTADT et al., 2024a; SHAHRIARI, 2019). The combination of the aforementioned techniques provides a comprehensive framework for understanding the reasons behind design choices.

2.1 Circulation rationale in building design

One of the main concepts in architectural theory and practice is movement through space. The circulation framework of a building is a crucial component in structuring its layout, making it a subject of interest for professionals engaged in post-occupancy review, including architects (NATAPOV et al., 2019). It is essential to prioritize effective circulation design to fulfil both functional and aesthetic objectives in architecture. This contributes significantly to the overall user experience and operational efficiency of a building (ARAFAT et al., 2024). Circulation in architecture can be broadly categorized into two types: horizontal circulation, encompassing corridors and pathways enabling movement on a single level, and vertical circulation, including stairs, ramps, elevators, and escalators facilitating movement between different levels (SHIN & LEE, 2019). Both types are crucial to ensure that users can navigate a building freely and comfortably (NATAPOV et al., 2019; SULLY, 2024). Moreover, building circulation design significantly impacts overall design quality, particularly in the early stages of building design (CHING, 2023).

Every building design incorporates various implicit considerations and specialized knowledge. Figure 2.2 illustrates the design process reasoning and levels of abstraction defined by its governing factors (ABUALDENIEN & BORRMANN, 2021). Each building project must adhere to a range of owner requirements, regulations, and boundary conditions. Architectural principles and concepts are selected and applied at the conceptual level to meet client needs and express them through the design. These concepts are then further developed by modelling and detailing each component, which includes geometric and semantic data, spatial relationships, and functional dependencies at the design level (ABUALDENIEN & BORRMANN, 2021).

Some prominent examples of implicit knowledge in spatial configurations for building circulation design are as follows:

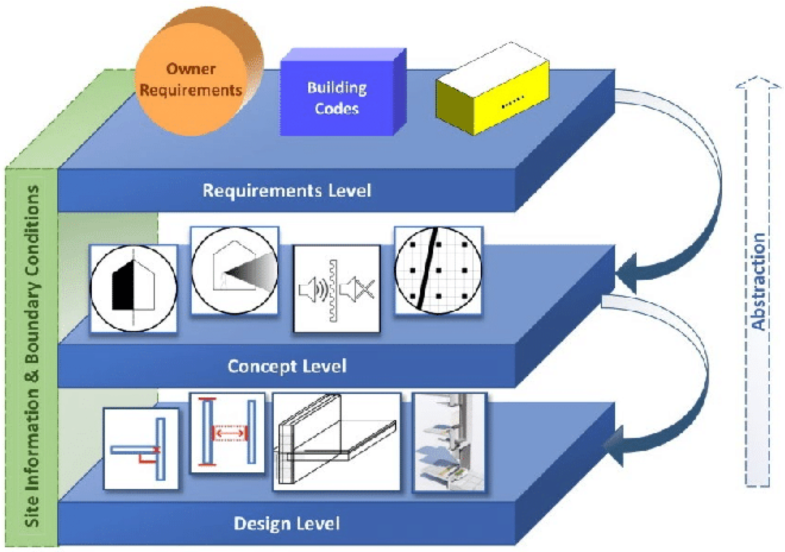


Figure 2.2: Design reasoning depicted using abstraction layers (ABUALDENIEN & BORRMANN, 2021)

1. Natural Wayfinding: Designers intuitively arrange corridors and pathways to guide people naturally without excessive signage. For instance, main corridors often align with sightlines to popular destinations like lobbies, exits, or focal points (e.g., a central staircase or atrium), helping users navigate intuitively (GROSS & ZIMRING, 1990).
2. Hierarchy of Spaces: Architects understand that circulation paths should reflect the importance of spaces. Primary pathways are often wider and more direct, leading to major areas, while secondary or tertiary paths branch off to less frequently used areas. This hierarchical structuring helps users differentiate between main routes and side passages (SHAHRIARI, 2019).
3. Strategic Placement of Nodes and Intersections: Designers often place intersections, waiting areas, or lounges at key points where people need to decide on directions or take breaks, such as near elevator lobbies or main entry points. This arrangement minimizes congestion and facilitates smoother transitions between spaces (SABRY, 2024).

Architectural circulation design has traditionally been approached through conceptual design sketches and spatial analysis, with circulation features primarily assigned to building plans. In classical architectural practice, architects would supplement specific plans with additional diagrams to illustrate circulation systems and other spatial features. These conceptual designs, reflecting architectural styles and designer attitudes in the primary analysis stage, were often informal and not included in official building documentation or construction presentations (J. K. LEE & KIM, 2014; NATAPOV et al., 2019).

To convey such conceptual design logic, design rationale systems have emerged as valuable tools for documenting and communicating design decisions (HORNER & ATWOOD, 2006). Circulation design rationale specifically focuses on the reasoning and justification behind the arrangement and flow of movement within a built environment. This aspect of design considers how users navigate through spaces, addressing both functional and aesthetic dimensions (NATAPOV et al., 2019). The rationale for circulation design encompasses various elements, including user experience (ease of wayfinding, clear visibility, walkability, etc), safety, accessibility, and spatial organization.

One of the key methods used to analyze and optimize circulation paths is space syntax. Space syntax is a set of analytical methods used to study the spatial configuration of buildings or urban areas, focusing on how spatial layouts influence movement patterns, accessibility, and social interactions (DETTLAFF, 2014). It allows architects and planners to predict human behaviours and social activities based on the spatial configuration of both indoor and outdoor environments (NATAPOV et al., 2015). Space syntax provides a configurative description of spatial networks, breaking spaces into components that can be represented as maps and graphs. This analytical method has been widely adopted in various domains such as architecture, urban design, and interior design. It helps designers foresee movement patterns and spatial interactions even before the physical development of buildings or urban systems, making the design process more evidence-based and data-driven. By integrating space syntax analysis into BIM models, designers can capture and visualize the spatial relationships and circulation logic embedded within the building design (see figure 2.3) (S. WU et al., 2004). Visualizing space syntax becomes particularly easy because these relationships are inherently embedded in BIM models. The ability to evaluate circulation design using these visual representations allows designers to understand how their models perform in terms of movement flow and spatial accessibility, ensuring that reused models maintain their intended circulation logic even when adapted to new contexts.

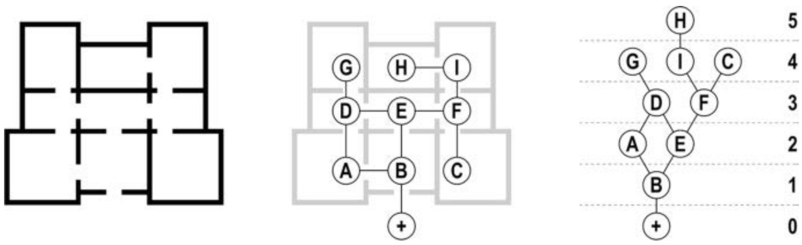


Figure 2.3: Space syntax illustrated: (1) Simple building plan, (2) annotated spatial accessibility plan, (3) justified graph of the accessibility plan (DAWES & OSTWALD, 2018)

2.2 Leveraging IFC for space-level analysis

The term openBIM refers to a collaborative approach to the design, realization, and operation of buildings, emphasizing the importance of open standards and workflows to foster collaboration for all project participants (buildingSMART INTERNATIONAL, n.d.). This approach enhances interoperability among different software tools and stakeholders, promoting a more efficient and collaborative workflow in the construction industry (SIBENIK, 2022). However, current digital collaboration practices are relatively rudimentary. This scenario is compounded by the proprietary nature of data formats, which restricts accessibility and control over information. For example, architectural models authored in older software iterations often encounter compatibility issues or data loss when accessed from current software versions (NOARDO et al., 2021). Traditional openBIM typically involves exporting and exchanging standardized files like IFC. In contrast, native openBIM aims to simplify workflows by directly utilizing shared, open-standard data formats. Furthermore, architectural data created using proprietary BIM authoring tools, as seen in traditional openBIM, often entails subscription fees, which can limit accessibility (MOULT, 2022).

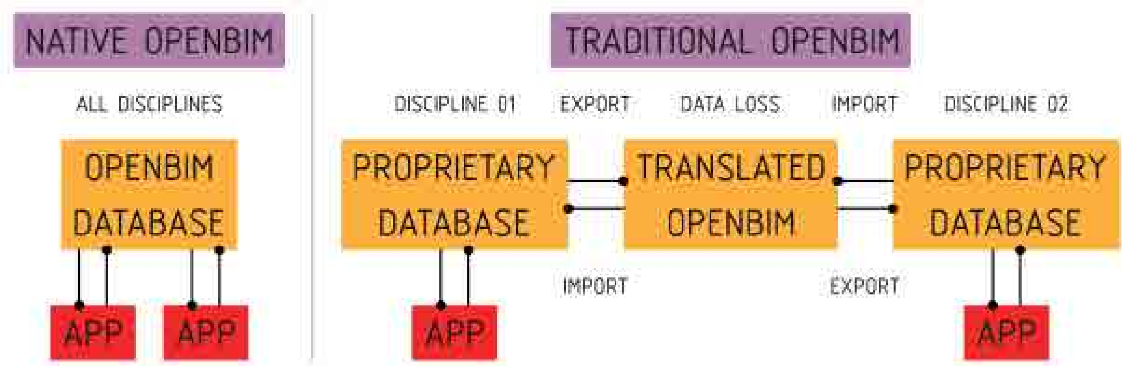


Figure 2.4: Comparison of native openBIM and traditional openBIM workflows (BONSAI DOCUMENTATION, 2024)

IFC provides the foundation to openBIM data exchanges (ALFIERI, n.d.; buildingSMART INTERNATIONAL, n.d.). IFC is a standardized, digital description of the built environment and provides a standardized data format for vendor-neutral data exchange. It is a data schema that may be used for many use cases, including representing buildings and associated activities, for example, designing, constructing, and maintenance (buildingSMART TECHNICAL, 2024b). IFC provides a detailed vocabulary for both alphanumeric information and the classification of architectural components.

However, IFC files often lack crucial information for practical use. While tools like the Solibri Model Checker are effective for automating building code compliance verification, they rely on predefined criteria that require accurate BIM model specifications (GREENWOOD et al., 2010). The performance of these tools can be negatively impacted by poor design practices, insufficient details from users, and language differences in component labelling. To improve model reuse and support advanced computations and planning, it is essential to reason IFC models semantically.

A Model View Definition (MVD) specifies a subset of the overall IFC schema that is customized for a particular data exchange scenario (buildingSMART TECHNICAL, 2024c). Different MVDs are created for specific purposes within a single IFC project, including Architectural, Structural Analysis, Energy Analysis, and more (buildingSMART TECHNICAL, 2024d). These model views ensure consistency and predictability across various software platforms for specific configurations. Depending on the exchange requirements, different types of design information—such as engineering properties, 3D geometry, and topological information—can be included in the view. There are three base MVDs that represent the foundational levels of software implementation for IFC: the Coordination View (IFC2x3), the Reference View (IFC4), and the Alignment View (IFC 4.3) (buildingSMART TECHNICAL, 2024c). Additional exchange requirements can be defined on top of these base MVDs.

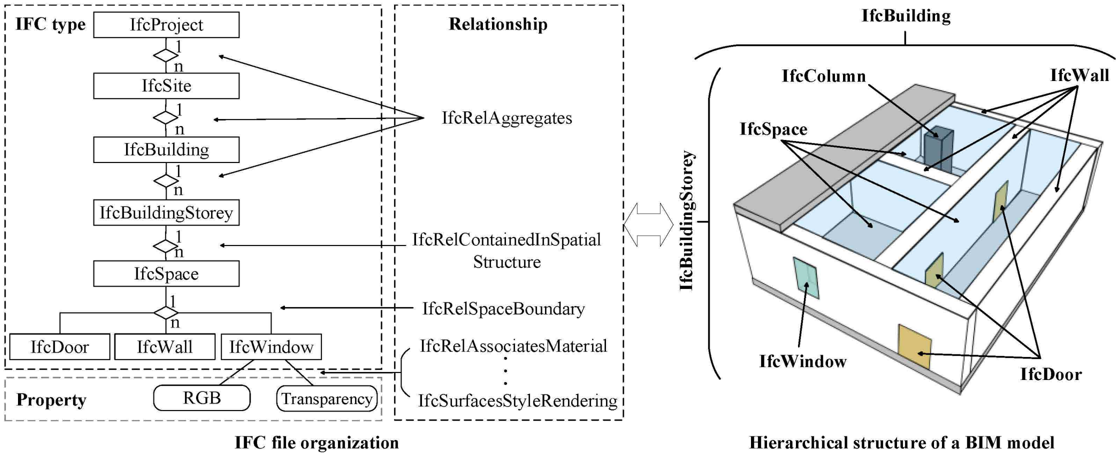


Figure 2.5: IFC Model hierarchy representation (CHEN et al., 2021)

The *IfcSpace* entity in IFC defines functional areas or volumes, representing spaces within a building model (buildingSMART INTERNATIONAL, 2024c). *IfcSpace* entities provide a fundamental structure for representing spatial data in BIM models, capturing the various areas that make up a building's layout. These spaces are organized by associating them with specific building stories, sites, or space collections. This hierarchical representation, shown in Figure 2.5, allows for effective management of spatial data across different levels of a building model (CHEN et al., 2021).

IfcRelSpaceBoundary is used to establish spatial relationships between *IfcSpace* and other building elements. This entity defines relationships between spaces and elements such as doors, walls, and openings (buildingSMART INTERNATIONAL, 2024b). By connecting *IfcSpace* entities with structural components, *IfcRelSpaceBoundary* enables an analysis of spatial interactions and accessibility pathways. This relationship modelling allows for the identification of direct and indirect access points, which is critical for understanding movement paths and connections across spaces (WEISE et al., 2011).

IFC-enabled spatial analysis has shown great potential in enhancing the evaluation of building circulation. For instance, J. K. LEE and KIM (2014) illustrate how BIM, through IFC space objects, supports computational modelling, visualization, and circulation analysis within buildings, moving from traditional agent-based to space-object-centred approaches. DIAKITE et al. (2022) developed *ifc2indoorgml*, an open-source tool that translates IFC models into IndoorGML, leveraging *IfcSpace* and *IfcRelSpaceBoundary* for spatial data processing. S. WU et al. (2004) proposed an automated method for analyzing building layout accessibility, which uses IFC to streamline design data transfer and improve accessibility assessments. BURUZS et al. (2022) proposed a framework using graph neural networks to enrich IFC BIM models with room function classifications by leveraging geometric algorithms and spatial connectivity information. Moreover, SHIN and LEE (2019) introduced the Indoor Walkability Index to quantify walkability in BIM models, helping designers assess and improve building circulation for enhanced functionality. Together, these studies underscore the versatility and analytical strength of IFC in supporting spatial analysis, accessibility, and connectivity within building models.

2.3 Space-level voxelization

Voxelization is a technique that converts continuous three-dimensional space into a discrete set of volumetric elements called voxels (volumetric pixels). This process transforms complex spatial geometries into a regular grid of cubic units, enabling efficient spatial analysis and computation (RIDZUAN et al., 2022). Voxelization involves the discretization of 3D space into consistently sized, axis-aligned cubic cells, with each voxel representing a discrete unit of spatial occupation and potentially associated attributes. Analogous to pixels in 2D imagery, voxels are the fundamental unit of 3D spatial representation, enabling regular and easily manageable spatial data structures (MITKO ALEKSANDROV & DIAKITE, 2024).

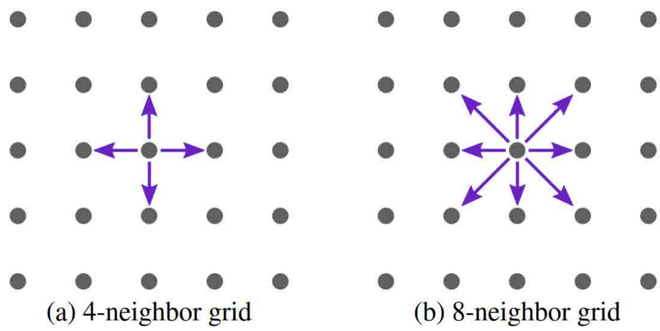


Figure 2.6: Illustration of (a) 4-neighbor and (b) 8-neighbor grid-based analytical techniques. (GOLDSTEIN et al., 2020)

Algorithms that involve geometry can generally be classified into two categories: vector-based and grid-based, depending on how they represent spatial information. The framework proposed in this thesis draws heavily from recent advancements in grid-based methodologies. Vector-based geometric representations use interconnected elements such as points, lines, curves, polygons, surfaces, and polyhedra. These methods offer the advantage of high precision and efficiency by employing dense configurations of points and surfaces in critical areas while simplifying less significant regions with fewer elements. However, practitioners often find it challenging to model only the most essential features accurately. Another advantage is that many architectural design tools already use vector-based methodologies (GOLDSTEIN et al., 2023).In contrast, grid-based geometric representations utilize a uniform array of points, each assigned specific states or characteristics. These approaches use traversal methods such as graph, tree, or array algorithms to process points by spreading information to predefined neighbouring points (Y. XU et al., 2021). In a 2D grid context, neighbouring points typically include the four adjacent points along the primary axes or potentially the eight points that include diagonal connections (GOLDSTEIN et al., 2020). This distinction is illustrated in Figure 2.6, which depicts two common grid-based neighbourhood systems: the 4-neighbour grid and the 8-neighbour grid. The 4-neighbour grid connects each grid point to its immediate horizontal and vertical neighbors, while the 8-neighbour grid extends these connections to include diagonal neighbors as well. These grid-based configurations are integral to spatial traversal and analysis algorithms, providing a structured framework for spatial connectivity and information propagation.

Grid-based analytical techniques are characterized by their simplicity and reliability. By modelling architectural spaces and physical elements through discrete 2D cells or 3D voxels, these methods avoid the geometric complications that often challenge vector-based algorithms, such as small gaps and thin overlapping regions. Moreover, while vector-based methods may require complex re-meshing to optimize model resolution, grid-based approaches provide a straightforward mechanism for adjusting the balance between computational speed and analytical precision by modifying grid spacing (GOLDSTEIN et al., 2023).

Voxelization has been applied in thermal forecasting for indoor environments to improve the spatial precision of temperature modelling. For instance, BJØRNSKOV and JRADI (2022) employs voxelized space segmentation to facilitate modular, neural network-based temperature prediction across different spatial zones. In pedestrian-hazard interaction modelling within BIM frameworks, MITKO ALEKSANDROV and DIAKITE (2024) utilize voxelization to construct a connectivity graph among entities such as IfcSpace, IfcDoor, and IfcWindow, enabling detailed hazard distribution and pedestrian movement analysis by defining navigable and uniquely classified voxels. The SpaceAnalysis tool is a notable example of a visual programming package that implements 2D grid-based spatial algorithms, and it uses a 8-neighbour grid approach for establishing connections (GOLDSTEIN et al., 2020). For thermal analysis of IFC-based building models, KRIJNEN et al. (2021) demonstrates that voxelization addresses the challenges of boundary representation geometries by providing a topologically consistent model. This consistency is crucial in retrofit scenarios, where voxelization allows for reliable before-and-after thermal performance comparisons across different design configurations.

2.4 Graph representation of building design data

Graph-based representations have been essential in architectural design, providing a means to model and analyze spatial relationships within buildings, as highlighted by EISENSTADT et al. (2024a). These representations are particularly significant within BIM, where they enable a topological approach to architectural analysis, supporting more abstract and strategic design decisions. A graph is a mathematical object composed of a finite and non-empty set of nodes, also called vertices, and a finite, unordered set of edges. Vertices represent points in the graph structure, which edges may connect (BONDY, MURTY, et al., 1976; P. ZHANG & CHARTRAND, 2006). Since graphs are dimensionally independent, visualizing their structure can often be misleading. Edges may appear to intersect when they exist entirely independently, and vertices may be positioned closely together without any direct relationship. This abstraction and deceptive dimensionality are essential to understand when relating graph structures to geometric objects. The complexity of a two-dimensional representation of graph structures increases significantly once a certain number of nodes and edges is reached. Vertices and edges in graphs are usually labelled with letters or numbers for easy reference. A key characteristic of graph edges is that they can be weighted, which creates a hierarchy among them and changes the classification of the graph from unweighted to weighted (BONDY, MURTY, et al., 1976).

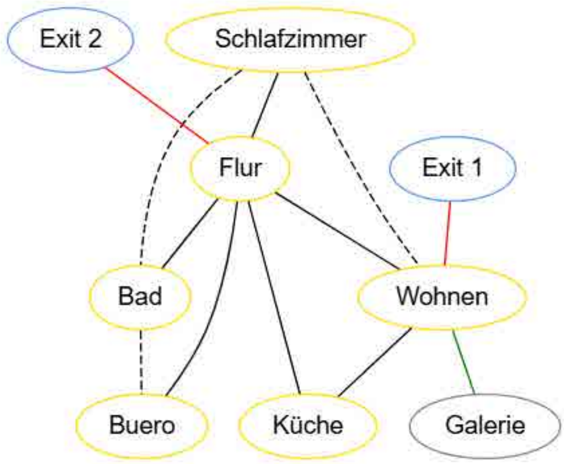


Figure 2.7: Graph-based representation of space-level relationship reasoning done on IFC model of a house

In the early stages of design, architects often use graph-based sketches like bubble diagrams to conceptualize spatial relationships and visualize connections before creating detailed floor plans (ROTH & HASHIMSHONY, 1982). Such diagrams allow designers to explore functional relationships and potential configurations without focusing on precise geometry, facilitating a flexible approach to space planning and early decision-making (H. LEE et al., 2014). Despite their value, graph representations are not yet widely adopted in BIM processes. This limited use may stem from the challenge of abstracting the IFC structure into graph form. However, the IFC's hierarchical organization, in which objects can be represented as nodes and relationships as edges, offers a foundation for more extensive graph-based integration in BIM (S. XU, 2018).

The integration of graph representations within IFC structures could enhance architectural workflows by enabling metadata such as relative distances, documenting conceptual connections, and facilitating automated analyses of spatial configurations. Such integration would support space planning, help evaluate resource efficiency, and encourage abstract thinking in design by focusing on functional relationships over specific measurements (JABI & CHATZIVASILEIADI, 2021). A topological approach in architectural analysis, emphasizing relationships over geometric details, presents distinct advantages. Topological graphs can highlight circulation paths and spatial organization without reliance on dimensions, offering organizational clarity and the flexibility to adapt geometry as needed (NATAPOV et al., 2015). Tools like TopologicPy[1], a Python API for decomposing architectural objects

[1] https://github.com/wassimj/topologicpy

into topological components, exemplify the potential of computational approaches to architectural topology. These tools enable designers to break down spaces and analyze their relationships more systematically, signalling the increasing role of computational methods in architectural design (AISH et al., 2018).

Recent research has introduced many graph-based methods in architectural design. LUDWIG ENGLERT (2024) developed a Linked Data approach using the Building Topology Ontology to identify potential building service issues early on, enabling feasibility checks for service lines and room relationships without detailed modelling. This method's compatibility with standards like ifcOWL and LBD ontologies supports integration into current workflows.

In design support, LANGENHAN et al. (2013) created a system that uses sketch-based input and subgraph matching to find similar building configurations in BIM databases, aiding iterative design through topological pattern matching. Additionally, JABI et al. (2023) explored combining TopologicPy with the Deep Graph Library, merging graph theory with machine learning to enhance spatial relationship analysis within architectural data. These advances underscore the potential of graph-based approaches for early decision-making, workflow efficiency, and design adaptability.

2.5 Graph-based analyses

2.5.1 Community detection

Community detection is a fundamental aspect of analyzing graph-based systems, as it facilitates the identification of groups of nodes that exhibit dense internal connections while maintaining sparser connections with other groups. This concept originated in social network analysis during the early 20th century and has since found applications in various fields, including biology, engineering, economics, and urban planning (FORTUNATO, 2010). Communities, clusters, or modules signify entities that share common properties or roles within the system. For instance, in the context of building graphs, these communities might correspond to clusters of spaces that serve similar functions or have strong accessibility relationships.

Real-world graph networks, such as those representing building data, exhibit characteristics that distinguish them from random graphs. Unlike the uniformity typically found in random graphs, real networks are inherently heterogeneous, characterized by diverse degree distributions and significant local clustering (M. E. NEWMAN, 2013). These variations often reveal community structures, where specific groups of nodes are densely interconnected, reflecting organized patterns in either spatial or functional arrangements. Community detection has both structural and practical significance. Structurally, it helps simplify complex graphs, uncover hierarchical relationships, and enhance the analysis of interconnected subsystems (FORTUNATO, 2010).

Although graph clustering may seem intuitive, it is not a well-defined problem. Key concepts such as community and partition lack rigorous definitions and are often fraught with ambiguities. These ambiguities frequently necessitate a combination of arbitrary decisions and common sense for resolution, resulting in a wide variety of clustering methods in the literature (JAVED et al., 2018). Notably, the identification of structural clusters is meaningful only in sparse graphs, where the number of edges (E) is comparable to the number of nodes or vertices (V). In contrast, for dense graphs (where $E \gg V$), the edge distribution becomes overly homogeneous, causing communities to lose significance and shifting the focus toward data clustering methods that depend on similarity measures or distances (FORTUNATO, 2010). One of the most widely used methods for community detection is

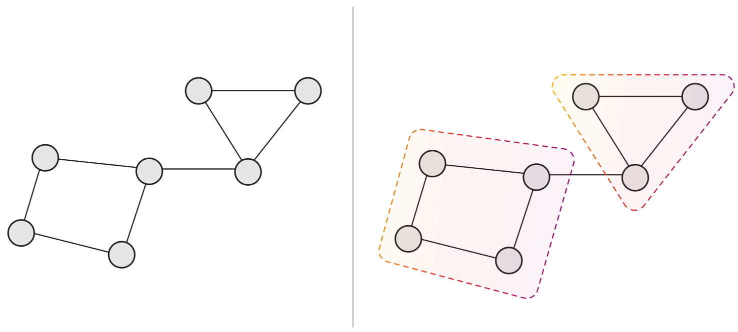


Figure 2.8: Commnity detection based on Girvan-Newman algorithm (PUSIC, 2024)

the algorithm proposed by M. E. J. NEWMAN and GIRVAN (2004). The algorithm is based on the concept of edge centrality, a measure of the importance of an edge in the graph, determined by its participation in specific processes (PROF. DR. MARKUS KRÖTZSCH, 2020). The steps of the algorithm are as follows (also illustrated in Fig. 2.8) (PROF. DR. MATTHIAS SCHUBERT, 2014):

1. Compute the centrality of all edges.
2. Remove the edge with the highest centrality. In the case of ties, one of the edges is chosen randomly.
3. Recalculate the centralities on the modified graph.
4. Repeat steps 2 and 3 until no edges remain.

M. E. J. NEWMAN and GIRVAN (2004) highlighted the concept of edge betweenness, which measures the number of shortest paths that traverse a particular edge between all pairs of nodes. Edges that connect different communities often exhibit high betweenness values as they facilitate numerous shortest paths between clusters. This type of analysis is instrumental in identifying functional zones, circulation patterns, and organizational hierarchies, thereby informing more cohesive design decisions. It illuminates the spatial divisions within a building's layout, ultimately enhancing our understanding of spatial interactions and optimizing functionality and flow (EISENSTADT et al., 2024b).

2.5.2 Centrality metrics

The concept of centrality was initially developed within the field of social sciences and subsequently applied to various other disciplines, including biology, urban planning, and spatial science. Within social networks, particular structures have become the focus of study, encompassing human groups, organizations, communities, markets, society, and the global system (NAMTIRTHA et al., 2023). The analysis of social networks centres on interpersonal relationships, a discipline referred to as sociometry. Centrality pertains to the position of an individual or organization that possesses a strategic advantage in influencing or controlling the community or organization in question. Such an individual or organization is regarded as central. Centrality can be defined for any node within a network, while centralization is used to characterize the network as a whole (BORGATTI & EVERETT, 2006).

FREEMAN (1977) formalized measures of centrality based on graph theory, initiating the conceptualization of social networks as simple graph structures. Key terms such as adjacency, degree, geodesic, path, and cycle were defined, forming the foundation of centrality theory. Freeman subsequently identified and simulated various centralities using straightforward patterns. For instance, within a star-shaped configuration, individuals situated at the centre are structurally more central. These basic point centralities serve as the groundwork for the formalization of graph centralities.

Numerous centrality measures exist within the existing literature; however, this research concentrates on betweenness centrality. Other centrality measures, including degree and closeness centrality, will be discussed briefly to elucidate the rationale for selecting betweenness centrality as the most pertinent concept for this study. Degree centrality assesses the ratio between the number of nodes directly linked to specific nodes and the overall number of nodes within the network (PENG et al., 2018). In the context of social networks, degree and closeness centrality signify how efficiently the information can reach an individual, whereas, in spatial science, they indicate the accessibility of one location from others. Betweenness centrality, on the other hand, quantifies the significance of a node in facilitating connections among other nodes. It is calculated by determining the number of shortest paths traversing a node divided by all possible shortest paths within the network. Consequently, an increased occurrence of shortest paths intersecting a node correlates with a higher value of that node's betweenness centrality (NOURIAN, 2016). Moreover, betweenness centrality is also crucial for analyzing circulation and accessibility in architectural layouts (NOURIAN, 2016). The following are the centrality metrics briefly explained (J. ZHANG & LUO, 2017):

- Degree Centrality: This metric is defined as the quantity of edges connected to a node within the graph. As illustrated in Fig. 2.9(A), the central node exhibits a degree of 6.

- Closeness Centrality: Closeness centrality refers to the average shortest distance between a given node and all other reachable nodes within the graph. As shown

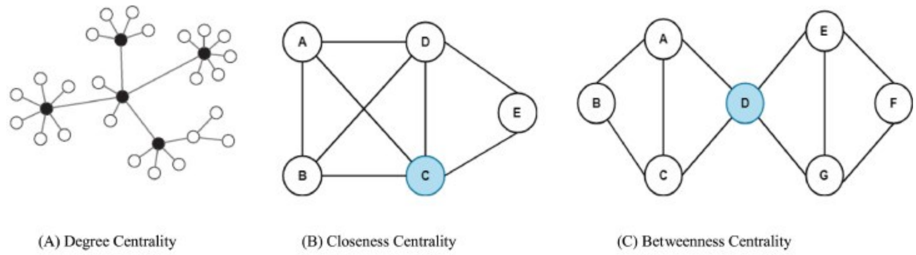


Figure 2.9: Centrality measures illustrated (A) degree centrality; (B) closeness centrality; (C) betweenness centrality (PENG et al., 2018)

in Fig. 2.9(B), node C demonstrates a higher closeness centrality, indicating its proximity to all other nodes within the graph.

- Betweenness Centrality: Betweenness centrality quantifies the frequency with which a vertex appears on the shortest paths between other nodes in the network, effectively serving as a connective bridge. In Fig. 2.9(C), it is evident that node D has the highest betweenness centrality, as it is included in the greatest number of shortest paths.

Chapter 3

Methodology

In this chapter, the proposed enrichment approach is outlined, aiming to reason the space-wise circulation design rationale derived from the design data extracted from the IFC model. As illustrated in Figure 3.1, the approach comprises the following main components: 1) IFC data extraction and processing, 2) Space-level relationship reasoning, and 3) Graph-based circulation path reasoning. The results of the proposed methodology encompass the following:

- Multi-level community detection: The identification of communities within the space-level graph across different levels of granularity, including building-wide communities and floor-specific communities.

- Centrality analyses: Performing centrality analyses at both the floor level and the community level to assess the significance of spaces within their respective contexts.

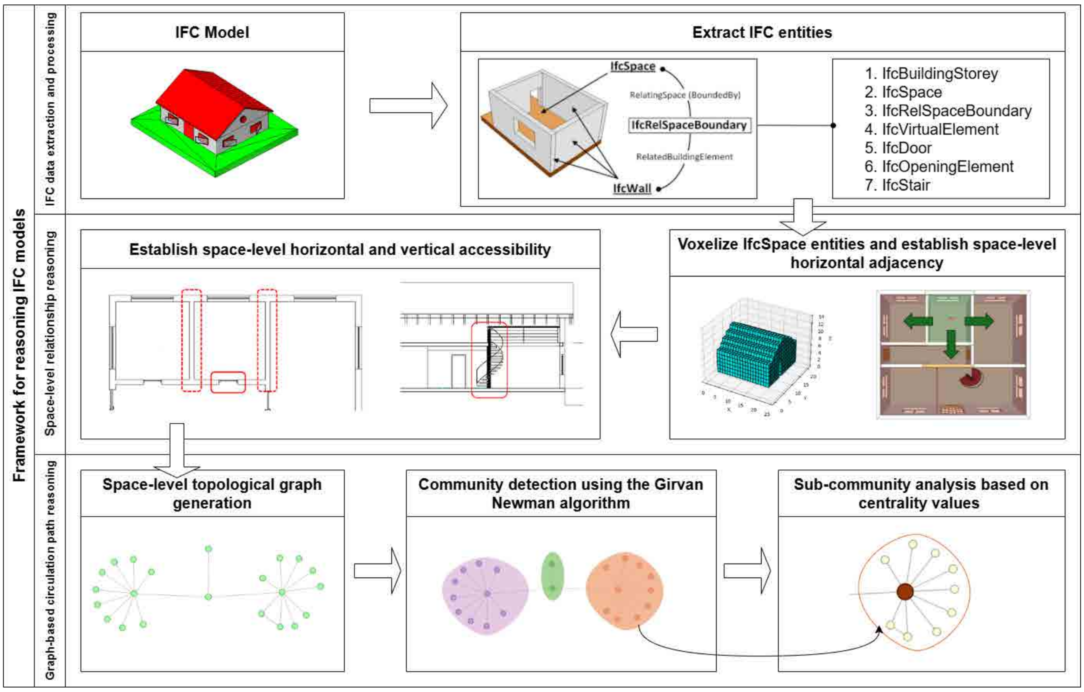


Figure 3.1: Proposed approach for reasoning IFC models for space-level circulation design rationale

3.1 Input information

3.1.1 Input IFC data model

This study focuses on specific entities within the IFC schema that are crucial for understanding space-level connectivity relationships within buildings. An appropriate MVD is essential to include key entities when analyzing these relationships. Therefore, the Coordination View (IFC 2x3) or the Reference View (IFC 4/4.3) should be adopted as the chosen MVD (buildingSMART Technical, 2024c). In this context, entities such as *IfcRelSpaceBoundary* and *IfcSpace* are fundamental. They explicitly model the connectivity relationships between related elements (like *IfcDoor* and *IfcOpeningElement*) and spaces (*IfcSpace*). Capturing these entities in the selected MVD supports comprehensive workflows for space-level analysis.

The key entities required for this proposed framework include *IfcBuildingStorey, IfcSpace, IfcRelSpaceBoundary, IfcVirtualElement, IfcDoor, IfcOpeningElement,* and *IfcStair*.

3.1.2 Topological relationship terminology

This section clarifies the terms connectivity, adjacency, and accessibility as used in this study. While these concepts are often used interchangeably in existing literature, they have distinct meanings in the context of our analysis. Understanding these specific definitions is essential for maintaining consistency throughout the study.

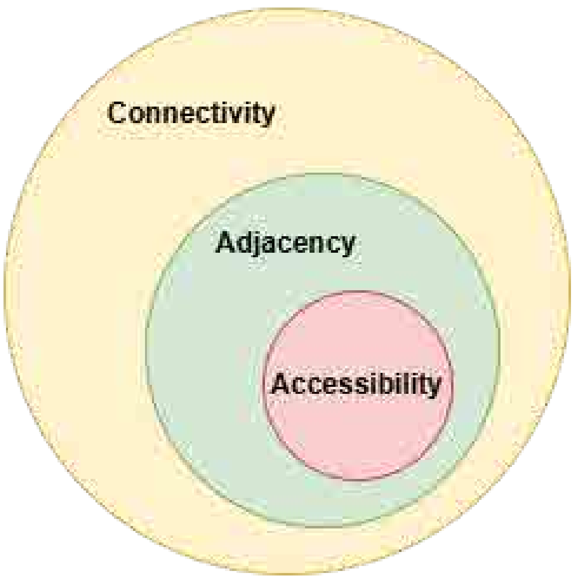


Figure 3.2: Relationship among connectivity, adjacency, and accessibility

Connectivity

Connectivity refers to the concept that describes how different spatial components within a system are linked together. It provides a broad perspective on spatial relationships, including both adjacency and accessibility. Understanding connectivity is essential for analyzing the spatial network of a building and determining how its various components interact to facilitate movement and functionality. In this study, we use connectivity as an overarching term that encompasses both adjacency and accessibility (See Figure 3.2). Space-level connectivity reflects not only physical proximity but also functional interactions, offering a comprehensive view of spatial relationships.

Connectivity also considers the relationship between internal spaces and external environments, often referred to as spatial connectivity to the outside. This is typically realized through access points such as exit doors, which provide a crucial link between a building's interior and the exterior environment. This type of spatial connectivity is illustrated in Figure 3.3.

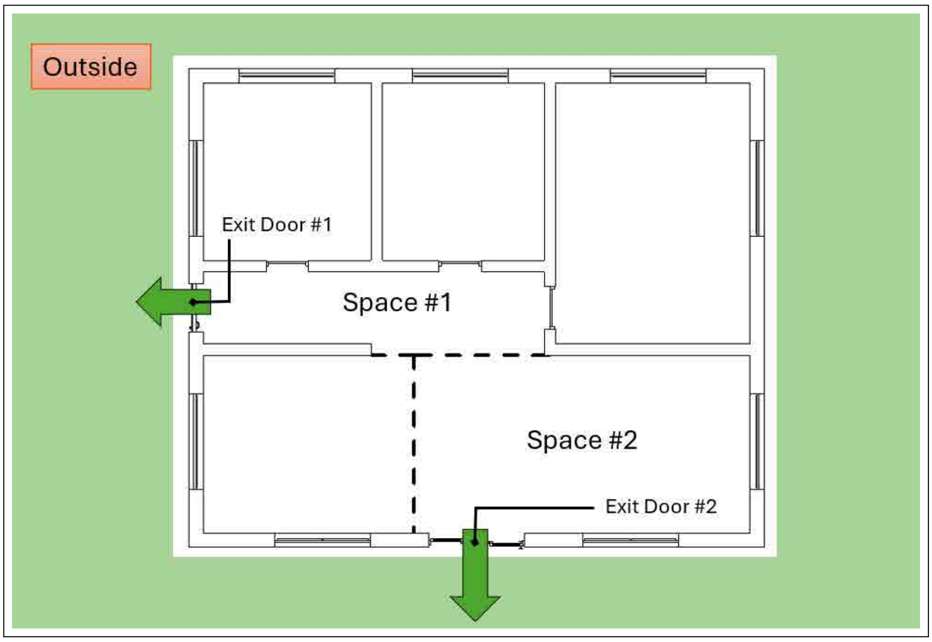


Figure 3.3: Space-level connectivity between internal space and external environment

Horizontal adjacency

Adjacency refers to the direct physical closeness between two spatial entities, indicating that they are neighbouring or share a boundary. This concept is essential for understanding how spaces are organized within a building; however, in the context of this thesis, more emphasis is laid on horizontal adjacency. Horizontal adjacency can be defined and interpreted through various criteria:

1. Shared Wall: Two spaces are considered adjacent if they share any part of a common wall or boundary, regardless of its size.
2. Proximity: Spaces that are immediately next to each other without any intervening area are deemed adjacent.

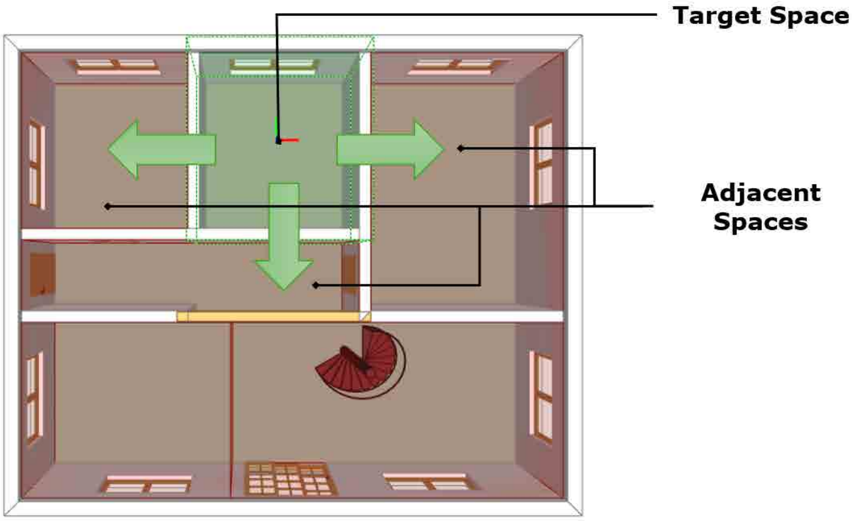


Figure 3.4: Adjacency illustrated

3. Functionality: The functional relationships between spaces also influence adjacency. Spaces designed for complementary purposes and intended to be easily accessible are more likely to be considered adjacent (for example see Fig. 3.5). Functional adjacency is explored further through network analysis in later sections.

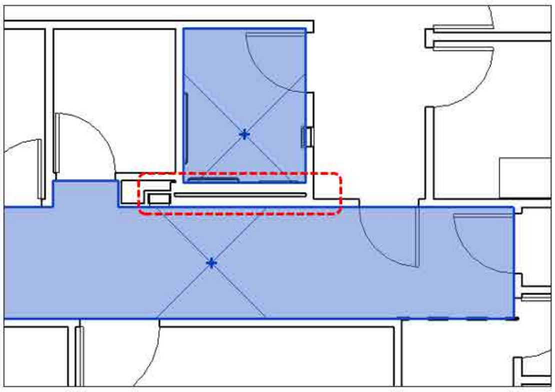


Figure 3.5: Illustration of horizontal adjacency with two thin partition walls separating two rooms.

Accessibility

Accessibility refers to the ability to transition from one space to another, focusing on the practical aspects of spatial connections. It emphasizes how movement is facilitated within a building, thereby ensuring functional and efficient circulation. Accessibility is divided into two main types: horizontal accessibility and vertical accessibility.

Horizontal accessibility Horizontal accessibility relates to movement between spaces on the same floor and can be achieved through the following means:

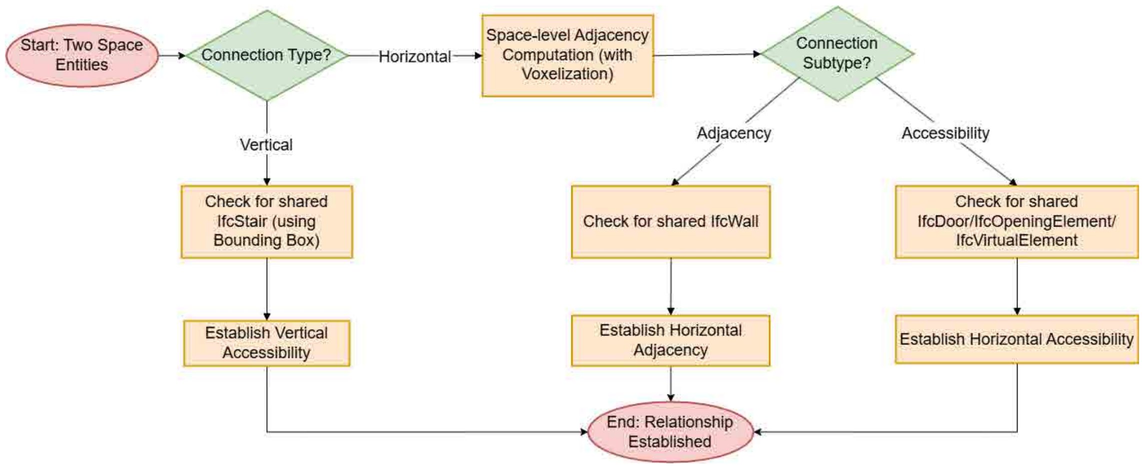


Figure 3.6: Developed approach for establishing space-level relationship reasoning

1. Through Doors: Spaces connected by doors allow for direct and controlled access, establishing clear entry and exit points between rooms or areas.
2. Unobstructed Transitions: Spaces are considered horizontally accessible when there are no physical barriers between them, such as walls or partitions.
3. Through Openings in Walls: Openings in walls allow access between spaces without the need for a door.

Vertical accessibility Vertical accessibility pertains to movement between different floors of a building and is supported by the following elements:

1. Stairs: Stairs provide direct vertical movement and serve as a primary means of connecting multiple floors in most buildings.
2. Elevators: Elevators enable efficient vertical circulation, especially for individuals with mobility challenges, offering a crucial alternative to stairs.

3.2 Space-level relationship reasoning

This section presents the process of analyzing IFC models to extract space-level data and establish space-level topological relationships among circulation design elements within buildings. To analyze these circulation design-related IFC elements, a custom Python script is developed using the IfcOpenShell library, which enables direct extraction of IFC data. The script processes fundamentally the space-level entities and space-boundaries based on the IfcRelSpaceBoundary relationships. Understanding this spatial morphology gives us a clear insight into how the layout of rooms influences the flow of movement within a building. By breaking down the building into different sections (such as rooms or hallways), we can construct a map that visualizes how these sections are interconnected. The approach for reasoning is illustrated in Fig. 3.6.

The establishment of space-level relationships focuses on *IfcSpace* entities, consolidated into three types of connections critical for understanding connectivity and circulation flow:

1. Horizontally accessible spaces: Two space entities have a direct and unobstructed connection. The point of interface between the two entities can be *IfcDoor, IfcOpeningElement, or IfcVirtualElement*. This connection typically indicates that the spaces are adjacent and/or share a common boundary, allowing immediate access.

2. Horizontally adjacent spaces: These spaces can be accessed from the specified space, but they require passing through one or more intermediate spaces. The interface between the two space entities is usually a *IfcWall*.

3. Vertically accessible spaces: Two spaces are connected through *IfcStair* or Elevators (*IfcTransportElement*).

The subsequent section delves into detail about how the individual connections are derived.

3.2.1 Space-level adjacency reasoning

The space-level adjacency reasoning process aims to identify the topological relationships between space-level entities, such as rooms or corridors. Drawing inspiration from recent work in spatial topological analysis (BJØRNSKOV & JRADI, 2022), the methodology involves utilizing a voxel-based spatial discretization of the geometry of space entities extracted from the IFC file. This section provides an overview of the framework used to reason space-level adjacency, which can be broken down into three steps (see fig. 3.7): 1) Geometry extraction, 2) Voxel grid-based analysis, 3) Adjacency detection.

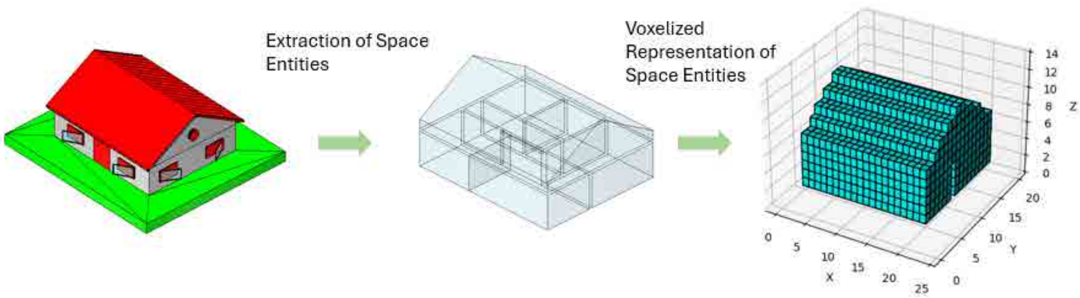


Figure 3.7: IfcSpace entities representation using voxels

Geometry extraction

After extracting the 3D geometry of each space S_k, the next step involves voxelizing the building into a 3D grid V, where each voxel represents a portion of usable space or is designated as "neutral" if outside these areas. The voxelization begins by defining a bounding box B that encloses all spaces. To determine the B, the spatial limits of the building are assessed along the x, y, and z axes. For each space entity, the smallest and largest values for the x, y, and z coordinates are extracted, and these values are organized into lists to compute the overall minimum and maximum coordinates.

The grid resolution is set by a user-defined voxel size v. Using this, a voxel grid G is created, where each voxel v_{ijk} is indexed by its coordinates along x-, y-, and z. The center c of each voxel is checked to determine if it lies within the geometry of any space S_k. Voxels with centers inside a space are assigned the corresponding space index k, while those outside are marked as "neutral." The result is a 3D voxel array representing the building's spaces and surrounding areas. Each voxel is indexed to indicate whether it belongs to a specific space or the neutral zone.

Voxel grid generation

After extracting the 3D geometry of each space S_k, the next step involves voxelizing the building into a 3D grid V, where each voxel represents a portion of usable space or is designated as "neutral" if outside these areas. The voxelization begins by defining a bounding box B that encloses all spaces. To determine the B, the spatial limits of the building are assessed along the x, y, and z axes. For each space entity, the smallest and largest values for the x, y, and z coordinates are extracted, and these values are organized into lists to compute the overall minimum and maximum coordinates. The process is detailed in Algorithm 1.

Algorithm 1 Voxel grid generation algorithm

Input: S, v
Output: V (Voxel grid with space indices)
$V \leftarrow \emptyset$ ▷ Initialize empty voxel grid
$B \leftarrow$ CalculateBoundingBox(S) ▷ Compute bounding box around all spaces
$G \leftarrow$ GenerateVoxelGrid(B, v) ▷ Generate grid based on bounding box and voxel size
for each voxel $v_{ijk} \in G$ **do**
    $c \leftarrow$ Center(v_{ijk}) ▷ Calculate center of current voxel
    for each space $S_k \in S$ **do**
        if $c \in S_k$ **then** ▷ Check if voxel center is inside space geometry
            $v_{ijk} \leftarrow$ AssignSpaceIndex(S_k) ▷ Assign space index to voxel according to space entity
        else
            $v_{ijk} \leftarrow$ Neutral ▷ Mark voxel as neutral if outside usable building space
        end if
    end for
end for
return V

The grid resolution is set by a user-defined voxel size v. Using this, a voxel grid G is created, where each voxel v_{ijk} is indexed by its coordinates along x-, y-, and z. The center c of each voxel is checked to determine if it lies within the geometry of any space S_k.

Voxels with centers inside a space are assigned the corresponding space index k, while those outside are marked as "neutral."

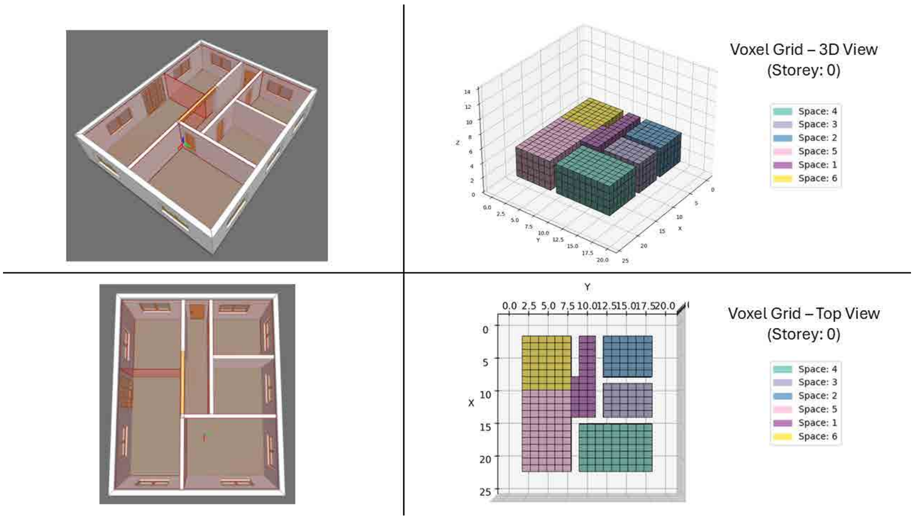


Figure 3.8: Visual comparison of IFC house model (top left, 3D view; bottom left, top view) and its voxel grid representation with v = 0.5m (top right, 3D view; bottom right, top view).

This method is applicable to both rectangular and non-orthogonal spaces, such as L-shaped corridors or irregularly shaped rooms. While the bounding box B provides an outer limit to the collective voxel grids, the precise shape of each space is accounted for during the voxel-to-space assignment. This is achieved through geometry intersection checks that test whether the voxel's center lies within the actual geometry of S_k, ensuring that only the voxels matching the actual shape of the space are assigned its index. It is important to note that the proposed method does not rely on the Manhattan world assumption. While the Manhattan world assumption typically assumes that spaces are orthogonally aligned along grid axes, this method is designed to handle both orthogonal and non-orthogonal geometries. For instance, it can process L-shaped corridors or irregularly shaped rooms, where spaces may not be strictly aligned along orthogonal axes. The result is a 3D voxel array representing the building's spaces and surrounding areas. Each voxel is indexed to indicate whether it belongs to a specific space or the neutral zone.

Horizontal adjacency detection

In this step, the algorithm analyzes the *voxel grid* V to detect space-level adjacencies between different space entities. The algorithm works by comparing each voxel v_{ijk} in the voxel grid with its adjacent voxels in the x-, y-, and z-directions, which correspond to the adjacent positions $(i \pm 1, j, k)$, $(i, j \pm 1, k)$, and $(i, j, k \pm 1)$, respectively. This procedure is outlined in Algorithm 2.

If two adjacent voxels, say v_{ijk} and $v_{i+1,j,k}$, belong to different spaces (i.e., have different space indices), this indicates a potential adjacency between those spaces (see fig. 3.9). The adjacent voxel detection is refined by ensuring that only *non-neutral* voxels are

Algorithm 2 Adjacency detection algorithm

Input: V, n
Output: A
$A \leftarrow \emptyset$ ▷ Initialize empty adjacency dictionary
for each voxel $v_{ijk} \in V$ **do**
  if $v_{ijk} \neq$ Neutral **then** ▷ Skip neutral voxels
    for each adjacent voxel v_{pqr} within range n **do**
      if $v_{pqr} \neq$ Neutral and $v_{ijk} \neq v_{pqr}$ **then** ▷ Check if adjacent voxel belongs to a different space
        $A \leftarrow$ AddAdjacency(v_{ijk}, v_{pqr}) ▷ Add adjacency between spaces
      end if
    end for
  end if
end for
$A \leftarrow$ RemoveDuplicates(A) ▷ Remove duplicate and self-adjacencies
return A

considered. Voxels marked as neutral (outside usable building space) are excluded from adjacency checks.

To further ensure accurate adjacency detection, a search for *adjacent voxels* is extended to a predefined range of n-search-blocks, where n is the user-defined maximum number of adjacent voxel layers to check. The algorithm searches in all three directions within this range, looking for voxel pairs that belong to different spaces but are space-wise adjacent. After adjacency pairs are identified, the algorithm filters out any duplicates and self-adjacencies (where a space is adjacent to itself), resulting in a clean adjacency mapping. The adjacency data is refined by filtering out connections between spaces on different storeys, using metadata that indicates the storey of each space.

The final output of the algorithm is an *adjacency dictionary*, A, where each key is a space index S_k and its corresponding value is a list of space indices representing the adjacent spaces. Neutral spaces are excluded from this dictionary to focus only on meaningful adjacencies between usable building spaces.

3.2.2 Determination of space-level topological relationships

The determination of space-level topological relationships assesses how spaces (represented as *IfcSpace* entities) are interconnected based on architectural features such as doors, walls, and stairs. This analysis relies on a previously computed adjacency dictionary, denoted as A. Through this examination, three primary types of connections between spaces are identified: horizontally accessible (H_{acc}), horizontally adjacent (H_{adj}), and vertically accessible (V_{acc}). Each of these relationships is defined according to the specific criteria outlined in the IFC schema.

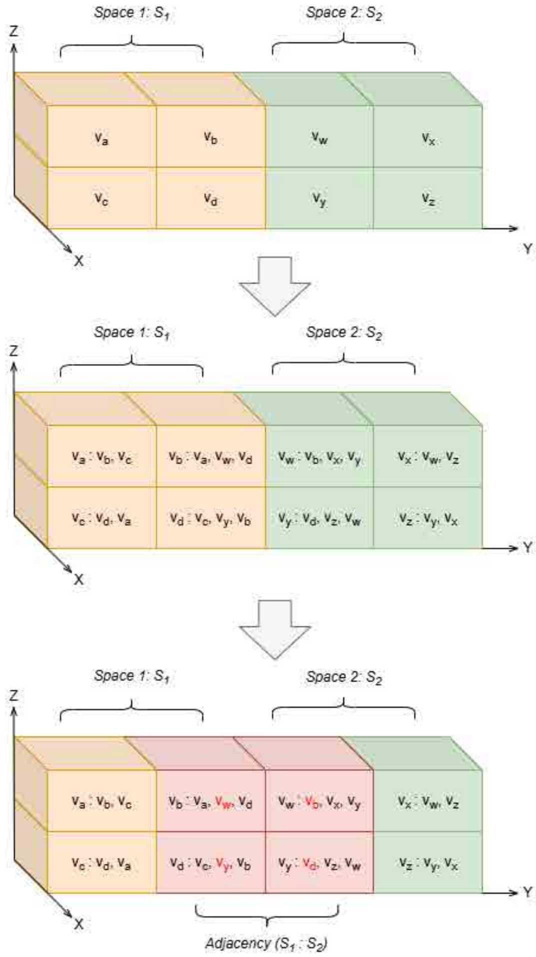


Figure 3.9: Illustration of horizontal adjacency detection

Horizontal accessibility

Horizontal accessibility between spaces can be established through three methods involving architectural components like doors, openings, or virtual elements.

- Through doors: In this scenario, two *IfcSpace* entities are directly connected by an *IfcDoor*. The connection is identified through the *IfcRelSpaceBoundary* relationship, which links the spaces to the door. This space-to-space relationship is already a part of the adjacency dictionary. When two spaces are found to be adjacent, and one is linked to a door, it confirms that there is horizontal accessibility between them.

- Through openings: The second method for establishing horizontal accessibility involves openings within walls. In this case, an *IfcOpeningElement* creates a void in an *IfcWall* that connects two adjacent spaces. The relationship chain starts with the *IfcRelSpaceBoundary*, which links the *IfcSpace* to the *IfcWall*. The wall is then linked to the *IfcOpeningElement* through another relationship called *IfcRelVoidsElement* (see Fig. 3.10). For this connection to be valid, a specific condition must be satisfied: $\min(Y_{\text{IfcRectangleProfileDef}}) = \min(Y_{\text{IfcOpeningElement}})$ where, $Y_{\text{IfcRectangleProfileDef}}$ represents the minimum Y-coordinate of the profile that defines the opening's geometry, and $Y_{\text{IfcOpeningElement}}$ corresponds to the minimum Y-coordinate of the opening itself. This condition ensures that the opening is located at the base of the wall (and is not a window element), making it suitable for connecting the two spaces.

- Through virtual element: The third method involves *IfcVirtualElement* entities, which represent non-physical boundaries. In this case, the *IfcSpace* entities are linked to the *IfcVirtualElement* through a second-level *IfcRelSpaceBoundary* relationship.

Figure 3.10: Relationship between IfcSpace and IfcOpeningElement

Horizontal adjacency

Horizontal adjacency connections between spaces are established when two spaces are adjacent but separated by a physical barrier, such as a wall. In this case, the relationship involves the *IfcWall* element. Two *IfcSpace* entities are linked to a wall through the *IfcRelSpaceBoundary* relationship, which confirms that the spaces are next to each other but not directly accessible without moving through an additional space (see Fig. 3.11). This form of connection indicates that although the spaces are in close proximity, there is no direct passage between them. Occupants are required to navigate through intermediate spaces in order to reach their destination.

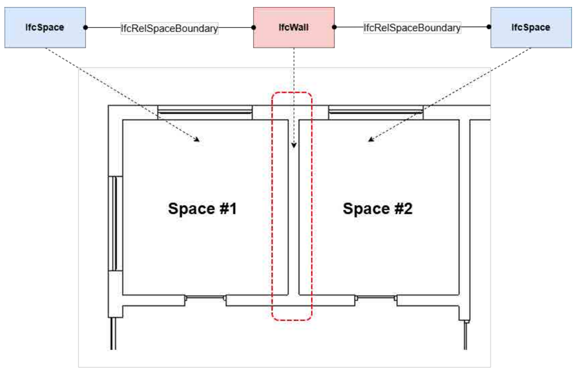


Figure 3.11: Space boundary relationship representation of wall element

Vertical accessibility

Vertical accessibility connections between spaces are established by stairs that facilitate movement between floors. To confirm such connections, we analyze the bounding boxes of the *IfcStair* and the connected *IfcSpace* entities. The bounding box of the *IfcStair* is denoted as B_{IfcStair}, while the bounding boxes of the connected spaces are denoted as B_{IfcSpace_1} and B_{IfcSpace_2}. A vertical connection exists when (also see fig. 3.12):

$$B_{\text{IfcStair}} \cap B_{\text{IfcSpace}_1} \neq \emptyset \quad \text{and} \quad B_{\text{IfcStair}} \cap B_{\text{IfcSpace}_2} \neq \emptyset$$

It is important to note that this analysis method has a drawback when the stairway intersects with multiple *IfcSpace* entities on the same horizontal level. Hence, such cases shall be excluded.

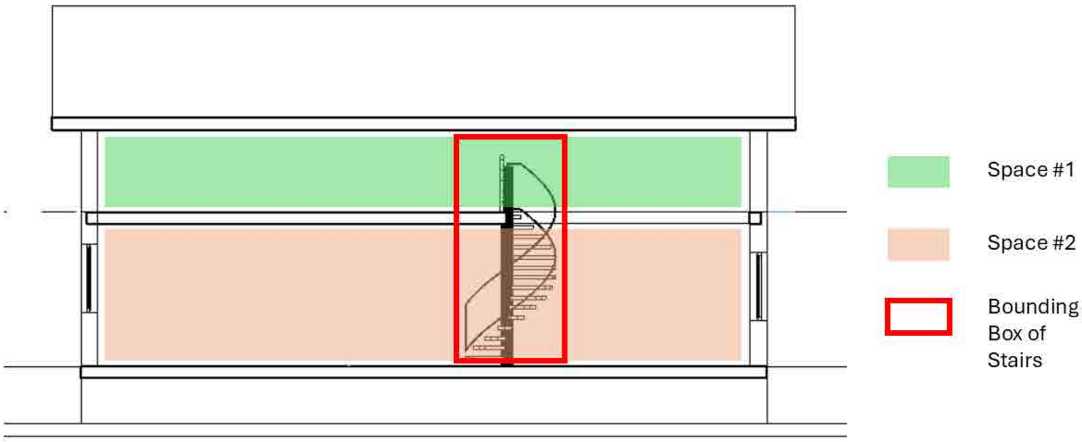


Figure 3.12: Establishing vertical accessibility between two spaces

3.3 Graph-based reasoning on circulation paths

Following the space-level analysis and topological relationships, the data is transformed into a graph-based representation to facilitate visualization and further analysis. The space-level relationships are modelled as an undirected graph $G = (V, E)$, where V represents the set of vertices corresponding to individual spaces, and E represents the set of edges corresponding to the relationships between spaces. For any vertex $v \in V$, a set of attributes A_v is defined:

$$A_v = id_v, type_v, level_v$$

where id_v is the Globally Unique Identifier (GUID) (buildingSMART Technical, 2024a) of the space, $type_v$ denotes the *LongName* (which contributes solely to the labelling of nodes and is not used in any further graph-based analysis) (buildingSMART International, 2024c), $level_v$ indicates the floor level as per *IfcBuildingStorey*. Similarly, for each edge $e \in E$ connecting vertices v_i and v_j, a set of attributes A_e is defined:

$$A_e = \text{type}_e, \quad \textit{type}_e \in \{H_{\text{acc}}, H_{\text{adj}}, V_{\text{acc}}\}, \quad \text{where } \textit{type}_e \text{ indicates the relationship type.}$$

The figure 3.13 provides an illustrative example of a graph-based representation of space-level relationship reasoning conducted on an IFC model of a house (the dotted lines represent the virtual room separation lines or *IfcVirtualElement*). This graphical representation visually encodes the space-level relationships among various spaces within the building (computed in Section 3.2.1 and 3.2.2), emphasizing their space-level connectivity.

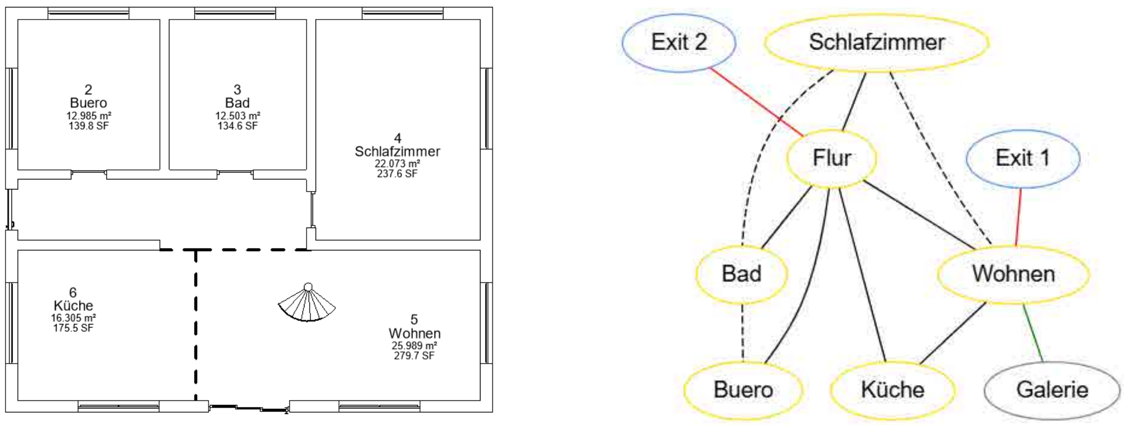


Figure 3.13: Graph-based representation of space-level relationship (right) reasoning done on IFC model of a house (left)

In this graph, vertices ($v \in V$) symbolize the space entities from the IFC model. The vertices are colour-coded to indicate the level ($level_v$) of each space; for example, yellow represents the ground floor, while grey denotes the first floor. This colour-coding helps visually distinguish between different building levels, with the exception of exit nodes, which are solely intended to represent exits and enhance graph-based analytics. The edges ($e \in E$) in the graph capture the relationships between spaces and are characterized by their attributes A_e. The figure represents these edges in the following ways:

- Solid edges indicate $type_e = H_{\text{acc}}$, showcasing horizontal accessibility.
- Dotted edges correspond to $type_e = H_{\text{adj}}$, illustrating horizontal adjacency.
- Red edges signify $type_e = V_{\text{acc}}$, representing vertical accessibility.
- Green edge highlights a specific instance of spatial connectivity where an internal space connects to the external environment, such as an exit door leading outside.

3.3.1 First-level community detection

At its core, the main task of all clustering algorithms is the automatic segmentation of provided data entities into coherent groups (clusters) to enable the exploration of cluster data separately from the entire dataset. Formally, given a set of spaces $S = s_1, s_2, ..., s_n$, the clustering process aims to find a partition $C = c_1, c_2, ..., c_k$ such that:

$$\bigcup_{i=1}^{k} c_i = S \text{ and } c_i \cap c_j = \emptyset \text{ for } i \neq j$$

where each cluster c_i represents a group of spatially or functionally related spaces. For architectural space-wise analysis, hierarchical clustering methods like Girvan-Newman are suitable because they do not require a predefined number of clusters, reveal the hierarchical structure of space-wise organization, and can identify both strong and weak connections between spaces.

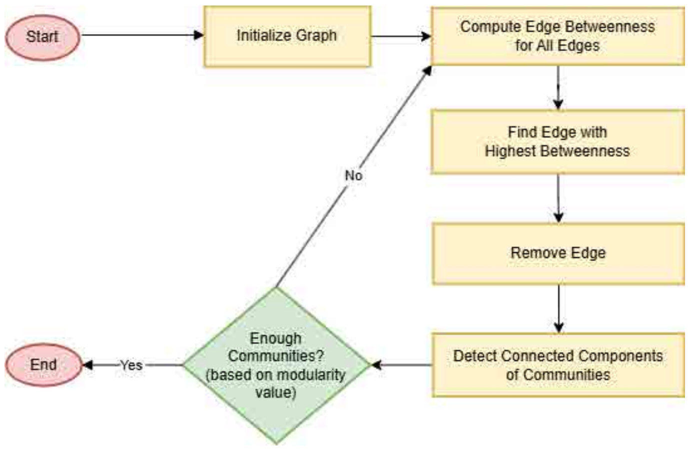


Figure 3.14: Flowchart of Girvan-Newman algorithm used for community detection

The algorithm operates on the principle of iteratively removing edges with high betweenness centrality, which act like bridges between communities. This process continues until the network breaks down into individual communities. The composition of these communities and their number, based on the highest modularity value achieved, are then considered. A visual representation of this process is provided in Fig. 3.14. The edge betweenness centrality $C_{betw}(e)$ for an edge e is defined as:

$$C_{betw}(e) = \sum_{s,t \in V} \frac{\sigma_{st}(e)}{\sigma_{st}}$$

where σ_{st} is the total number of shortest paths between vertices s and t, and $\sigma_{st}(e)$ is the number of those paths passing through edge e. Community detection in a graph involves several key steps aimed at identifying spatial clusters based on the graph's structure. This can be achieved by progressively removing edges with high centrality and observing the resulting connected components.

Edge filtering

In the first step of the process, the graph undergoes pre-processing to remove edges representing indirect connections, such as walls, as these are not relevant for direct community detection. The specific pre-processing approach depends on the level and type of analysis. In Global edge analysis, all edge types, including horizontal accessibility (H_{acc}), horizontal adjacency (H_{adj}), and vertical accessibility (V_{acc}), are retained without filtering, resulting in a graph $G = (V, E)$, where E includes all edge types. In Horizontal adjacency edge analysis, performed at the floor level, only horizontal adjacency edges are considered, and vertical accessibility edges are filtered out, resulting in a subgraph $G' = (V', E')$, where $E' = \{e \in E : \text{type}_e \neq V_{\text{acc}}\}$. Further restricting the analysis to Horizontal accessibility edges excludes both horizontal adjacency and vertical accessibility edges, producing a filtered subgraph $G'' = (V'', E'')$, where $E'' = \{e \in E : \text{type}_e = H_{\text{acc}}\}$.

Calculating betweenness centrality and iterative edge removal

For each edge e in the edge-filtered graph, the betweenness centrality $C_{\text{betw}}(e)$ is calculated. Betweenness centrality identifies edges that often occur on the shortest paths between nodes. After the centrality is computed, the edges are sorted in descending order of their betweenness centrality scores. Once ranked by their centrality, the algorithm iteratively removes the edge with the highest centrality from the graph. After each edge removal, the betweenness centrality of the remaining edges is recalculated to account for the changes in the graph structure. This process is repeated until a stopping criterion is met, as depicted in Fig. 3.15, where the removal of edges with the highest betweenness values is illustrated.

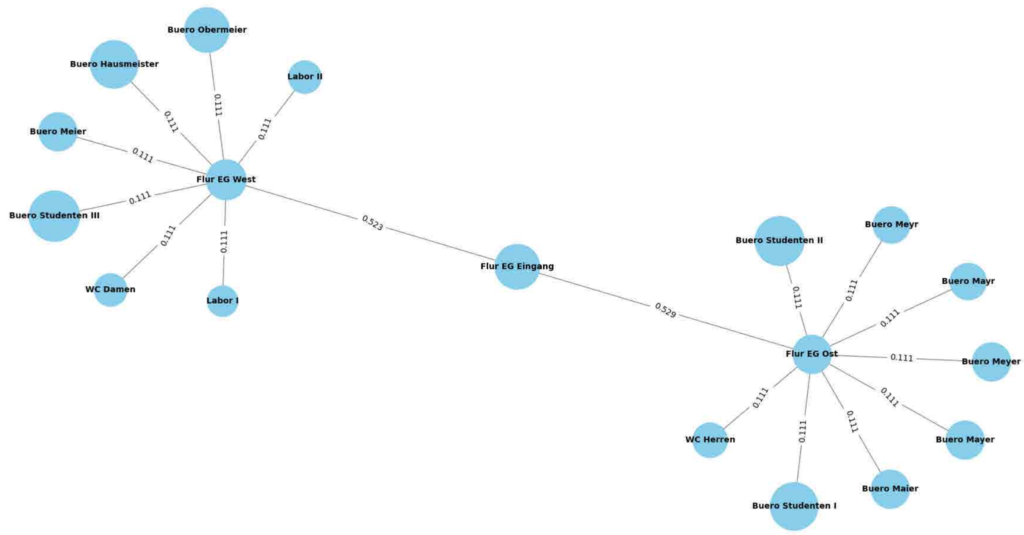


Figure 3.15: Betweenness centrality values calculated and edges with highest betweenness removed

The stopping criterion is determined based on the modularity value Q, which measures the quality of the detected community structure. It can also be expressed as:

$$Q \propto \sum_{s \in S} [(\#\text{edges within cluster } s) - (\text{expected \# edges within cluster } s)]$$

where S represents the set of all communities in the graph. The expected number of edges between nodes i and j of degrees k_i and k_j is given by $\frac{k_i k_j}{2m}$. This expression emphasizes that modularity evaluates how much the actual number of edges within a group exceeds the expected number of edges if edges were distributed randomly. The modularity formula is:

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j)$$

where:

- A_{ij} is the adjacency matrix of the graph.

- k_i and k_j are the degrees of nodes i and j.

- m is the total number of edges in the graph.

- $\delta(c_i, c_j)$ is 1 if nodes i and j are in the same community, and 0 otherwise.

The stopping criterion is reached when the modularity Q is maximized. The identified communities at this stage represent the most meaningful community structure. The graph illustrated in fig. 3.16 showcases the modularity trend during the Girvan-Newman community detection process for Fig. 3.15. The x-axis represents the number of edges removed from the graph, while the y-axis shows the corresponding modularity value at each step. The maximum modularity observed (in this case $Q = 0.4411$) before the steady decline represents the optimal point for community detection. This analysis is crucial as it ensures that the detected communities are not arbitrary but are, instead, well-defined clusters based on the graph's structure. The modularity trend thus guides the process by showing where the separation of communities is strongest, enabling a more meaningful detection of the underlying structure.

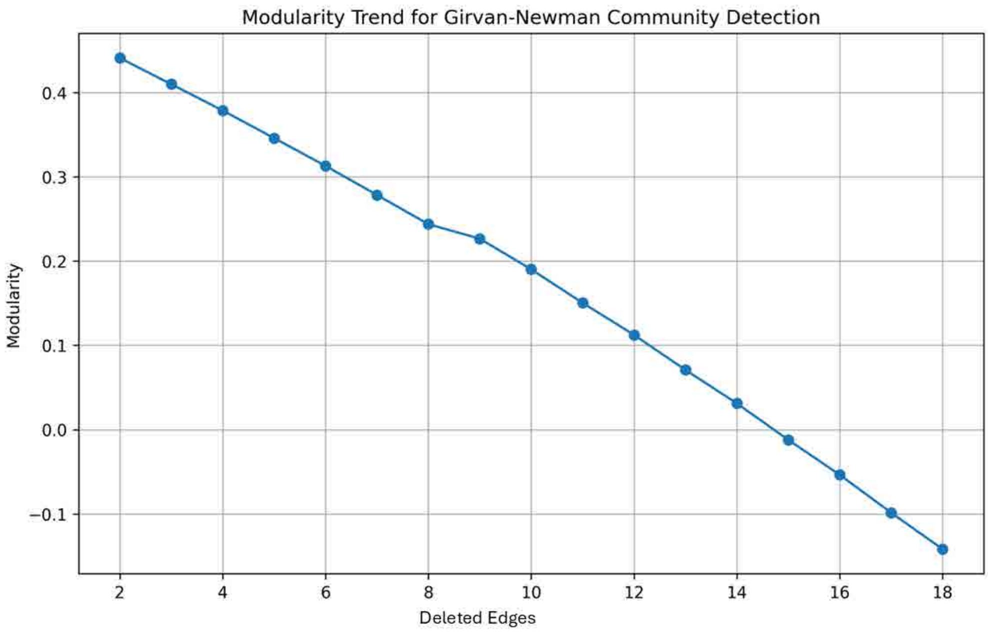


Figure 3.16: Modularity trend for Girvan-Newman community detection algorithm to determine optimal number of clusters

Identifying connected components

At each step of the edge removal process, the connected components of the graph are identified. A connected component is a subset of nodes where each node is reachable from any other node within the subset. These connected components represent potential spatial clusters. However, modularity-based approaches cannot detect small communities in large networks. Small communities are often merged into larger ones because such merging results in a higher Q value. This leads to a loss of granularity in the detected community structure. Further analysis will be performed in the next section to address this drawback and identify smaller sub-communities.

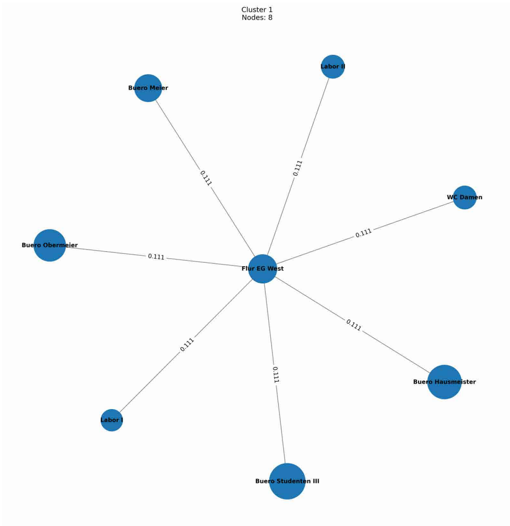


Figure 3.17: Cluster no. 1 formed by Community Detection

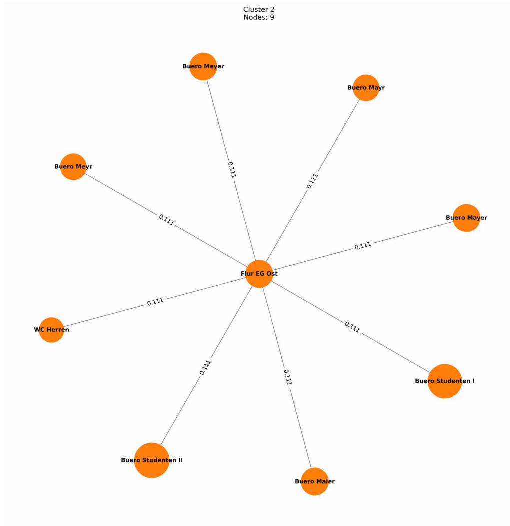


Figure 3.18: Cluster no. 2 formed by Community Detection

3.3.2 Sub-community analysis

A sub-community refers to a smaller, cohesive grouping within a larger community, created by decomposing an excessively large community into more manageable units to enable detailed and focused analysis. This analysis will be conducted in two distinct phases:

Second-level community detection

In this phase, the identified communities in Section 3.3.1 are taken as a basis. While these larger communities offer insights, they often contain complex internal structures that need further examination. The goal is to break down communities into smaller units for further analysis, allowing exploration of hierarchical structures and a multi-level view of the network.

Sub-cluster analysis

The second phase involves sub-cluster analysis, which examines smaller clusters by using centrality-based metrics. These metrics assess the importance of nodes in the sub-community's structure and connectivity (see fig. 3.19). The centrality metrics listed below will be used for analysis:
Degree Centrality (C_{deg}): Measures the number of direct connections a node has. A high degree centrality indicates that a node plays a significant role within a network. The degree

centrality (C_{deg}), defined as:

$$C_{deg}(i) = \frac{deg(i)}{|N| - 1}$$

where, $deg(i)$ represents the number of direct connections for node i and $|N|$ denotes the total number of nodes.

Betweenness Centrality (C_{betw}): This metric is already discussed in section 3.3.1.

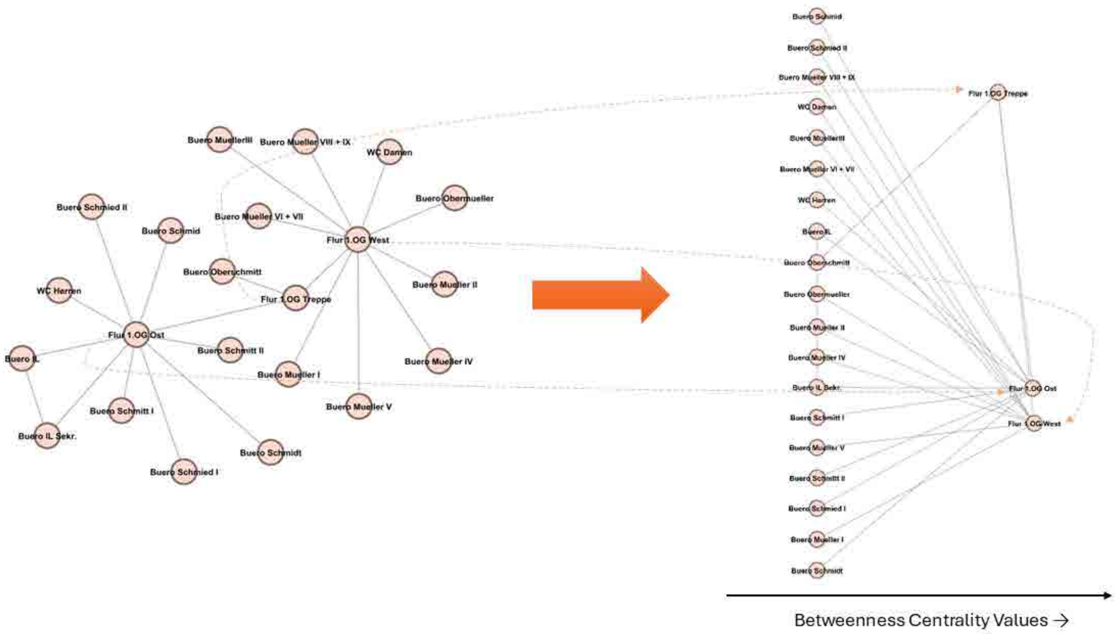


Figure 3.19: Centrslity analysis based on betweenness centrality values

The graph in Figure 3.19 illustrates the betweenness centrality analysis applied to the first-floor layout of the IFC model of an office building. The nodes, representing rooms or spaces, are positioned according to their space-level horizontal accessibility within the layout. The analysis reveals distinct roles of the nodes based on the centrality measure used: According to degree centrality, only two spaces, "Flur 1.OG Ost" (Corridor on the first floor, East) and "Flur 1.OG West" (Corridor on the first floor, West), emerge as key nodes due to their high number of direct space-level connections with other spaces. These corridors function as key hubs, connecting various rooms. It is important to note that the names of the nodes in the graph, such as "Flur 1.OG Ost" and "Büro Mueller II," are derived from the "LongName" attribute of the IfcSpace entity. This attribute provides descriptive labels for spatial elements in the IFC model. However, when examining betweenness centrality, additional insights arise. In addition to "Flur 1.OG Ost" and "Flur 1.OG West," "Flur 1.OG Treppe" (Staircase on the first floor) becomes a critical node. The staircase space entity functions as a bridge between different spatial clusters, facilitating movement across various sections of the building. Comparing degree and betweenness centrality reveals the complementary nature of these measures in understanding the space-level network. Degree centrality identifies nodes like "Flur 1.OG Ost" and "Flur 1.OG West" as essential hubs with the highest number of direct connections. These corridors enhance localized accessibility by directly linking neighboring spaces. For instance, "Büro Schmid I" and "Büro Mueller IV" rely on these corridors for immediate navigation. On the other hand, betweenness centrality highlights nodes that serve as strategic connectors within the network. While "Flur 1.OG Ost" and "Flur 1.OG West" remain significant, the analysis also identifies "Flur 1.OG Treppe" as a vital node. For example, a user traveling from "Buero IL" to "WC Damen" (Ladies' restroom) would pass through "Flur 1.OG Treppe," which acts as a bridge between clusters. This metric underscores the importance of nodes that lie on the shortest paths between spaces, even if they have fewer direct connections. In summary, degree centrality identifies highly connected hubs such as corridors, while betweenness centrality uncovers nodes with strategic significance in maintaining circulation flow. Together, these measures offer a better understanding of the space-level network, highlighting both localized and global connectivity within the building.

Chapter 4

Case study and results

4.1 Experiments

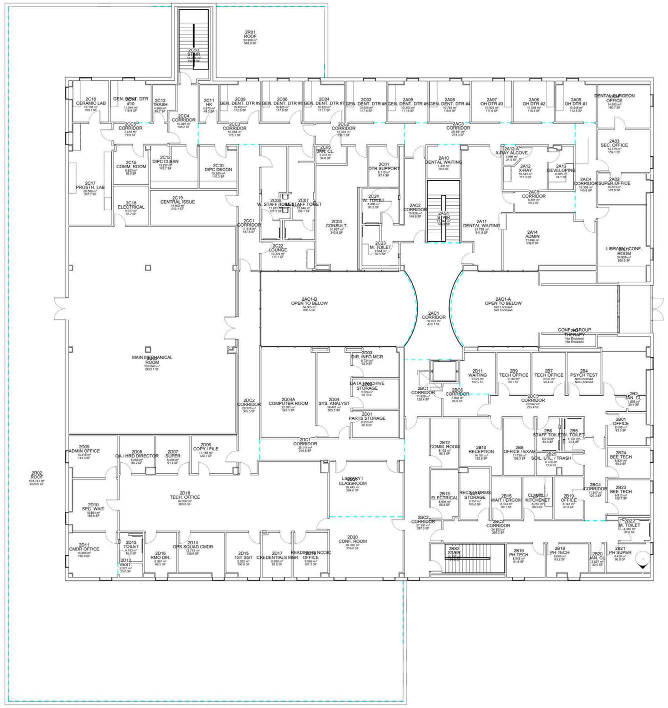
This chapter presents a case study and the demonstration of results, aimed at testing and validating the functionality of the proposed framework. Medical clinic building model shall be taken as input for this chapter ("Medical Clinic", 2016). The chosen model is formatted in IFC version 2x3 and exported using the Coordination View of the MVD standard (buildingSMART TECHNICAL, 2024c). The building comprises of two floors, each housing a variety of departments that reflect real-world complexity, including medical, dental, pediatric, and imaging suites (see fig. 4.1). The first floor contains 153 space entities, while the second floor has 109 space entities.

In this model, each *IfcSpace* entity also includes attributes for "*LongName*" and "*Name*", providing additional semantic context (buildingSMART INTERNATIONAL, 2024c). The "*LongName*" attribute typically describes the functional designation of the space, such as MECH. YARD. The "*Name*" attribute serves as a shorthand identifier for the space and is labelled using an alphanumeric scheme, such as 1A31, 1D32, 2B22, 2C12, and 1DC7. The labelling convention encodes spatial and organizational information which shall be used for validation purposes. For example:

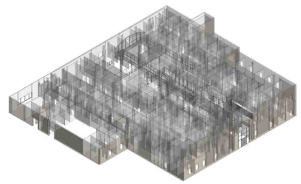
- The first symbol represents the floor number.
- The second symbol denotes the zone to which the space belongs. This zoning reflects the intended spatial organization of the building, as illustrated in Figure 4.2 and 4.4.
- For instance, in the label 1DC7, the third character, 'C', signifies circulation spaces. These circulation areas are essential for movement within the building and are visually represented in Figure 4.3 and 4.5.

The structured approach adopted in this chapter is designed to thoroughly assess the capabilities of the framework in managing and interpreting spatial and relational aspects of building environments already presented in chapter 3. In the next three pages, we will present the following layouts: 1) Floor plans and a 3D view of the case study model, 2) Zoning representation based on the *LongName* attribute of *IfcSpace* entities, and 3) Circulation entities representation based on the *LongName* attribute of *IfcSpace* entities.

Floor plan of the medical clinic: first floor



Floor plan of the medical clinic: second floor



3D perspective view of the medical clinic

Figure 4.1: Floor plans and 3D View of the medical clinic

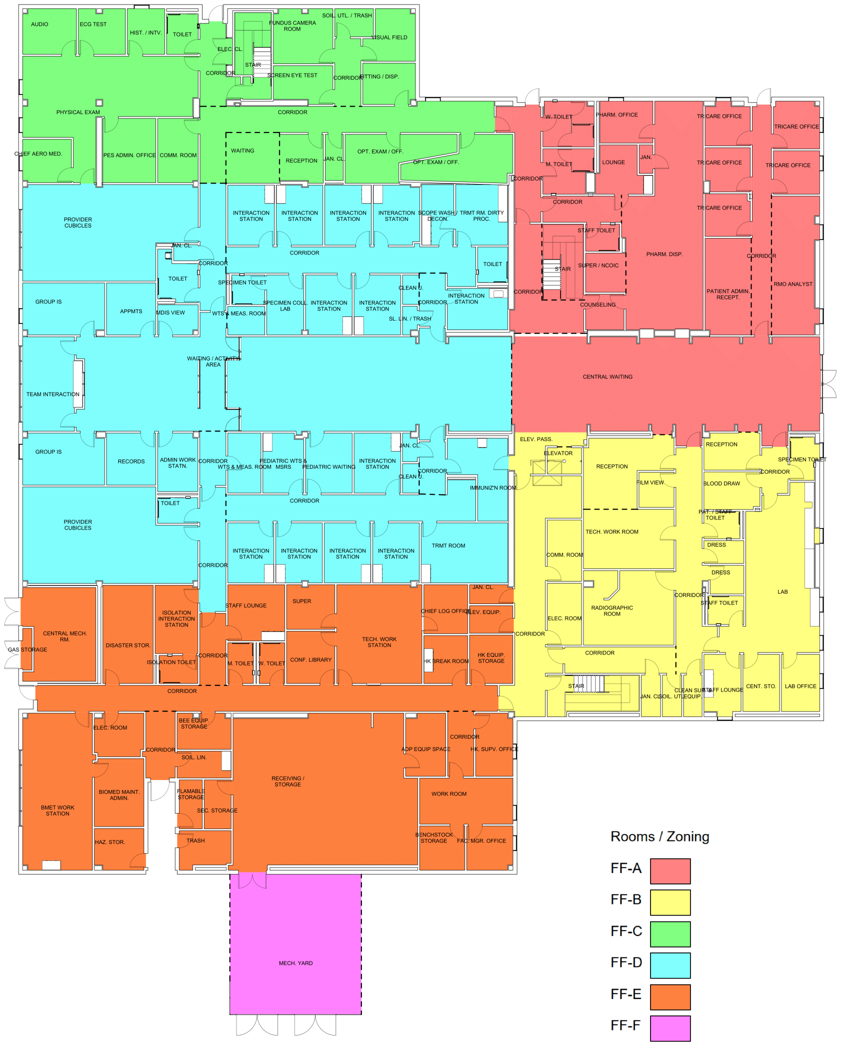


Figure 4.2: Case study model first floor zoning representation based on IfcSpace labels

Figure 4.3: Case study model first floor circulation entities representation based on IfcSpace labels

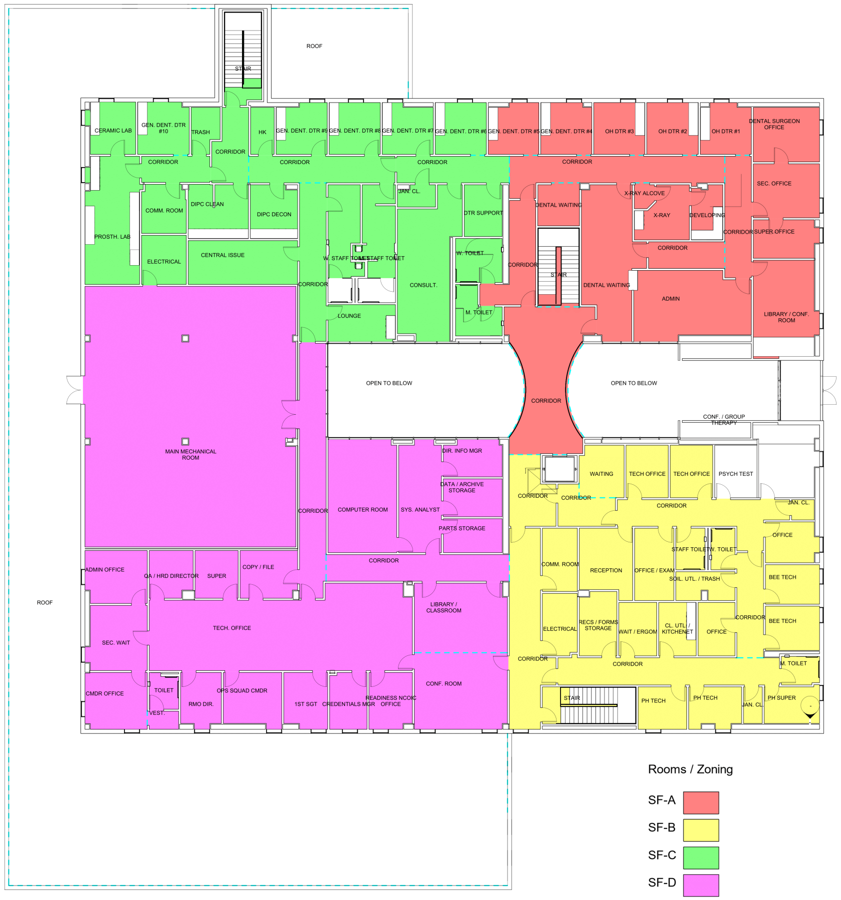


Figure 4.4: Case study model second floor zoning representation based on IfcSpace labels

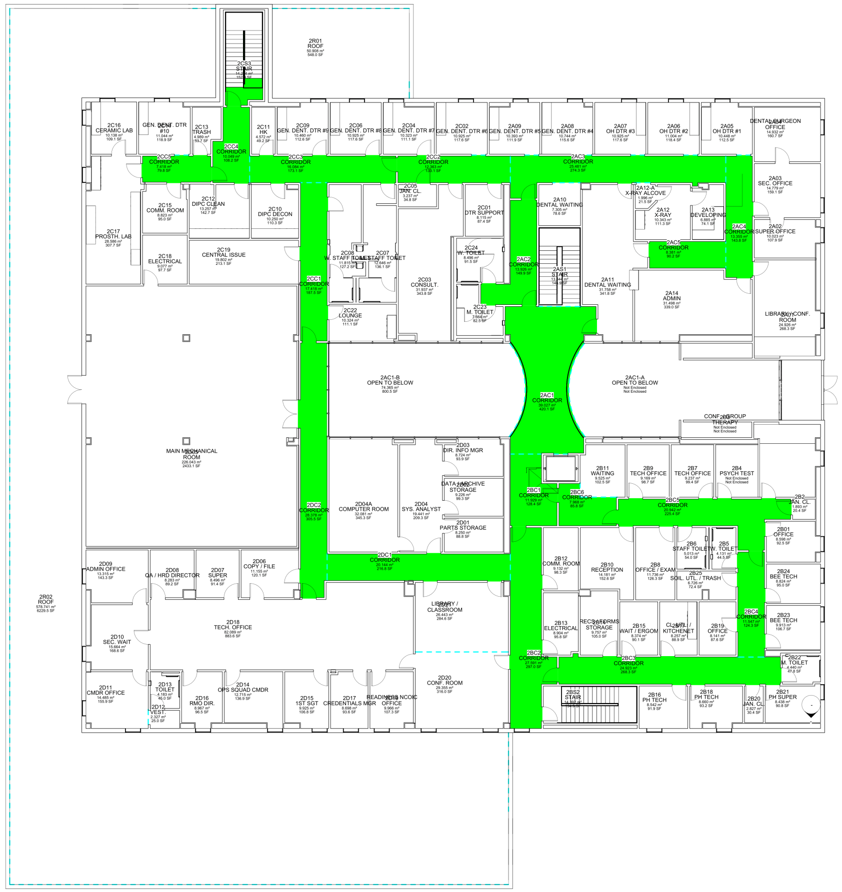


Figure 4.5: Case study model second floor circulation entities representation based on IfcSpace labels

4.2 Space-level relationship reasoning findings

4.2.1 Space-level horizontal adjacency findings

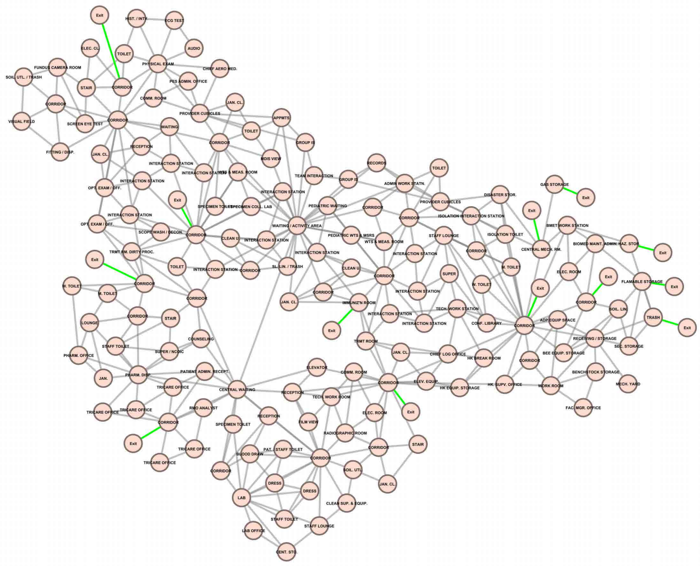


Figure 4.6: Space-level horizontal adjacency result of first floor of case study model represented in graph format

Existing studies on adjacency computation have predominantly leveraged the *IfcRelSpaceBoundary* entity to establish space-level relationships between rooms and other building elements (DIAKITE et al., 2022; J. K. LEE & KIM, 2014). However, this relationship entity often struggles to represent these relationships effectively, particularly when two thin partition walls separate two rooms (see Figure 4.7). To overcome this limitation, a voxel-based approach offers an explicit space-wise representation, allowing for objective analysis of *Ifcspace* connections. For the case study model, a voxel grid distance $v = 0.5$ was taken, and the number of adjacent voxel search blocks $n = 2$ was considered. These parameters were chosen to avoid tiny gaps and other geometric anomalies by accounting for search blocks during adjacency computation. Also, as illustrated in figure 4.6, there are no isolated nodes here in this graph as every space entity has an adjacent space entity as opposed to figure 4.8 where isolated nodes are formed as some spaces are accessible only through external environment. This graph will have more edges (as compared to graphs from section 4.2.2), as adjacency does not require direct access. Figure 4.6 represents space-level proximity, emphasizing physical layout rather than functional connections.

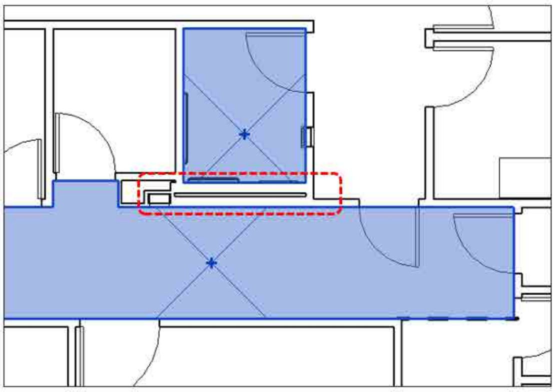


Figure 4.7: Illustration of space-level horizontal adjacency with two thin partition walls separating two rooms.

4.2.2 Space-level accessibility findings

Horizontal accessibility

After computing horizontal accessibility, it is essential to refine the network through an initial filtering step that removes specific nodes. As illustrated in Figure 4.8 (top-left quadrant), isolated clusters can be identified within the graph. These clusters are accessible only through the external environment and do not contribute to the main circulation network of the building (see Fig. 4.9). To resolve this issue, a giant component filter is implemented. This method isolates the largest connected component of the graph, which comprises the nodes that form the core of the network (PEREZ & GERMON, 2016). As a result, extraneous clusters that do not support the primary circulation function are effectively removed. However, in case indirect edges are considered, these isolated nodes are taken into consideration.

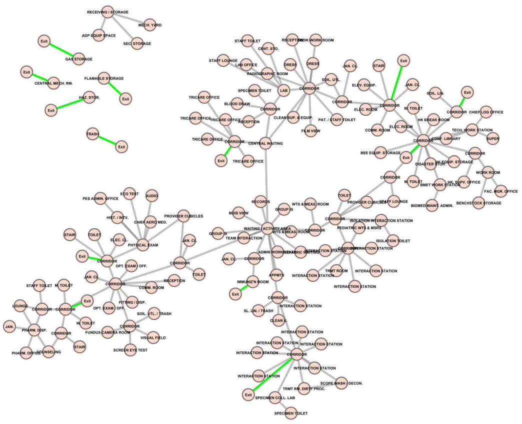


Figure 4.8: Space-level horizontal accessibility result of first floor of case study model represented in graph format. Isolated clusters are evident in the top left quadrant.

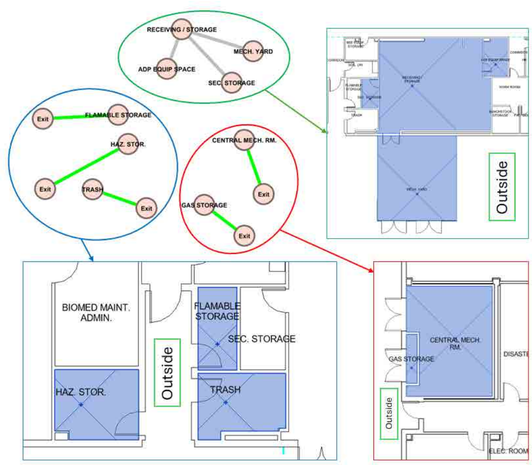


Figure 4.9: Magnified look at the isolated clusters identified in Figure 4.8.

Vertical accessibility

In the case study model, elevators were represented not through the prescribed *IfcTransportElement* entity, but rather as *IfcSpace* entities labelled "Elevator" (See fig. 4.10). This modelling approach constitutes a drawback, as it deviates from the integration of elevator spaces into the vertical accessibility analysis.

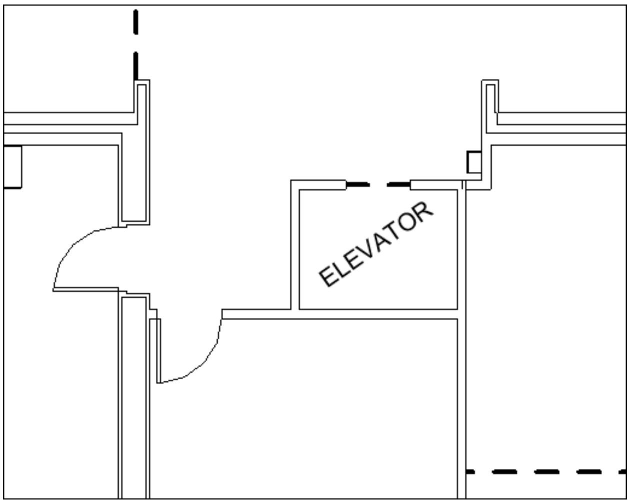


Figure 4.10: Elevator as *IfcSpace* in Case Study Model

4.3 Graph-based circulation path reasoning findings

Building on the findings from space-level relationship analysis, graph-based reasoning serves as an effective methodology for representing the results. Additionally, it facilitates further analysis through graph analytics and community detection techniques (see Table 4.1 for an overview of the analyses conducted).

Table 4.1: Overview of analyses conducted

Analysis Type	**Description**
Community Detection	
Global edge analysis	Considers all edges in the space-level topological graph
Horizontal adjacency edge analysis	Considers horizontal adjacency edges
Horizontal accessibility edge analysis	Considers horizontal accessibility edges
Levels of Community Detection	
First-Level	Initial community detection analysis
Second-Level	Refined community detection for large communities
Centrality Analysis	
Building Storey Level	Centrality metrics analyzed at the storey level
Community Level	Centrality metrics analyzed within individual first-level communities

4.3.1 Multi-level community detection findings

In this section, scenarios shall be presented as already discussed in section 3.3.1, however, implemented on the case study model.

Global edge analysis

In global edge analysis (first-level community detection), a total of 9 communities were identified, with 6 on the first floor and 4 on the second floor, matching the number of zones defined in the IfcSpace-based zoning plan (see figure 4.11 and 4.12). However, differences in spatial grouping emerge upon closer analysis. For instance, on the first floor, zones such as FF-C and FF-D appear more fragmented in the community detection results, with spaces grouped into multiple smaller communities.

Horizontal adjacency edge analysis

In horizontal adjacency edge analysis (community detection), a local analysis was conducted focusing on the first floor, as it contains more rooms and is spatially more complex compared to the second floor. The analysis identified a total of 8 communities on the first floor, reflecting a finer subdivision of communities emphasizing more on adjacency. The modularity value still reflects a reasonably strong community structure. However, it is lower than the modularity value achieved in horizontal accessibility edge analysis. This implies that the division into communities is less pronounced, with more connections crossing between communities. Some discrepancies were noted in the community detection results (see fig. 4.13). For instance, the toilet located in the top middle part of the corridor from FF-3 is categorized as part of community FF-5; however, it logically belongs to FF-3 due to its horizontal accessibility from that room. Similarly, two interaction stations have been incorrectly classified under community FF-7, as they are horizontally accessible through the corridor from community FF-8.

Community Name	Number of Rooms	Percentage (%)
FF-1	32	20.8
FF-2	19	12.3
FF-3	21	13.6
FF-4	19	12.3
FF-5	19	12.3
FF-6	10	6.5
FF-7	15	9.7
FF-8	19	12.3
Total Rooms	**154**	**100.0**

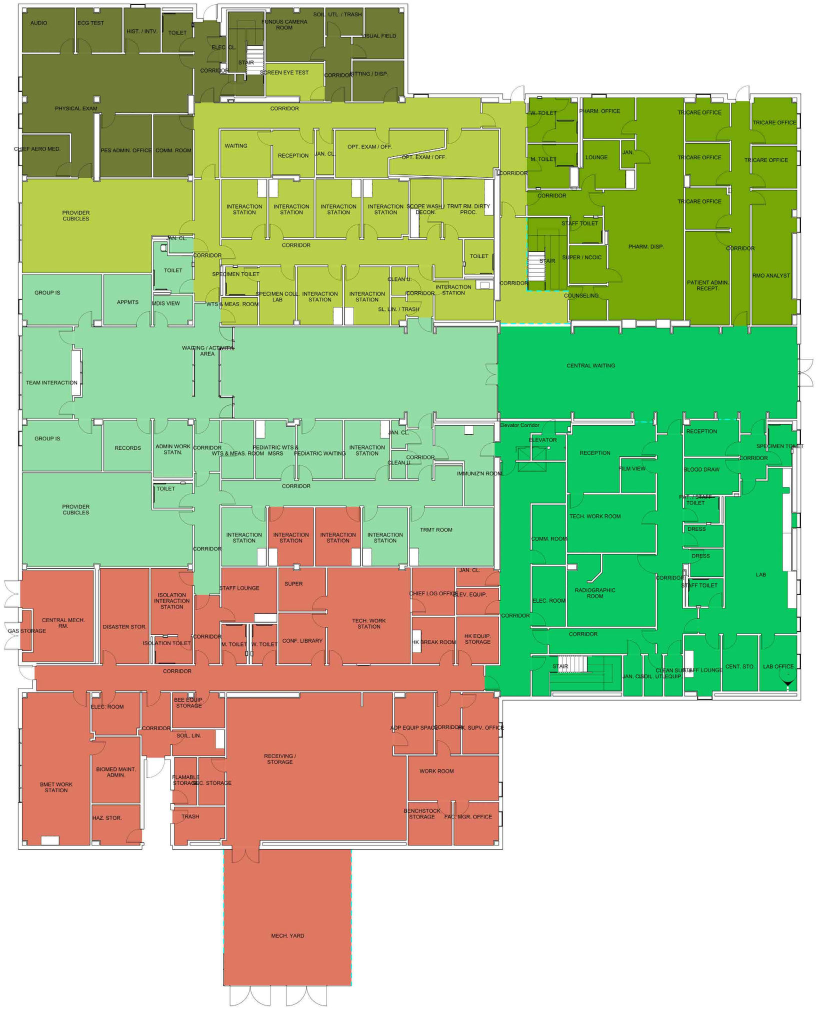
Table 4.2: Community-wise distribution of rooms and their percentages for horizontal adjacency edge analysis

Horizontal accessibility edge analysis

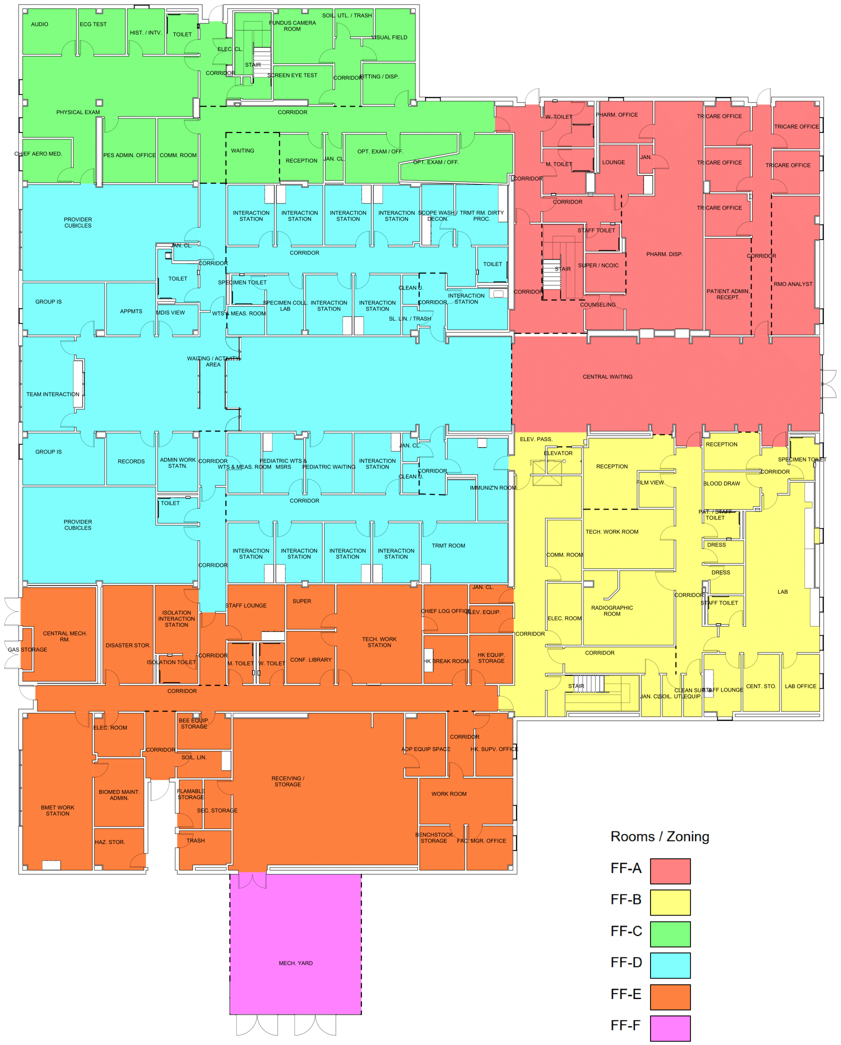
In horizontal accessibility edge analysis, the analysis of the first floor identified a total of 11 communities, indicating a more granular division of spaces compared to horizontal adjacency edge analysis. This higher number of communities suggests a detailed fragmentation of spatial relationships based on accessibility. A modularity of 0.823 suggests a stronger division of the graph into well-defined communities. Nodes within each community are more densely connected to each other and less connected to nodes in other communities. Here, the communities are formed based on circulation spaces as the "central" node, with rooms around them grouped into the same community. For example, the FF-1 community is a well-demarcated cluster with the corridor at its centre, and the horizontally accessible rooms surrounding it are considered part of the community (see fig. 4.14). This reflects the space-wise hierarchy and the role of circulation in defining the functional grouping of spaces.

Community Name	**Number of Rooms**	**Percentage (%)**
FF-1	8	5.5
FF-2	13	9.0
FF-3	15	10.3
FF-4	7	4.8
FF-5	20	13.8
FF-6	13	9.0
FF-7	17	11.7
FF-8	22	15.2
FF-9	10	6.9
FF-10	15	10.3
FF-11	5	3.4
Total rooms	**145**	**100**

Table 4.3: Community-wise distribution of rooms and their percentages for horizontal accessibility edge analysis

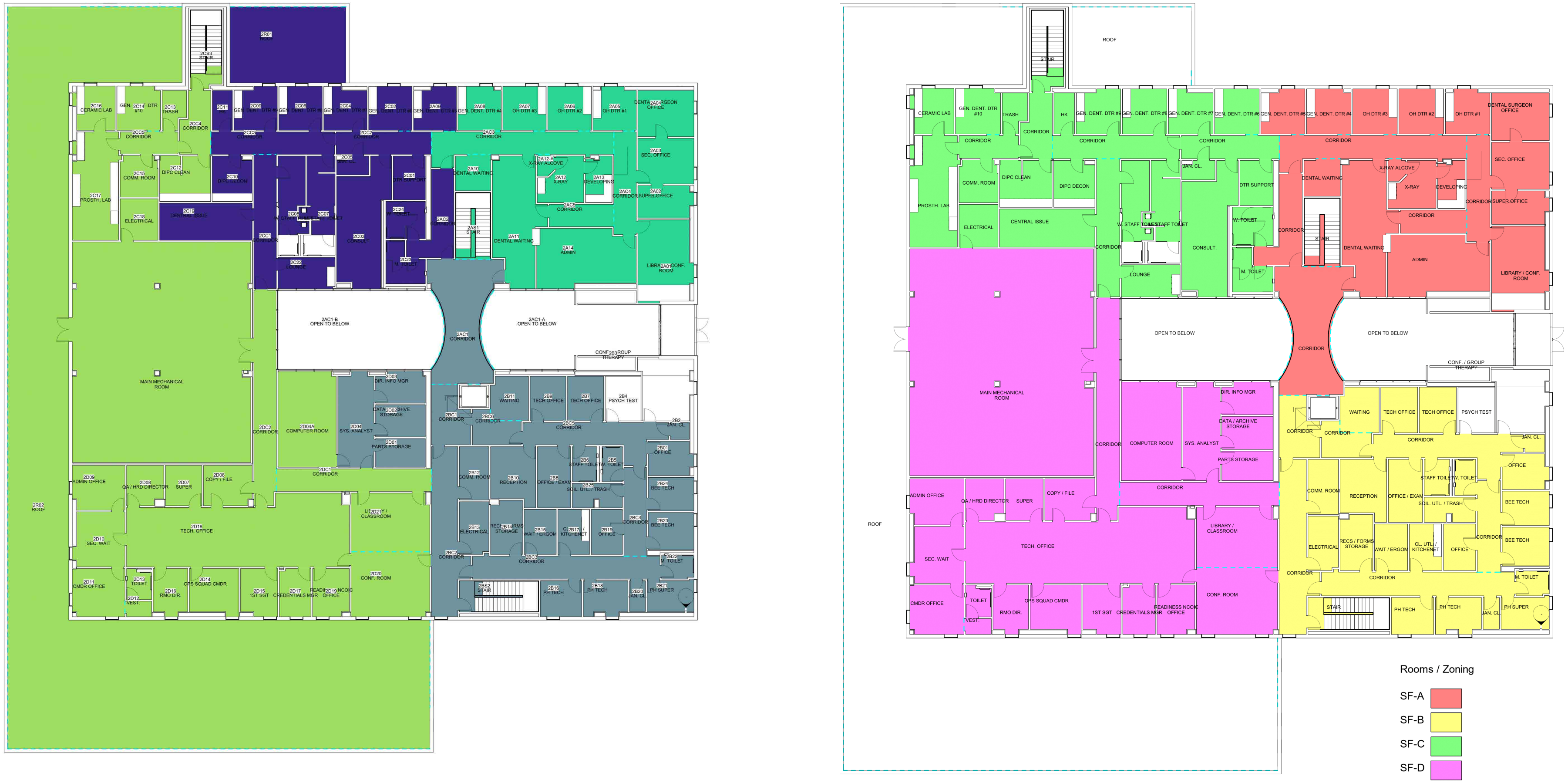


(a) First-level community detection as per global edge analysis



(b) Zoning representation based on IfcSpace labels

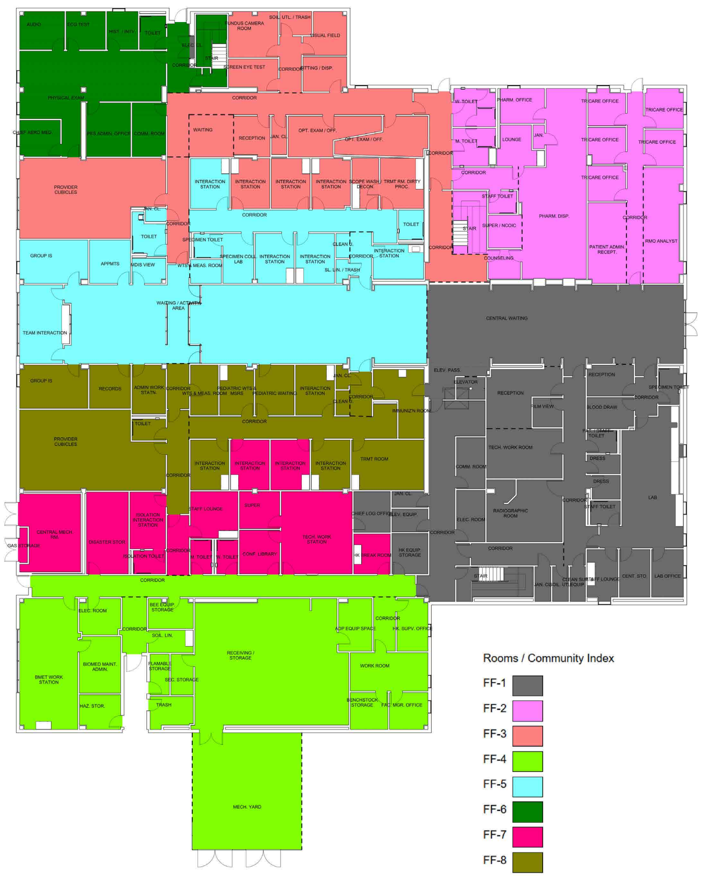
Figure 4.11: First-level community detection comparison as per global edge analysis (case study model first floor)



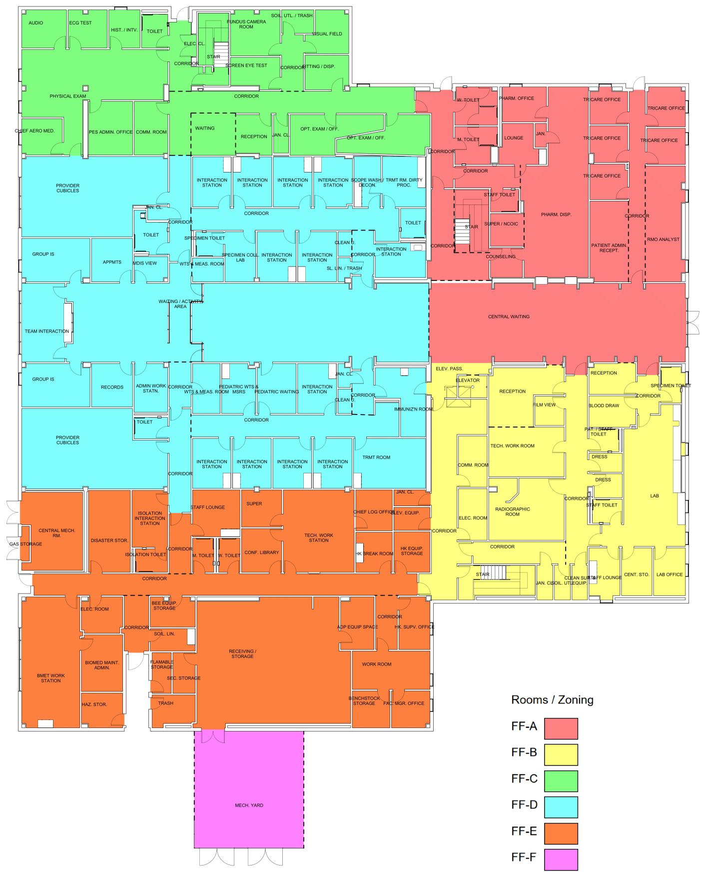
(a) First-level community detection as per global edge analysis

(b) Zoning representation based on IfcSpace labels

Figure 4.12: First-level community detection comparison as per global edge analysis (case study model second floor)

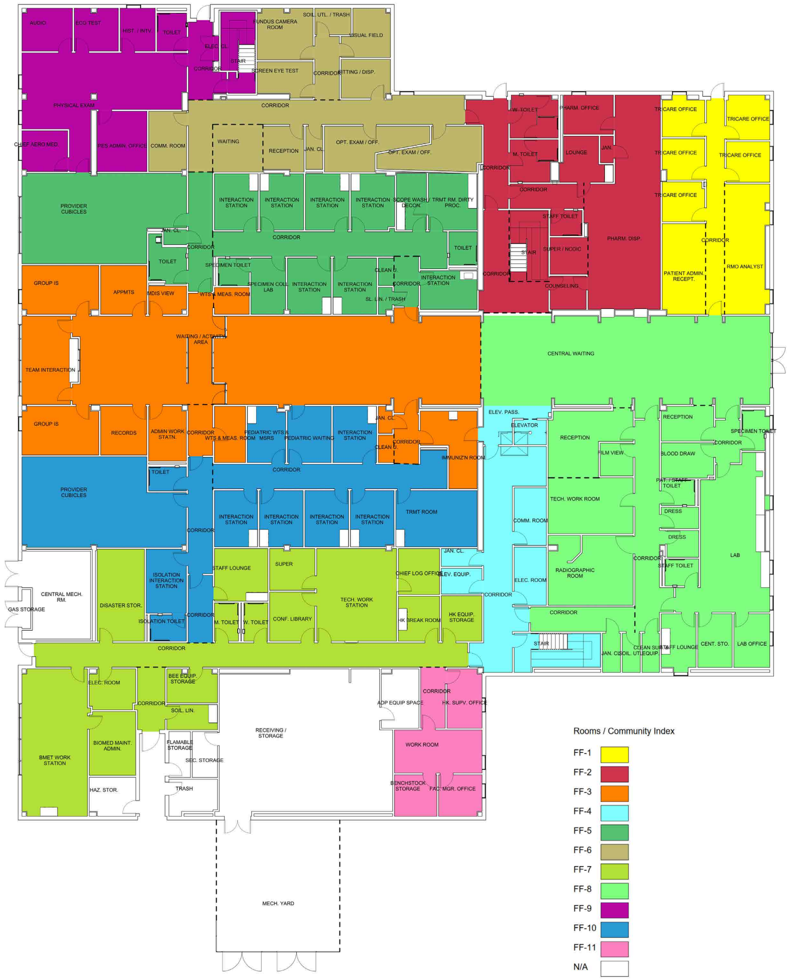


(a) First-level community detection as per horizontal adjacency edge analysis

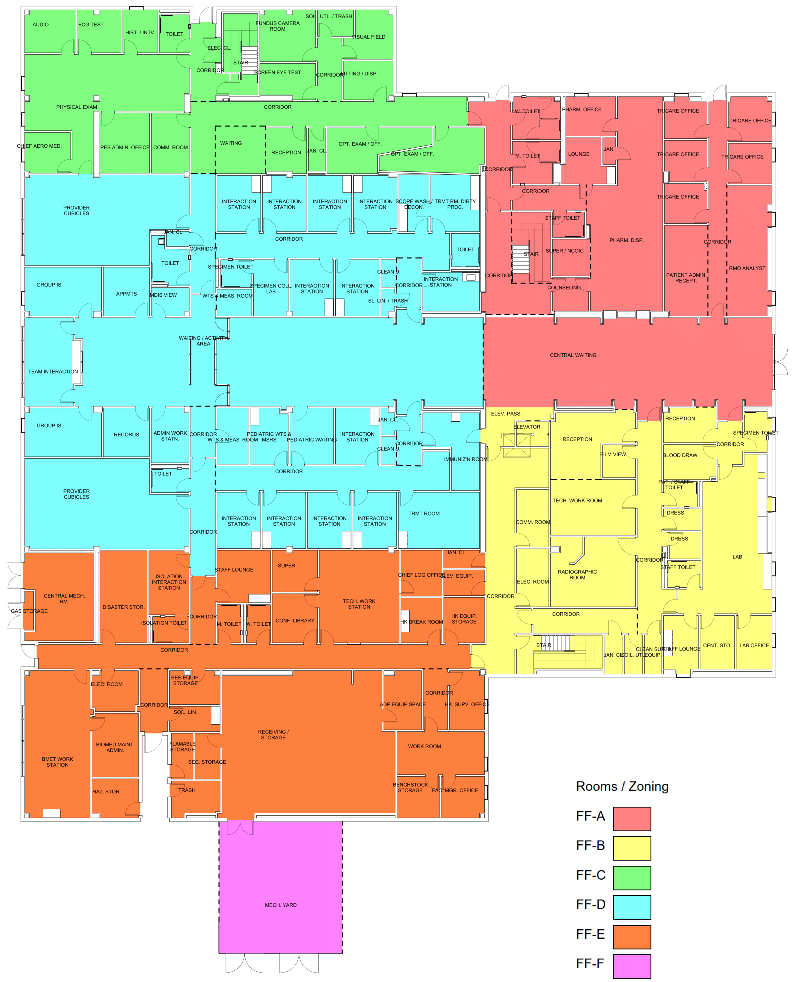


(b) Zoning representation based on IfcSpace labels

Figure 4.13: First-level community detection comparison as per horizontal adjacency edge analysis (case study model first floor)



(a) First-level community detection as per horizontal accessibility edge analysis

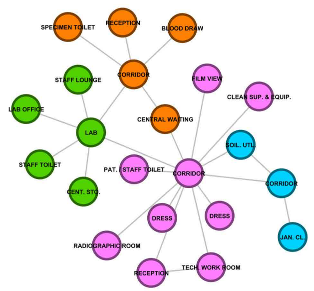


(b) Zoning representation based on IfcSpace labels

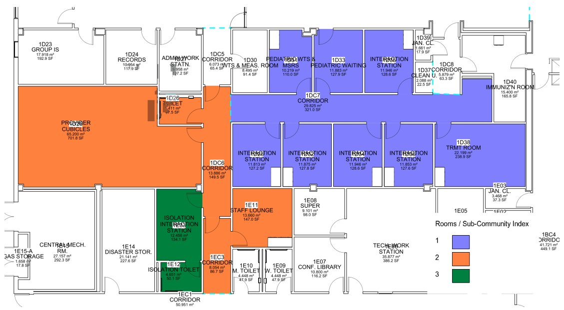
Figure 4.14: First-level community detection comparison as per horizontal accessibility edge analysis (case study model first floor)

Figure 4.15 illustrates the second-level community detection within the larger clusters identified in the first-level community detection, focusing specifically on FF-8 and FF-10 (as those are larger identified first-level communities). This detailed breakdown highlights how sub-communities (or second-level communities) are organized around key circulation nodes. In the case of FF-8, two distinct sub-communities emerge. The *sub-community 1* is centred around 1BC2 - CORRIDOR, which serves as the key circulation node connecting several spaces within the sub-cluster. The *sub-community 2*, however, is formed around 1B04 - LAB. Although 1B04 is not classified as a circulation entity according to the fig. 4.3, it plays a critical role as a restricted-access space frequently used by staff.

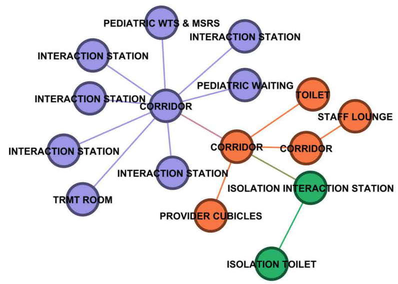
(a) Second-level community detection: FF-8



(b) Second-level community detection: FF-8



(c) Second-level community detection: FF-10

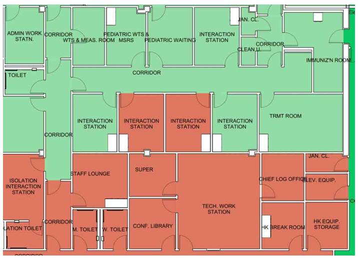


(d) Second-level community detection: FF-10

Figure 4.15: Second-level community detection of horizontal accessibility edge analysis: FF-8 and FF-10

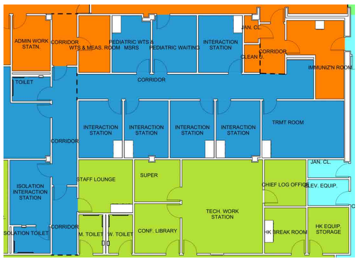
Comparison of first-level community detection analyses

This section compares the findings across the three levels of edge analysis—Global Edge Analysis, Horizontal Adjacency Edge Analysis, and Horizontal Accessibility Edge Analysis—focusing on community distribution, and alignment with the zoning based on IfcSpace labels.



(a) Global edge analysis

(b) Horizontal adjacency edge analysis

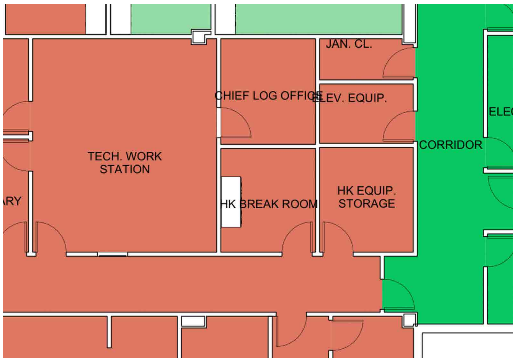


(c) Horizontal accessibility edge analysis

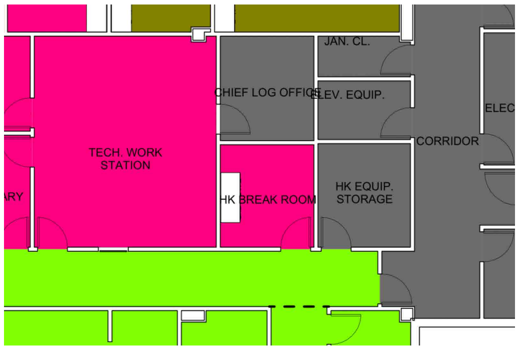
Figure 4.16: Comparison of IfcSpace entities - "INTERACTION STATION" across community detection findings (zoomed-in views of the IfcSpace entities - "INTERACTION STATION" taken from fig. 4.11 (a), 4.13 (a), 4.14 (a))

As shown in Figure 4.16, the two IfcSpace entities labelled "INTERACTION STATION" are misclassified in both the global edge analysis (Figure 4.16 (a)) and the horizontal adjacency edge analysis (Figure 4.16 (b)). These entities should belong to the same community as the IfcSpace entity "CORRIDOR." The reason for this misclassification is that both the global edge analysis and horizontal adjacency edge analysis only consider adjacency edges. In these analyses, the IfcSpace entities associated with "INTERACTION STATION" have a higher number of adjacency edges connecting them to entities such as "STAFF LOUNGE," "SUPER," and "TECH. WORK STATION." This results in their incorrect classification within the community comprising these entities. However, this issue is resolved by applying the horizontal accessibility edge analysis, which considers accessibility edges instead of adjacency edges. Through this approach, the "INTERACTION STATION" spaces exhibit stronger relationships with the "CORRIDOR," leading to their correct classification.

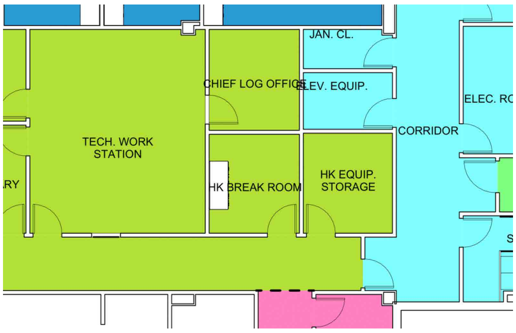
As shown in Figure 4.17, the classification of certain spaces varies across different analytical approaches. For the spaces "JAN. CL." and "ELEV. EQUIP.," the global edge analysis (Figure 4.17 (a)) and the zoning representation (Figure 4.17 (d)) incorrectly group these entities with the left-side community. This misclassification occurs because the global



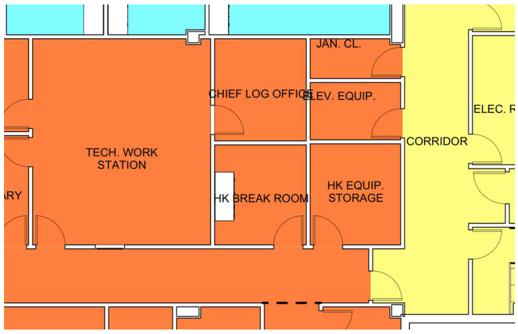
(a) Global edge analysis



(b) Horizontal adjacency edge analysis



(c) Horizontal accessibility edge analysis



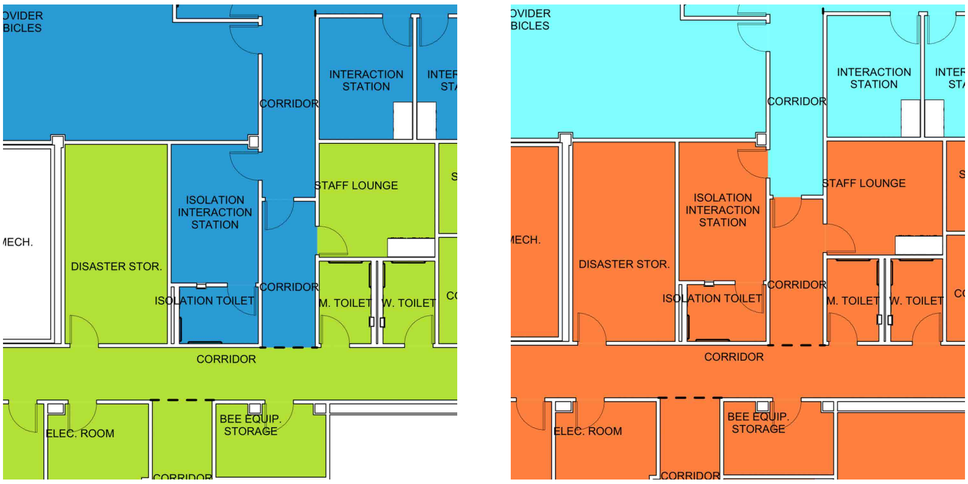
(d) Zoning representation based on Ifc-Space labels

Figure 4.17: Comparison of IfcSpace entities - "JAN. CL." and "ELEV. EQUIP." across community detection findings (zoomed-in views of the IfcSpace entities - "JAN. CL." and "ELEV. EQUIP." taken from fig. 4.11 (a), 4.13 (a), 4.14 (a), 4.11 (b))

edge analysis relies on the higher number of edge connections in that direction. In contrast, both the horizontal adjacency analysis (Figure 4.17 (b)) and the horizontal accessibility analysis (Figure 4.17 (c)) correctly classify these spaces with the "CORRIDOR" community, accurately reflecting their functional relationship with circulation spaces. The zoning representation's misclassification emphasizes the limitations of spatial-only classification approaches, as it relies on visual proximity rather than functional relationships. For the "CHIEF LOG OFFICE," the horizontal adjacency edge analysis misclassifies this space by grouping it with the right-side community due to its higher number of edge connections in that direction.

In Figure 4.18, the spaces "ISOLATION INTERACTION STATION" and "ISOLATION TOILET" are misclassified in the zoning representation based on IfcSpace labels. However, the horizontal accessibility edge analysis correctly classifies these spaces by considering space-level accessibility relationships with "CORRIDOR".

Figures 4.19 and 4.20 illustrate the modularity trends for horizontal adjacency edge analysis and horizontal accessibility edge analysis, respectively. These analyses evaluate how modularity, a measure of the quality of community structure, evolves as edges are progressively removed from the network. The comparison highlights that the space-level horizontal adjacency graph, with its higher edge density, forms more robust communities



(a) Horizontal accessibility edge analysis

(b) Zoning representation based on IfcSpace labels

Figure 4.18: Comparison of IfcSpace entities - "ISOLATION INTERACTION STATION" and "ISOLATION TOILET" across community detection findings (zoomed-in views of the IfcSpace entities - "ISOLATION INTERACTION STATION" and "ISOLATION TOILET" taken from fig. 4.11 (a), 4.13 (a), 4.14 (a))

that are less dependent on specific edges. This structural advantage ensures greater resilience in maintaining community integrity under disruptions. On the other hand, the space-level horizontal accessibility graph, with fewer edges, exhibits a more fragile community structure that is prone to fragmentation when critical edges are removed. This difference is also reflected in the number of communities produced by both analyses, where the horizontal adjacency graph tends to produce fewer, larger communities, while the horizontal accessibility graph results in a greater number of smaller, more fragmented communities.

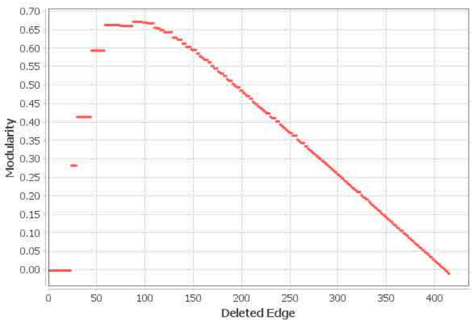


Figure 4.19: Modularity trend for horizontal adjacency edge analysis

Figure 4.20: Modularity trend for horizontal accessibility edge analysis

Comparison of modularity trend

4.3.2 Centrality analysis

The centrality analysis will be conducted on two levels to provide a comprehensive understanding of the space-wise hierarchy and connectivity within the building.
Building Storey Level: At this level, centrality metrics will be calculated for the entire building storey. This analysis will help identify key nodes that play a significant role in overall accessibility throughout the storey. It will also reveal how different spaces interact on a broader scale, highlighting areas of high centrality that function as critical hubs within the space-level network.
Community level (communities formed by first-level community detection): At this more detailed level, centrality metrics will be applied to the individual communities identified through first-level community detection. This will provide insights into the internal structure and connectivity within each community. For instance, it will highlight which nodes are central within their respective communities and how space-level relationships are organized around these key points. This localized analysis is essential for understanding the functionality and accessibility of spaces at a granular level, such as the influence of circulation nodes on adjacent rooms.

The difference in centrality values between these two levels will arise from the scope of analysis: at the building storey level, the values will reflect the broader, global connectivity across the entire space, while at the community level, they will provide a more detailed picture of the role of nodes within smaller, more defined clusters of spaces.

Building storey level

Degree centrality and betweenness centrality analyses were performed for graphs based on horizontal adjacency edge analysis and horizontal accessibility edge analysis. The centrality analysis for horizontal adjacency edge analysis produced ambiguous results due to the high number of edges, making it ineffective. In contrast, the centrality analysis for horizontal accessibility edge analysis was successful, revealing key circulation entities from a storey-level perspective. The analysis identified the following circulation spaces: 1C18 - PHYSICAL EXAM (located in the top left of the plan); 1B04 - LAB (positioned in the bottom right of the plan); and 1A16 - PHARM. DISP. (found in the top right of the plan). Although these spaces are not included in the IfcSpace-based circulation plan, their names suggest they represent restricted circulatory areas. For instance, in 1B04 - LAB and 1A16 - PHARM. DISP., the primary contributors to circulation are likely to be staff members. In contrast, for 1C18 - PHYSICAL EXAM, both staff and patients designated for physical exams would mainly contribute to the circulatory traffic (this was highlighted in both degree centrality and betweenness centrality analyses, see fig. 4.23 and 4.24). The table 4.4 presents the top ten degree and betweenness centrality values for the first-floor case study model horizontal accessibility edge analysis. As observed, "PHYSICAL EXAM" and "LAB" exhibit higher degree centrality values. However, these spaces do not feature among the top ten for betweenness centrality. This indicates that while degree centrality reflects the immediate connectivity of a space, betweenness centrality provides a more reliable measure of its significance in facilitating movement and access throughout the building. This discrepancy emphasizes that betweenness centrality more effectively captures the functional roles of spaces that enable circulation across different areas.

Degree Centrality			Betweenness Centrality		
LongName	**Community Index**	**Value**	**LongName**	**Community Index**	**Value**
CORRIDOR	FF-7	15	WAITING / ACTIVITY AREA	FF-3	6940
WAITING / ACTIVITY AREA	FF-3	14	CORRIDOR	FF-5	4195
CORRIDOR	FF-8	12	CORRIDOR	FF-6	3608
CORRIDOR	FF-5	11	CENTRAL WAITING	FF-8	3274
CORRIDOR	FF-6	10	CORRIDOR	FF-7	3072
CORRIDOR	FF-10	9	CORRIDOR	FF-10	2661.5
CORRIDOR	FF-4	8	CORRIDOR	FF-8	2627
PHYSICAL EXAM	FF-9	7	CORRIDOR	FF-3	2339.5
CORRIDOR	FF-1	7	CORRIDOR	FF-10	2204
LAB	FF-8	6	CORRIDOR	FF-5	1974

Table 4.4: Degree and Betweenness Centrality Values - Building Storey Level (horizontal accessibility edge analysis)

Figure 4.21: Degree centrality analysis

Figure 4.22: Betweenness centrality analysis

Comparison of circulation spaces for horizontal adjacency edge analysis (building storey level)

Figure 4.23: Degree centrality analysis

Figure 4.24: Betweenness centrality analysis

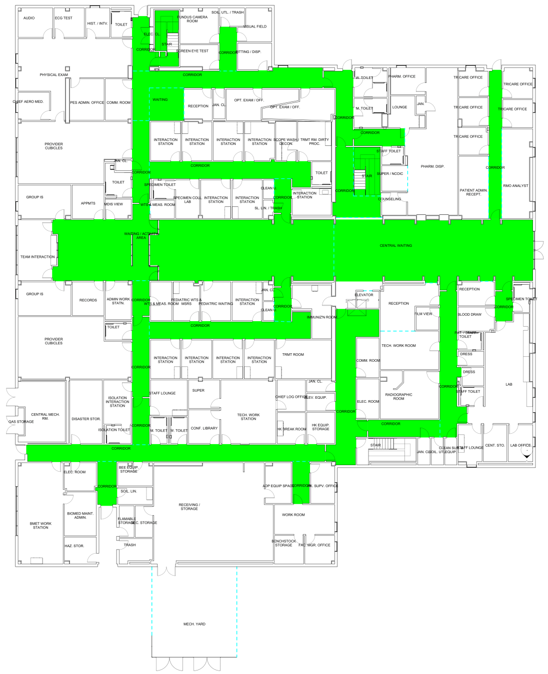


Figure 4.25: Circulation entities representation based on IfcSpace labels

Comparison of circulation spaces for horizontal accessibility edge analysis (building storey level)

Community level

In addition to the building storey level analysis, centrality metrics were applied to the communities identified through first-level community detection. However, due to ambiguous results from the building storey level analysis in horizontal adjacency edge analysis, this scenario was not analyzed at the community level. This analysis for horizontal accessibility edge analysis, on the other hand, offered a deeper understanding of the localized space-level dynamics that may not be as apparent in the broader storey-level analysis.

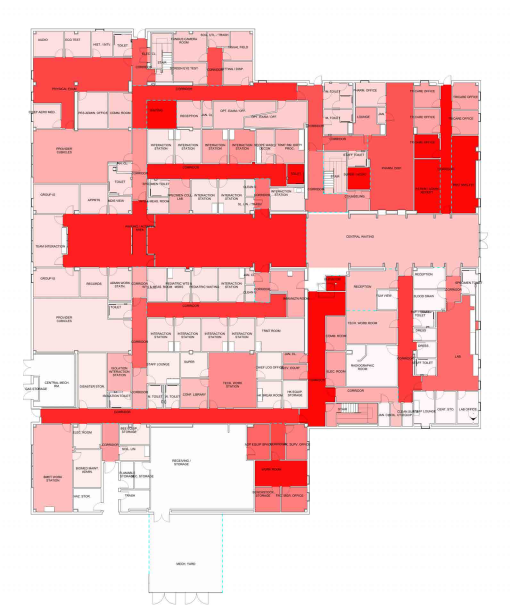


Figure 4.26: Degree centrality analysis

Figure 4.27: Betweenness centrality analysis

Comparison of circulation spaces for horizontal accessibility edge analysis (community level)

The community FF-8 based on horizontal accessibility edge analysis, as illustrated in Figure 4.28, was analyzed using community-level and building storey-level centrality metrics. The corresponding centrality values for degree and betweenness metrics are presented in Table 4.5. The findings reveal differences in how spaces are ranked based on their centrality values across these two levels of analysis. At the community level, most spaces' degree and betweenness centrality rankings are relatively consistent, with minor variations. However, one notable exception is the "CENTRAL WAITING" space. In the degree centrality analysis, "CENTRAL WAITING" is ranked fifth, indicating fewer direct connections than other community spaces. In contrast, the betweenness centrality analysis ranks "CENTRAL WAITING" fourth. It suggests that while it does not have many direct connections, it is a bridge or intermediary for movement between other spaces. At the building storey level, the rankings for "LAB" and "CENTRAL WAITING" exhibit more pronounced differences. In the degree centrality analysis, "LAB" is ranked higher than "CENTRAL WAITING," reflecting its relatively greater number of direct connections at this level. Conversely, the betweenness centrality analysis assigns a higher rank to

"CENTRAL WAITING," recognizing its role as a critical pathway in the overall circulation of the floor. These differences underscore the varying importance of these spaces depending on the centrality metric used. From a practical perspective, "CENTRAL WAITING" holds significant importance in the context of the building's functionality. It is directly connected to the main entrance and serves as the primary corridor, facilitating access to various floor areas. In contrast, the "LAB" is a restricted-access space primarily used by staff and certain patients with specific permissions. This restricted access reduces its overall role in the floor's circulation network despite its higher degree of centrality at the building storey level. These results highlight the complementary nature of degree and betweenness centrality metrics in understanding space-level circulation entities. While degree centrality identifies spaces with extensive direct connections, betweenness centrality provides insight into the strategic importance of spaces as connectors within the circulation network.

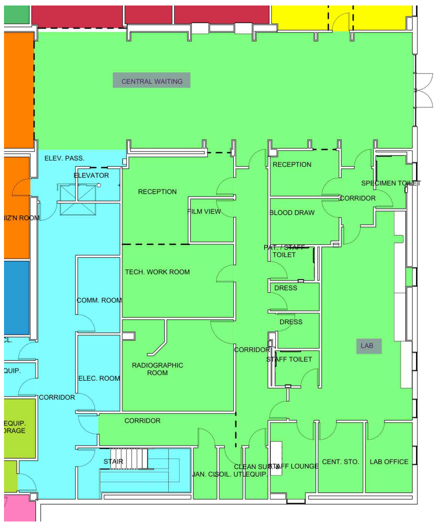


Figure 4.28: Community FF-8 from first-level community detection

Community level					
Degree Centrality			**Betweenness Centrality**		
LongName	**Community Index**	**Value**	**LongName**	**Community Index**	**Value**
CORRIDOR	FF-8	12	CORRIDOR	FF-8	163.5
LAB	FF-8	6	LAB	FF-8	98
CORRIDOR	FF-8	5	CORRIDOR	FF-8	59.5
CORRIDOR	FF-8	3	CENTRAL WAITING	FF-8	24
CENTRAL WAITING	FF-8	2	CORRIDOR	FF-8	20
Building Storey Level					
Degree Centrality			**Betweenness Centrality**		
CORRIDOR	FF-8	12	CENTRAL WAITING	FF-8	3274
LAB	FF-8	6	CORRIDOR	FF-8	2627
CORRIDOR	FF-8	5	CORRIDOR	FF-8	1465
CENTRAL WAITING	FF-8	4	CORRIDOR	FF-8	656
CORRIDOR	FF-8	4	LAB	FF-8	650

Table 4.5: Community level and building storey level centrality values

The community FF-5 is based on horizontal accessibility edge analysis, as illustrated in Figure 4.29. There is a vertical corridor and a horizontal corridor within this community FF-5. However, at the building storey level, the vertical corridor exhibits a higher betweenness value, while at the community level, the horizontal corridor shows a greater betweenness centrality value, as detailed in the tables 4.6 and 4.7.

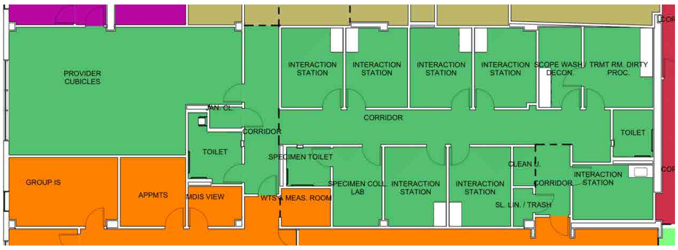


Figure 4.29: Community FF-5 from first-level community detection

Building Storey Level			
GUID	**LongName**	**Community Index**	**Betweenness Centrality Value**
0ztdC3L1HAzhbhMHypqcak	CORRIDOR	FF-5	4195
0ztdC3L1HAzhbhMHypqcaa	CORRIDOR	FF-5	1974
0ztdC3L1HAzhbhMHypqcaZ	CORRIDOR	FF-5	1516
0ztdC3L1HAzhbhMHypqcAu	PROVIDER CUBICLES	FF-5	648
0ztdC3L1HAzhbhMHypqcA7	SPECIMEN COLL. LAB	FF-5	143

Table 4.6: Betweenness centrality values of FF-5 at building storey level

Community-level			
GUID	**LongName**	**Community Index**	**Betweenness Centrality Value**
0ztdC3L1HAzhbhMHypqcaZ	CORRIDOR	FF-5	97
0ztdC3L1HAzhbhMHypqcaa	CORRIDOR	FF-5	39
0ztdC3L1HAzhbhMHypqcAu	PROVIDER CUBICLES	FF-5	33
0ztdC3L1HAzhbhMHypqcAU	INTERACTION STATION	FF-5	33
0ztdC3L1HAzhbhMHypqcak	CORRIDOR	FF-5	25

Table 4.7: Betweenness centrality values of FF-5 at community level

4.4 Additional validation examples

The following figures illustrate space-level relationship findings and graph-based circulation path reasoning findings of an IFC model of office building.

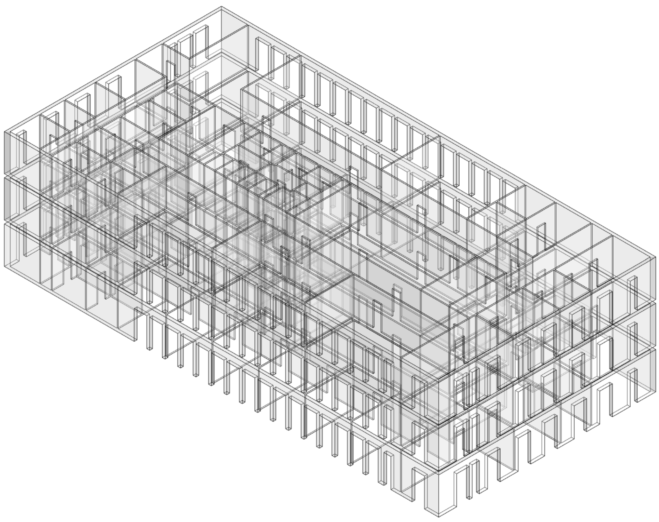


Figure 4.30: 3D perspective view of office building

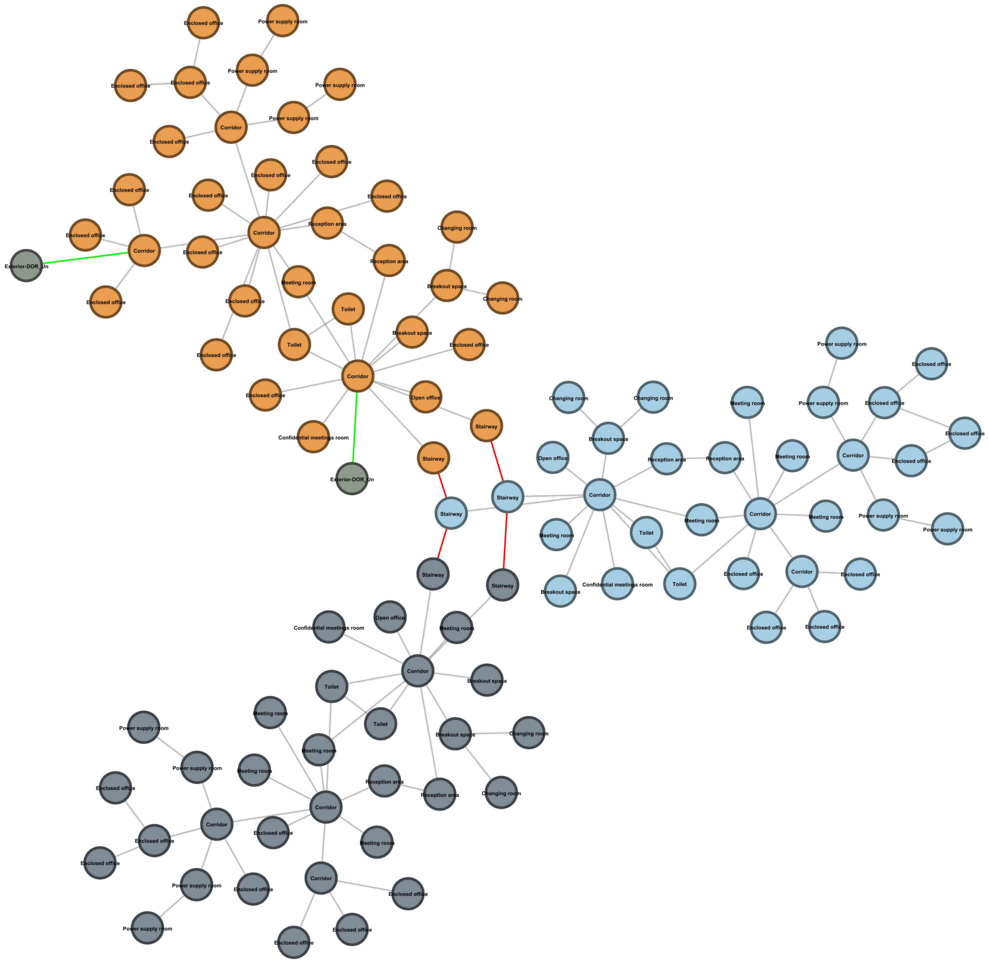


Figure 4.31: Horizontal accessibility edge analysis of office building (nodes are coloured as storey level)

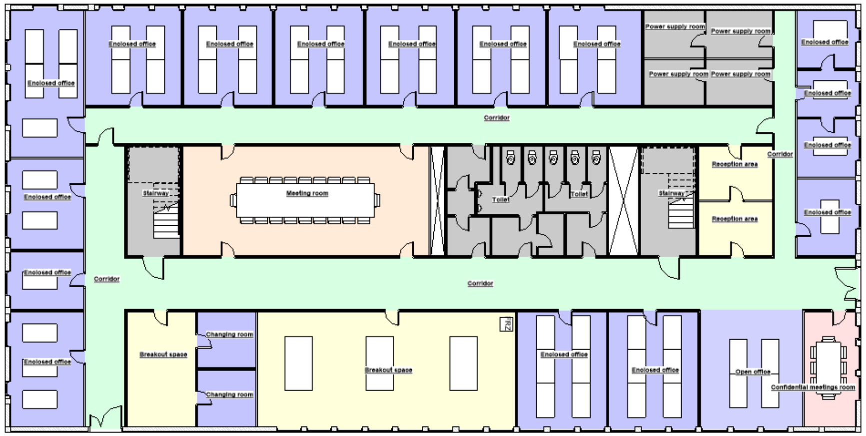


Figure 4.32: Floor plan of office building: ground floor

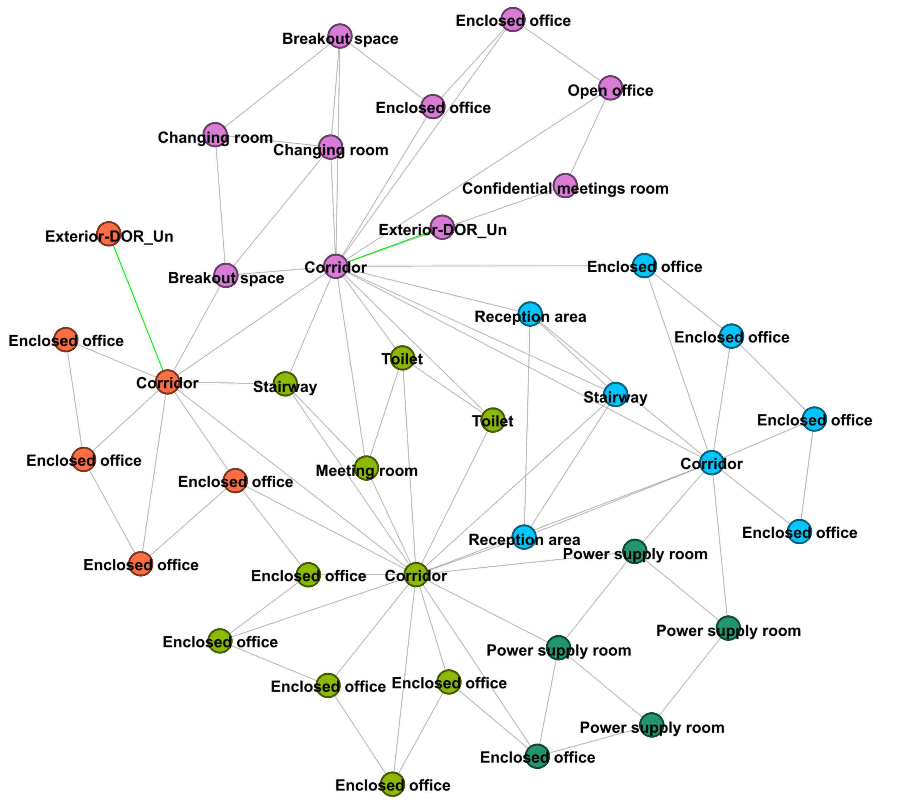


Figure 4.33: Community Detection of the graph obtained from horizontal accessibility edge analysis of office building: ground floor (nodes are coloured as identified community)

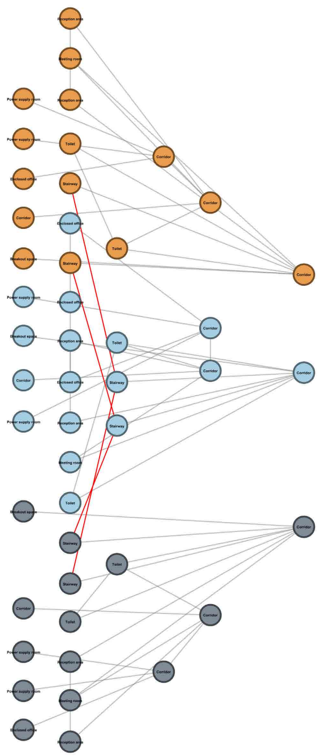


Figure 4.34: Degree centrality analysis (in hierarchical graph format and nodes having value<2 are filtered out) of the graph obtained from horizontal accessibility edge analysis of the office building (nodes are coloured as storey level)

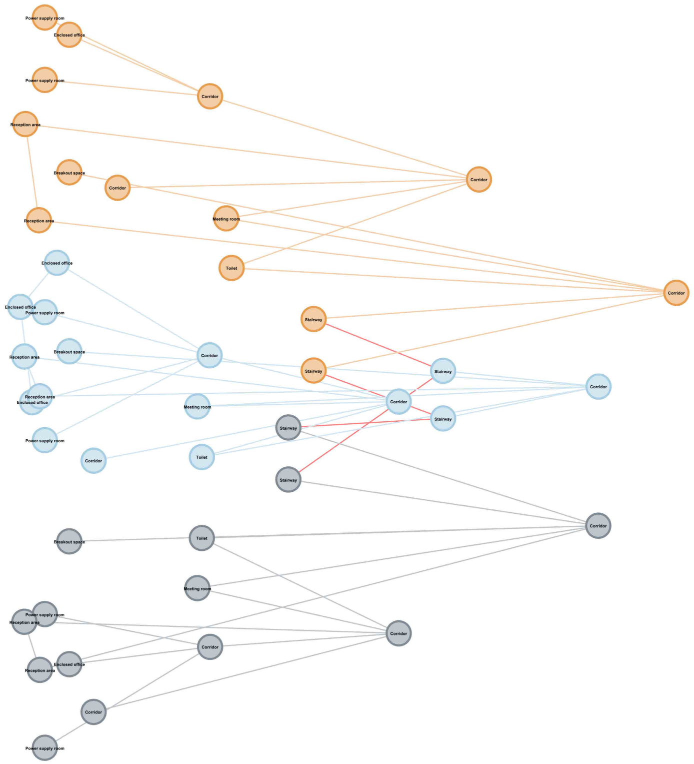


Figure 4.35: Betweenness centrality analysis (in hierarchical graph format and nodes having value=0 are filtered out) of the graph obtained from horizontal accessibility edge analysis of the office building (nodes are coloured as storey level)

Chapter 5

Conclusions

5.1 Contribution

The study addresses the challenges in analyzing space-level circulation design rationale in IFC models by proposing a graph-based methodology that integrates space-level topological detection, community detection, and centrality analysis. The main contributions of the study are outlined as follows:

- Resolving issues with incomplete or missing *IfcRelSpaceBoundary* data: The proposed approach reinforces space-level horizontal adjacency detection by addressing limitations posed by incomplete or missing IfcRelSpaceBoundary data. Utilizing a voxel-based system with adjustable resolution, the method reliably detects space-level horizontal relationships, even in cases where explicit boundary information is unavailable. This includes detecting adjacencies through complex geometric configurations such as double walls and irregularly shaped spaces. Furthermore, the methodology accommodates configurable thresholds for connectivity and adjacency detection, providing flexibility to adapt to diverse architectural layouts. Unlike traditional approaches constrained by the Manhattan world assumption, this method supports the analysis of both orthogonal and non-orthogonal geometries, including L-shaped corridors and irregular rooms.

- Community detection in space-level topological relationships: The study introduces a multi-level community detection framework to analyze spatial organizations at various topological scales. By applying the Girvan-Newman algorithm, the framework identifies hierarchical community structures, offering insights into the organization of spaces within a building. Large communities detected during the first-level analysis are further subdivided, enabling a granular understanding of spatial clustering. This capability ensures comprehensive community detection across diverse cases, ranging from localized clusters to building-wide topological relationships.

- Identification of key circulation nodes through centrality analysis: The method incorporates centrality-based analyses to identify critical circulation nodes at multiple levels, including building storey and community levels. Degree centrality is used to highlight nodes with extensive direct connections, marking them as important hubs for localized accessibility. Betweenness centrality, on the other hand, identifies nodes that serve as essential pathways for movement between spaces, emphasizing their role in maintaining overall connectivity. By integrating these metrics, the study offers a dual perspective that enhances the understanding of space-level connectivity and the significance of circulation nodes within each community. This multi-level analysis aids in identifying key spatial elements that are crucial for efficient circulation planning.

This study contributes to enhancing IFC models by integrating graph-based methodologies for space-level circulation design rationale. By using voxelization and community detection, the approach enriches IFC data, addressing issues like incomplete boundary information and supporting diverse geometries. Additionally, it enables the reuse of IFC models for different design scenarios, offering a tool for analyzing circulation design across various building layouts.

5.2 Limitation

Several limitations of this study are acknowledged and indicate areas for potential improvement.

- Uniform treatment of space-level relationships: The current methodology operates as an unweighted analysis, treating all relationships between space-level entities uniformly. This approach overlooks critical variations that could influence circulation patterns, such as differences in door sizes, plan area of space-level entities, or specific geometric features. For instance, a narrow doorway might naturally limit the flow of movement compared to a large, open passage, yet both are treated equivalently in the current model. Similarly, larger spaces with higher capacity or functional importance (e.g., meeting rooms or atriums) may play a more significant role in circulation dynamics but are not given additional weight in the analysis. Incorporating these factors in future iterations, potentially through weighted graphs or customized metrics, could lead to a more accurate and nuanced understanding of space-level relationships.
- Neglect of node distance in graph-based analysis: The proposed methodology does not consider the physical distance between nodes in the generated graphs. This limitation can lead to an oversimplification of relationships, as spatial proximity often plays a critical role in circulation design. For example, two spaces connected via a long corridor may have less interaction or movement between them compared to adjacent spaces, even if the graph treats these connections equivalently. Incorporating distance-based weighting in graph representation could enhance the methodology by better reflecting real-world circulation dynamics.
- Lack of multi-floor community relationships: A limitation of the proposed methodology is its inability to identify communities that establish meaningful relationships among multiple floors of a building. While the vertical adjacency analysis highlights the space-level connections between different levels (e.g., via stairs or elevators), the community detection algorithm operates primarily within the context of individual floor plans. As a result, the methodology cannot reveal how spaces across floors

function together as part of an interconnected system. This limitation reduces its effectiveness for analyzing circulation patterns in multi-storey buildings where cross-floor interactions play a critical role, such as vertically integrated workspaces. Future advancements could focus on extending the community detection process to consider cross-floor relationships, providing a more holistic view of building-wide spatial organization.

- Reliance on a single centrality metric: This methodology relies on individual centrality metrics—such as degree centrality or betweenness centrality—during the reasoning process. However, using only one centrality metric may result in an incomplete understanding of the space-level topological relationships within the building. For example, degree centrality identifies spaces with the highest number of direct connections, emphasizing local importance, while betweenness centrality highlights spaces that act as critical connectors within the overall graph. Both metrics provide complementary insights and ignore one in favour of the other risks overlooking key space-level entities. A combined consideration of multiple centrality metrics is essential to capture both the local and global significance of spaces, leading to a more comprehensive reasoning process.
- Computational complexity: One of the primary challenges lies in the computational intensity of the voxel-based approach. The resolution of the voxel grid directly impacts the processing time and memory usage, with finer grids offering greater accuracy at the cost of higher resource consumption. This becomes particularly problematic for large or complex building models, where the number of voxels can grow exponentially. For example, high-rise buildings or large-scale facilities with intricate spatial layouts may require substantial computational resources, making the approach less practical for real-time analysis or integration into iterative design workflows. Optimization techniques, such as parallel processing, could help mitigate this limitation.

5.3 Future work

In light of the findings and in response to the noted limitations, several directions for future research are proposed. A further direction is the incorporation of parametrization, which could allow the method to dynamically adapt to different design parameters. Additionally, exploring the use of Graph Neural Networks (GNNs) offers an opportunity to leverage AI-driven methods to automate the identification of circulation features and spatial relationships, improving efficiency in large-scale building models (Buruzs et al., 2022). The integration of weighted spatial relationships is essential, as it enables the method to account for factors such as door dimensions, wall thickness, and geometric influences on movement. This enhancement is expected to provide a more nuanced understanding of interactions at the spatial level. Additionally, refining the community detection process is vital for generating more precise insights into spatial organization. Improving the analysis of vertical adjacency is also crucial. Developing methodologies that better represent and analyze vertical connections, including multi-level circulation dynamics, would significantly broaden the method's applicability. By pursuing these avenues, the proposed method possesses the potential to evolve into a more comprehensive framework for architectural space-level analysis, yielding deeper insights and expanding its range of applications. Finally, enhancing the IFC model's robustness to incomplete data could improve the method's reliability and adaptability across different project scenarios. This could involve designing a methodology to handle variability in model quality.

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Declaration

I hereby affirm that I have independently written the thesis submitted by me and have not used any sources or aids other than those indicated.

Location, Date, Signature