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Research Article

Benchmark-Guided Graph Repair for Compliance-Oriented Spatial Layout Networks

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Abstract

Manual layout evaluation workflows in architecture often rely on labor-intensive inspection to verify adherence to complex spatial requirements, such as adjacency, accessibility, and program-specific constraints. As building programs grow in scale and interdependency, manual verification becomes increasingly inconsistent and difficult to integrate into rapid, early-stage design iterations. This paper addresses the critical problem of automatically identifying and repairing non-compliant spatial layouts represented as graphs, while preserving the original designer's intent and ensuring the interpretability of all necessary modifications. The study introduces a benchmark-guided graph repair method for compliance-oriented spatial layout networks. In this framework, a candidate layout is encoded as an attributed, weighted graph, while benchmark requirements are formalized as a target graph capturing expected spatial entities, relations, and attribute ranges. The approach first performs structured compliance checking by aligning candidate and target graphs to detect two primary failure categories: structural violations, such as missing spaces or incomplete connections, and attribute violations, such as incorrect areas or constraint-relevant labels. The proposed method then applies modular repair operators, including node insertion, edge completion, weight correction, and constraint-aware attribute adjustment, to generate a revised graph that optimises benchmark conformity. Crucially, each operation is logged alongside its triggering violation and the resulting change in compliance metrics, enabling transparent auditing and traceability for reviewers. Experiments across multiple scenarios demonstrate that the methodology consistently reduces violations and improves benchmark alignment. This research provides a robust post-processing quality assurance layer for generative tools, while future work focuses on scaling to noisier benchmarks and multi-objective designer preferences.

Keywords: graph repair; spatial layout networks; compliance checking; benchmark-guided optimisation; design automation.

Highlights

- Introduces a benchmark-guided graph repair method for automated spatial layout auditing.
- Bridges the gap between IFC-based BIM data and interpretable graph-based compliance repair.
- Utilizes GNN-based scoring to quantitatively evaluate layout quality post-automated repair.

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1 Introduction

Architectural spatial layouts must simultaneously satisfy functional requirements, regulatory constraints, and user-experience considerations. In practice, verifying whether a building layout complies with design guidelines, accessibility standards, or operational requirements remains a largely manual process (Greenwood et al., 2010; Peng & Liu, 2023; Zhang & El-Gohary, 2022). Designers typically inspect two-dimensional plans or Building Information Models (BIM) to determine whether spatial adjacencies, circulation paths, and programme areas meet project specifications. As building programmes become more complex, particularly in specialised facilities such as healthcare, education, or neuro-inclusive environments, manual auditing becomes time-consuming, error-prone, and difficult to scale during early design stages. To address these challenges, researchers have increasingly explored computational representations of spatial layouts (Al-Harasis & Jabi, 2025; van Engelenburg et al., 2023; Xie & Ding, 2023). One influential approach represents buildings as networks in which spaces are modelled as nodes and their relationships, such as adjacency or circulation, are represented as edges. This idea originates from Space Syntax theory, which demonstrated that spatial configuration can be analysed quantitatively using graph structures to study accessibility and movement patterns within buildings (Hillier & Hanson, 1984; Penn, 2003). More recent computational design research has extended graph representations to support automated analysis and optimisation of architectural layouts (Duarte, 2005; Turrin et al., 2011). Despite these advances, most existing research focuses either on analysing spatial layouts or generating new layouts through optimisation algorithms and machine-learning models. Generative design systems, for instance, have been developed to synthesise floor plans that satisfy spatial constraints using evolutionary or constraint-based approaches (Merrell et al., 2010; Michalek et al., 2002; Xie et al., 2017). However, architectural practice often requires evaluating and improving existing layouts rather than generating designs from scratch. Designers typically begin with preliminary layouts, either manually drafted or derived from BIM models, and require tools capable of diagnosing and correcting spatial configurations that deviate from programme requirements.

This paper addresses this gap by proposing a benchmark-guided graph repair framework for compliance-oriented spatial layout networks. The proposed method converts BIM models encoded in the Industry Foundation Classes (IFC) format into attributed spatial graphs representing functional spaces and their connectivity. The extracted graph is compared with a benchmark graph encoding spatial requirements derived from design guidelines or programme specifications, and detected deviations are corrected through interpretable repair operations applied directly to the graph structure. To evaluate spatial layouts quantitatively, the framework integrates a Graph Neural Network (GNN) that predicts a graph-level performance score based on spatial configuration and node attributes. GNNs have demonstrated strong capabilities for learning relational patterns in structured data, including spatial networks (Wu et al., 2021). In this context, the GNN provides a continuous evaluation metric that complements rule-based compliance checks by capturing higher-order spatial relationships. A key contribution of this work is the interpretability of the repair process. Instead of producing opaque optimisation outputs, the framework generates a transparent repair log describing which spatial elements and connections were modified to improve compliance. Specifically, this study introduces: (i) a method for extracting spatial layout graphs directly from IFC models using explicit door-based adjacency relationships, (ii) a benchmark-guided graph repair framework capable of detecting and correcting structural and attribute violations, (iii) an interpretable repair pipeline that records the sequence of graph modifications applied during compliance improvement, and (iv) a GNN-based evaluation model that quantitatively assesses spatial layout performance before and after repair.

2 Background

Automating the evaluation and improvement of spatial layouts requires the integration of multiple research domains, including BIM, automated compliance checking, and graph-based spatial analysis. This section reviews the evolution of these fields and situates the proposed benchmark-guided graph repair framework within existing research.

2.1.1 IFC-Based Spatial Data Extraction

BIM provides a structured digital representation of buildings that supports information exchange across the architecture, engineering, and construction (AEC) lifecycle (Sacks et al., 2018). The IFC standard is a vendor-neutral data model developed by buildingSMART that enables interoperability between BIM platforms by defining a common schema for building components and their relationships (buildingSMART, 2026). Within IFC models, spatial entities are typically represented by `IfcSpace` objects, while physical connections such as doors are represented by `IfcDoor` elements. Spatial relationships between building elements are expressed through relational entities such as `IfcRelSpaceBoundary`, which link spaces to enclosing building components. These relationships allow computational systems to extract spatial topology and analyse how spaces connect within a building model. Previous research has demonstrated the potential of IFC for automated spatial analysis and rule-based validation. Monteiro et al. (2014) proposed a framework for translating building regulations into computable rule sets that can be evaluated against BIM models. Pauwels et al. (2017) explored semantic querying of IFC models to enable automated reasoning about building data using linked-data approaches. Despite these capabilities, extracting reliable spatial relationships from IFC models remains challenging in practice. BIM models frequently exhibit inconsistent modelling practices, incomplete boundary definitions, or missing relational data, which can hinder automated spatial analysis (Eastman et al., 2009; Pauwels et al., 2017). In particular, `IfcRelSpaceBoundary` relationships are often partially defined or absent, complicating the identification of spatial adjacency between rooms and limiting the reliability of spatial reasoning processes based on IFC data (Isikdag & Underwood, 2010; Ren et al., 2011). Consequently, several researchers have proposed transforming BIM data into simplified computational structures such as graphs to facilitate robust spatial analysis (Isikdag & Underwood, 2010; Pauwels et al., 2017).

2.1.2 Automated Compliance Checking (ACC) in BIM

Automated Compliance Checking (ACC) has been a longstanding research objective within the BIM domain (Eastman et al., 2009; Labonnote et al., 2016). ACC systems aim to automatically verify whether building designs satisfy regulatory requirements by translating textual rules into computational logic that can be applied to digital building models (Amor & Dimyadi, 2021; Monteiro et al., 2014). Early work in this field focused on rule-based approaches, where building codes were encoded as deterministic statements evaluated against BIM data (Eastman et al., 2009; Monteiro et al., 2014). While rule-based ACC systems provide transparent validation mechanisms, they often struggle with complex spatial relationships or ambiguous regulatory language. As a result, recent research has explored integrating machine learning and data-driven techniques into compliance analysis workflows (Bloch et al., 2023). These developments have shifted the focus of ACC research from purely deterministic rule checking toward hybrid systems that combine rule-based reasoning with predictive models. Such approaches allow building designs to be evaluated not only in terms of strict regulatory compliance but also in terms of overall spatial quality or functional performance.

2.1.3 Graph-Based Representation of Spatial Layouts

Graph theory provides a powerful framework for representing spatial configurations in architecture. In graph-based representations, spaces are modelled as nodes while relationships such as adjacency, accessibility, or visibility are modelled as edges (Wilson, 1996). This abstraction enables quantitative analysis of spatial structure independent of geometric complexity. The use of graph representations in

architectural research can be traced to Space Syntax theory, which demonstrated that spatial configuration influences patterns of movement and social interaction within buildings and urban environments (Hillier & Hanson, 1984). Subsequent research extended these ideas to computational design applications, where graph structures are used to analyse circulation networks and functional relationships between spaces (Aalaei et al., 2023; Al-Harasis & Jabi, 2025; Xie & Ding, 2023). In recent years, graph representations have been increasingly used in generative design and layout optimisation. Massafra et al. (2025) utilised graph representation for developing semi-automated approach for generating a dataset of residential buildings. Díaz-Vilariño et al. (2022) developed an automated system that converts facility layouts into graph representations to verify compliance with design specifications. Graph-based models are particularly well suited for compliance checking because many spatial requirements can be expressed as relationships between spaces. However, the reliability of graph-based analysis depends heavily on how spatial adjacency is defined. Many studies infer adjacency from geometric proximity or shared boundaries, which can introduce ambiguous or unintended connections. To maintain interpretability in compliance workflows, some researchers advocate extracting adjacency only from explicit circulation elements such as doors or openings, ensuring that graph connections represent verifiable access relationships rather than inferred spatial proximity (Buruzs et al., 2022).

2.2 Research Gap

Although significant progress has been made in BIM-based compliance checking and graph-based spatial analysis, relatively little research has addressed the automated repair of spatial layout graphs derived from BIM models. Existing ACC systems typically focus on identifying violations rather than correcting them, while generative design approaches often produce new layouts without providing interpretable explanations of how compliance requirements are satisfied. Most existing workflows either rely exclusively on rule-based validation or exclusively on machine-learning models. This research addresses these limitations by introducing a benchmark-guided graph repair framework that: (i) extracts spatial layout graphs directly from IFC building models, (ii) detects structural and attribute violations relative to benchmark spatial requirements, (iii) applies interpretable graph repair operations to correct detected violations, and (iv) evaluates spatial layout quality using a GNN-based scoring model.

3 Methodology

3.1 Research Framework

This study proposes a computational framework for evaluating spatial layouts encoded in Industry Foundation Classes (IFC) models using graph representations and benchmark-based comparison. The approach combines deterministic graph analysis with a trained Graph Neural Network (GNN) regressor to assess spatial layout quality. Rather than modifying the IFC model directly, graph representations are constructed in memory to evaluate different levels of benchmark alignment. The workflow operates through three graph states. State 1 represents the spatial graph extracted from the IFC model using door-based adjacency. State 2 aligns the graph with benchmark requirements through area adjustments and adjacency modifications without introducing new spaces. State 3 produces a benchmark-complete graph by adding missing programme instances and required spatial relations. These stages allow comparison between the original layout, a benchmark-aligned configuration, and a fully benchmark-compliant configuration. Graph performance is evaluated using a pre-trained GNN that predicts a continuous layout quality score.

3.2 IFC Spatial Graph Extraction

Spatial graphs are extracted from IFC models using `lfcOpenShell`. Each *IfcSpace* is represented as a node with associated attributes such as semantic label and area. Labels are obtained from custom IFC properties when available, otherwise falling back to space names and subsequently normalised to

enable consistent comparison with benchmark data. Adjacency relations are derived from door-based circulation information. The workflow traverses *IfcRelSpaceBoundary* relations and maps openings to *IfcDoor* elements. Two spaces are connected only when they share a door, producing an openings-only adjacency graph in which all edges correspond to explicit circulation paths. Edge weights represent the strength of adjacency relationships.

3.3 Benchmark Representation and Scenario Selection

Benchmark spatial requirements are provided through two datasets: an adjacency dataset defining required relationships between space types and a geometry dataset specifying programme instances and area ranges. Both datasets are normalised using the same label-processing procedures applied to IFC data. When multiple benchmark scenarios are available, the framework automatically selects the most appropriate scenario by comparing the set of space types present in the IFC model with benchmark definitions. The scenario with the highest Jaccard similarity between space-type sets is selected for evaluation.

3.4 Graph-Based Representation

Before evaluation, spatial graphs are converted into PyTorch Geometric data objects. Node features are derived from spatial attributes and graph topology, enabling the GNN to analyse both spatial configuration and attribute distribution. Graph-level evaluation is performed using a pre-trained GraphConv regression model that outputs a single scalar performance score for each graph.

3.5 Benchmark Alignment

Following graph extraction, an evaluation-only alignment stage adjusts the graph according to benchmark requirements while preserving the original IFC model. This process involves three operations: (i) Area alignment, which adjusts space areas when they fall outside benchmark ranges, (ii) missing adjacency insertion, which introduces edges corresponding to required benchmark relationships between existing nodes, (iii) extra adjacency removal, which eliminates edges not required by the benchmark specification. The resulting graph constitutes State 2, representing a layout aligned with benchmark requirements without introducing new programme instances.

3.6 Benchmark Completion

To analyse a fully compliant configuration, the workflow optionally performs benchmark completion. Missing programme instances defined in the benchmark geometry dataset are introduced as synthetic nodes. Existing IFC spaces are matched to benchmark instances where possible, while additional instances are created when required counts exceed the available spaces. Synthetic nodes are assigned benchmark target areas and connected according to benchmark adjacency lists. The resulting graph forms State 3, representing a benchmark-complete spatial configuration.

3.7 Evaluation and Output Analysis

Each graph state is evaluated using the trained GNN model. Predicted scores enable quantitative comparison between the original IFC-derived layout and its benchmark-aligned variants. In addition to these scores, the framework produces diagnostic outputs describing structural deviations from benchmark requirements, including missing programme instances, area adjustments, added or removed adjacency relations, and remaining mismatches. Visual outputs are also generated by overlaying the extracted spatial graph on the IFC floor plan to support interpretation.

4 Results

4.1 Experimental Setup

The framework was evaluated using three IFC spatial layouts representing different programme scales: Project A (150 occupants), Project B (120 occupants), and Project C (200 occupants). For each case, the workflow extracted door-based spatial adjacency graphs and evaluated them against benchmark spatial requirements corresponding to the relevant occupancy scenario. Evaluation was conducted across the three graph states defined in the methodology: (i) State 1: IFC-derived spatial graph, (ii) State 2: Benchmark-aligned graph (evaluation-only adjustments), (iii) State 3: Benchmark-complete graph (synthetic benchmark expansion). Each graph was evaluated using the trained GNN model. Figure 1 illustrates the overall workflow.

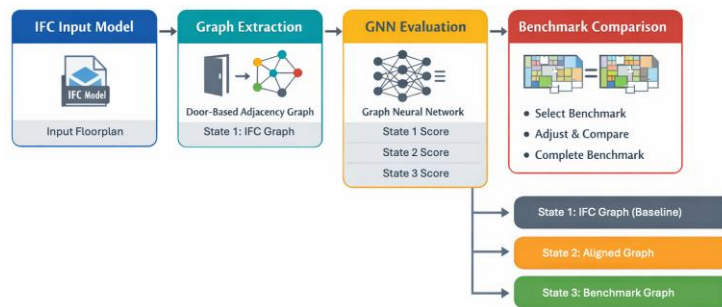


Figure 1. The overall workflow

4.2 Graph Extraction from IFC

The IFC parsing process successfully extracted spatial graphs for all three case studies. In each model, *IfcSpace* entities were converted into graph nodes, while door-based adjacency relations were derived from *IfcRelSpaceBoundary* and door-fill relationships. The resulting graphs therefore represent circulation connectivity within each layout. Figure 2 presents the IFC floor plans alongside the extracted spatial graphs. Visual inspection confirms that graph edges correspond to explicit door-based circulation paths, supporting the validity of the openings-only extraction strategy.

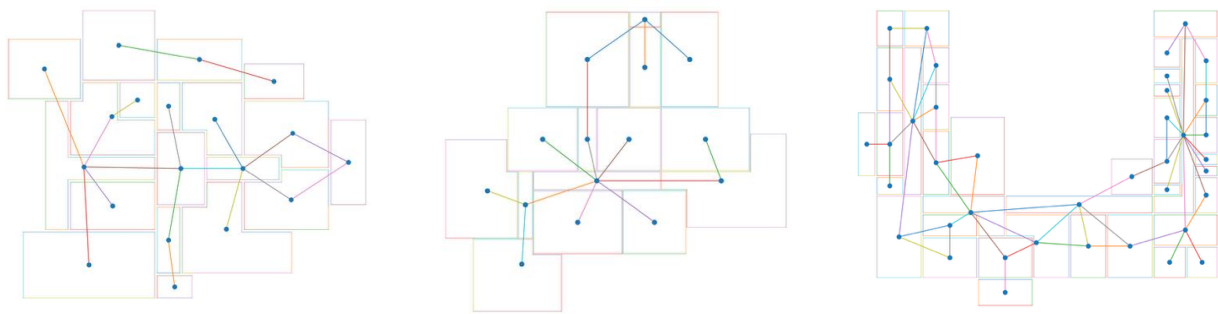


Figure 2. IFC-derived floorplan and extracted door-based spatial graphs for Projects A, B, and C

4.3 Graph Evaluation Across States

Table 1 summarises the graph-level evaluation scores for the three projects across the three assessment states.

Table 1. Graph-level evaluation scores

Graph State	Description	Project A	Project B	Project C
State 1	IFC-derived spatial graph	0.3494	0.3530	0.3386
State 2	Benchmark-aligned graph (evaluation-only)	0.7681	0.6690	0.7265
State 3	Benchmark-complete graph	0.9705	0.9785	0.9914

Baseline scores in State 1 ranged from 0.3386 to 0.3530, indicating substantial deviation from benchmark spatial requirements. Despite differences in project scale, similar baseline values suggest comparable programme and connectivity mismatches across the three layouts. Applying benchmark alignment in State 2 produced substantial improvements. Scores increased to 0.7681, 0.6690, and 0.7265 for Projects A, B, and C respectively, indicating that many deviations were attributable to correctable adjacency and area mismatches. Project B exhibited the lowest intermediate score, suggesting greater adjustment was required to approach benchmark conformity. The highest scores were obtained in State 3, after benchmark completion introduced missing programme instances and required spatial relations. Final scores reached 0.9705, 0.9785, and 0.9914, indicating near-complete alignment with benchmark requirements. This consistent pattern across all case studies demonstrates that the framework can reliably detect and quantify spatial deviations while distinguishing between connectivity misalignment and programme incompleteness.

4.4 Programme and Adjacency Diagnostic

Beyond graph-level scores, the framework generated diagnostic outputs describing deviations between IFC layouts and benchmark specifications. Programme comparisons identified missing or additional space instances, while adjacency diagnostics highlighted absent or unnecessary spatial connections. During benchmark alignment, required connections were introduced and non-required edges removed, producing graph structures more consistent with benchmark programmes. These diagnostics allow designers to identify the specific programme and connectivity conditions responsible for deviations from benchmark expectations.

Table 2. Sample of detected spatial deviations

Space Name	Required spaces	Present in IFC	Missing in IFC	Extra in IFC
Dining Space	1	0	1	0
Office	1	0	1	0
Library	1	1	0	0
Nursery	1	2	0	1

Table 3. Sample of detected Area deviations

Space Name	IFC Area	Target Minimum Area	Target Maximum Area
library	27.806	80	80
Sensory space	32.443	35.75	41.65
Classroom	13.415	41.65	48.55
Nursery	29.602	59	70

4.5 Benchmark Completion Analysis

The benchmark-completion stage introduced synthetic nodes representing programme spaces required by the benchmark but absent from the IFC model. These nodes were assigned benchmark target areas and connected according to benchmark adjacency definitions. The resulting graphs represent theoretical reference configurations that fully satisfy benchmark requirements. The high scores observed in State 3 demonstrate that benchmark completion substantially improves structural alignment with the target programme. Importantly, these modifications are applied only within the evaluation graph and do not alter the original IFC model. The comparison between States 2 and 3 therefore distinguishes between deviations caused by adjacency misalignment and those resulting from missing programme instances.

5 Discussion

5.1 Interpretation of the Multi-State Evaluation

The results demonstrate that the proposed framework can identify structural differences between IFC-derived layouts and benchmark spatial programmes across multiple case studies. Baseline scores in State 1 ranged from 0.3386 to 0.3530, indicating substantial divergence from benchmark configurations. Because adjacency is derived strictly from door-based relations, these scores reflect the spatial structure encoded in the BIM models and reveal programme discrepancies not easily detectable through geometric inspection. Significant improvements were observed in State 2, where evaluation-only benchmark alignment corrected adjacency relations and spatial attributes while preserving the original node set. This suggests that many deviations between IFC layouts and benchmark requirements arise from correctable connectivity and area mismatches rather than

missing spaces. In State 3, benchmark completion introduced missing programme instances and required adjacencies, producing scores above 0.97 across all projects. The smaller improvement from State 2 to State 3 indicates that connectivity structure had a stronger influence on layout performance than programme completeness in the evaluated cases. Similar improvement patterns across all projects confirm that the framework can consistently identify and quantify spatial deviations across different layouts.

5.2 Contribution to BIM-Based Spatial Analysis

The proposed approach contributes to research integrating BIM with graph-based spatial analysis. Unlike many existing studies that infer spatial networks from geometric proximity or visibility relations, the present method derives adjacency directly from circulation elements encoded in the IFC schema. Using door-based adjacency ensures that graph connections represent actual circulation paths rather than inferred spatial proximity, improving the interpretability of the extracted spatial graphs. A further contribution is the integration of deterministic spatial diagnostics with learning-based graph evaluation within a unified workflow. The deterministic component identifies programme deviations such as missing spaces, incorrect adjacency relations, and area mismatches, while the GNN produces a continuous graph-level performance score capturing broader structural patterns within the spatial network. This hybrid approach addresses limitations of purely rule-based or purely data-driven systems by combining interpretable diagnostics with quantitative evaluation.

5.3 Implications for Early Design Evaluation

From a design-support perspective, the framework enables the evaluation of spatial layouts during early design stages when detailed geometry may not yet be fully defined. Because the method operates on graph representations derived from IFC models, it can be applied to BIM models containing only basic spatial definitions and circulation elements. The three-state evaluation structure supports design exploration by comparing the baseline layout, a benchmark-aligned configuration, and a benchmark-complete configuration. This allows designers to identify whether deviations arise from incorrect adjacency relationships, missing programme elements, or both. More broadly, the framework addresses the lack of methods for repairing spatial layout graphs derived from BIM models. Existing compliance-checking systems typically detect violations without proposing interpretable corrections, while generative design approaches often produce new layouts without explaining how compliance requirements are satisfied. By combining diagnostic analysis with structured graph modification, the proposed benchmark-guided framework extends BIM-based compliance analysis from passive rule checking toward a more explainable spatial evaluation process.

5.4 Limitations

Despite its potential, the framework has several limitations. First, the accuracy of the extracted spatial graph depends on the quality of the IFC model. Incomplete or inconsistent modelling of entities such as `IfcSpace`, `IfcDoor`, or `IfcRelSpaceBoundary` may lead to missing or inaccurate adjacency relations, meaning the extracted graph may not fully represent the intended spatial connectivity of the building. Second, the graph representation considers only door-based connectivity. Additionally, the benchmark-completion stage introduces synthetic nodes and edges that do not correspond to actual geometric elements in the IFC model. Although useful for analytical comparison and identifying programme gaps, this step should not be interpreted as automatic layout generation.

5.5 Future Work

Future research could extend the framework in several directions. One improvement is the incorporation of additional spatial relations beyond door-based adjacency, such as visual connections or shared boundaries, enabling the graph representation to capture a wider range of

spatial interactions. Additionally, the benchmark-complete graph generated in State 3 could also serve as a target configuration for generative design algorithms, supporting automated exploration of layouts that satisfy benchmark requirements.

6 Conclusions

This paper presented a computational framework for evaluating spatial layouts encoded in IFC models using graph-based analysis and a Graph Neural Network (GNN). The framework converts IFC spatial data into a door-based connectivity graph, compares this representation against benchmark programme requirements, and evaluates layout quality through a learning-based scoring model. The workflow operates through three evaluation states: the IFC-derived graph, a benchmark-aligned graph, and a benchmark-complete graph. This structure enables comparison between the existing design condition, potential improvements through adjacency alignment, and a fully benchmark-compliant configuration. The results demonstrate that the approach can identify structural differences between spatial layouts and benchmark requirements while providing interpretable diagnostics related to programme completeness, adjacency mismatches, and area deviations. In addition, the GNN produces a continuous graph-level score that enables quantitative comparison between spatial configurations. By combining BIM-derived spatial graphs, benchmark-based analysis, and machine-learning evaluation, the proposed framework provides a structured and interpretable method for analysing spatial layouts. Although the current implementation focuses on autism-centre programmes, the methodology can be extended to other building types and design contexts.

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All data is available per request

Conflicts of Interest

The authors declare no conflict of interest