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A STUDY ON THE QUANTIFICATION OF A FLOOR PLAN USING NPCS WITH NEEDS BASED AI IN A 3D SIMULATION

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Abstract

In recent years, AI has been increasingly utilized in the construction industry to address labour shortages and improve efficiency. While AI applications in construction management and site operations are advancing, their use in architectural design remains limited. This study proposes a novel method for evaluating floor plans quantitatively by simulating NPC (Non-Player Characters) within a 3D environment.

Using a BIM-based CAD software and game engine, we developed a system that enables NPCs to navigate a 3D floor plan and interact with furniture and spaces. The system integrates need-based AI-driven NPC behaviours to assess spatial efficiency and usability. Data is transferred between CAD and the simulation environment via an external data-sharing platform, allowing real-time updates and automated synchronization.

NPCs are designed with human-like needs and behaviour patterns, implemented using an AI model inspired by an existing need-based decision-making framework. Each NPC autonomously moves through the environment, interacting with designated objects based on predefined parameters such as hunger, work tasks, and movement efficiency. This allows for quantifying accessibility, privacy, and spatial bottlenecks.

The study conducted simulations on simple residential and office layouts, measuring average travel distances and comparing movement complexity through a calculated movement distance ratio. Results suggest that this method provides valuable insights for optimizing spatial design, particularly in larger environments such as office spaces.

Future work aims to refine the system by incorporating room-specific usage frequency analysis, subjective user-experience modelling, and diverse NPC profiles to simulate different lifestyles and work behaviours. This research contributes to advancing AI-based architectural evaluation tools, bridging the gap between traditional CAD-based design and real-world usability assessment.

Keywords: AI, NPCs, Quantification, BIM, Game Engine.

1. Introduction

AI use in the construction industry has greatly increased in recent years, with a market value estimate of $2.5 Billion dollars in 2022 according to Global Market Insights [1]. It is currently being used in Field Management, Project Management, etc… to streamline the construction process. However, in terms of planning and designing the layout of the architecture, there exists relatively fewer research articles, and much less actual field-tested cases of AI being used. While its applications in field and project management are well documented, AI-driven layout planning and evaluation remain largely unexplored. This gap stems from the scarcity of behaviourally relevant datasets and the complexity of defining "good" layouts beyond static metrics. Addressing this, our study introduces a needs-based simulation approach, aiming to provide dynamic, human-cantered floor plan evaluations.

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2. Literature Review

Research on the quantitative evaluation of spatial configurations can be traced back to the development of Space Syntax by Hillier and Hanson (1984) [2]. Space Syntax introduced a systematic methodology for analyzing spatial layouts using graph-based representations, quantifying properties such as integration, connectivity, and visibility to predict human movement patterns and social interactions within built environments. Although primarily applied to two-dimensional plans, the underlying principles of accessibility, visibility, and movement dynamics remain crucial even today. This study builds upon these foundational ideas by extending them into dynamic, three-dimensional simulations, where the impact of layout configurations is evaluated through agent-based interactions rather than static metrics.

Subsequent research shifted toward automating the generation of floor plans. Early computational approaches include the work of Michalek et al. (2002), who introduced a genetic algorithm that produced alternative floor plan layouts based on user-defined constraints, demonstrating the promise of optimization techniques in supporting architectural design [3]. Later, Merrell et al. (2011) proposed a data-driven framework that learned spatial rules from existing architectural datasets, enabling the generation of new, functionally plausible layouts by capturing implicit human design logic [4]. Nauata et al. (2021) further advanced this field by applying deep learning models to predict room arrangements that reflect human-like spatial reasoning, effectively modelling adjacency preferences and circulation patterns [5]. However, despite these technological advances, most studies have remained focused on generation rather than evaluation. Generated floor plans often lack the nuanced usability, inhabitability, and design judgment found in human-designed layouts, limiting their practical adoption in real-world projects.

In parallel, the broader construction industry has seen an increasing integration of AI technologies. As Ali (2023) points out, Machine Learning (ML), Artificial Neural Networks (ANN), Deep Learning (DL), Computer Vision (CV), and Robotics have been applied across construction management, safety monitoring, and remote site supervision [6]. For instance, ANN has been utilized for construction cost forecasting, CV and DL for machinery activity monitoring and safety enforcement, and Natural Language Processing (NLP) for analysing accident reports. These applications highlight the growing trust in AI systems to not only perform predictive tasks but also to support decision-making in dynamic and uncertain environments, suggesting the feasibility of applying similar approaches to spatial evaluation tasks.

Recent facility layout research has recognized the importance of simulation-based evaluation under uncertainty. Garcia et al. (2018) emphasized the need to incorporate dynamic simulation models during the early stages of layout design to progressively manage and reduce uncertainties in manufacturing environments [7]. Their work supports the idea that simulation, rather than static analysis alone, can better inform layout decisions, particularly under conditions of uncertainty about human behaviour or environmental variability. The methodology aligns closely with the current study's approach of using agent-based simulation to dynamically test layout effectiveness.

While generative design algorithms and AI-based planning systems have matured, there remains a notable gap in the evaluation of layouts through simulated occupation and behavioural analysis. By integrating foundational concepts from Space Syntax, modern generative modelling, AI applications in construction, and simulation-based optimization strategies, the present study proposes a novel framework for dynamic, quantitative floor plan evaluation using needs-driven NPCs in a 3D environment.

3. Research Goals and Objectives

The primary goal of this research is to establish a novel methodology for evaluating architectural floor plans through simulation-based analysis. This evaluation method is intended to serve as a foundational framework for future studies in automated floor plan generation, especially those involving artificial intelligence and behavioural modelling. While various algorithmic approaches have been proposed for generating architectural layouts, a key limitation remains: the functional performance of these layouts is often not assessed in dynamic, human-centric contexts. This research addresses this gap by introducing an AI-driven simulation environment in which virtual agents—Non-Player Characters (NPCs)—navigate and interact within 3D representations of architectural layouts.

The core hypothesis is that the most accurate assessment of a floor plan's usability and spatial efficiency can be achieved by observing how simulated occupants behave within the space. Rather than relying solely on static geometrical metrics, this study proposes a behavioural evaluation model, wherein autonomous NPCs operate according to human-like needs, perform context-driven actions, and generate data that reflects the experiential quality of the layout.

To achieve this goal, the research is structured around the following specific objectives:

- **Development of a 3D Simulation Environment:**
  Construct a simulation framework that integrates Building Information Modelling (BIM) data with a game engine, allowing for accurate spatial representation and dynamic updates.
- **Implementation of Need-Based NPC Behaviour:**
  Design and implement an AI model that drives NPC behaviour based on fluctuating internal states (e.g., hunger, fatigue, focus), enabling realistic decision-making and movement patterns within the simulated environment.
- **Design of an Evaluation and Logging System:**
  Develop scripts to monitor and record NPC interactions with the environment, including travel distances, interaction durations, and object utilization frequency. These logs provide quantifiable data on layout performance.
- **Data Structuring for AI Learning:**
  Format the collected simulation data into structured datasets suitable for training machine learning models. These datasets are intended to support future research in predictive layout evaluation or generative design systems.

Each objective builds upon the previous step to construct a coherent system in which architectural layouts can be tested and scored based on lived simulation. The expected outcome is a functional pipeline that not only enables the evaluation of existing floor plans but also contributes to a feedback mechanism for automated design tools, ultimately bridging the gap between generative algorithms and human-centred spatial validation.

4. Methodology

This study employs a simulation-based methodology using a hybrid workflow between the BIM Software and the game engine, with the objective of evaluating the functional performance of architectural floor plans. The methodology integrates accurate BIM-based modelling, needs-driven AI behaviour, and real-time agent-based simulation to assess spatial usability. The following subsections detail the implementation process. **Figure 1** shows the workflow of this research.

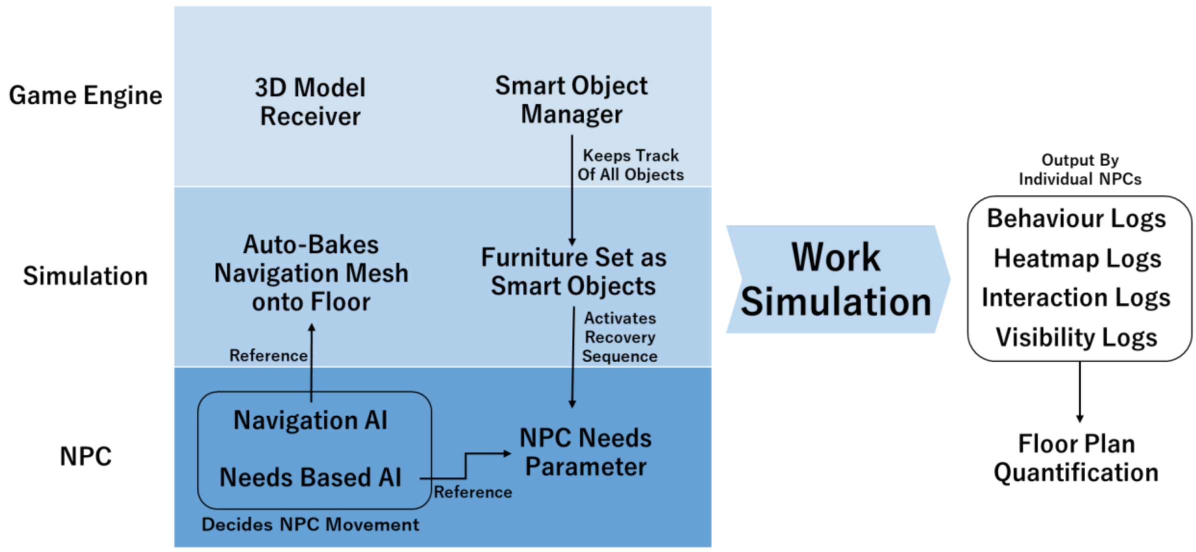

Fig. 1 The Flow of the System Created

4.1. Floor Plan Modelling and Data Transfer

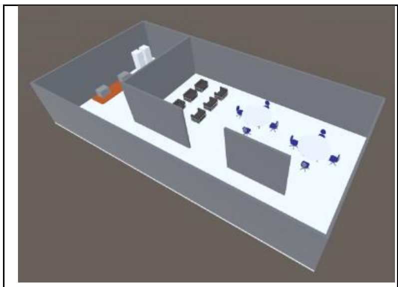	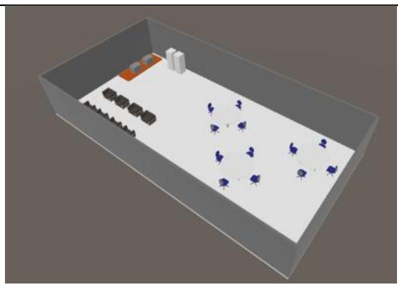	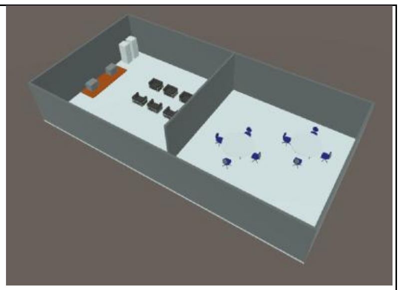
Office Layout A	Office Layout B	Office Layout C

Fig. 2 Office Layout Model used in the Simulations

The architectural floor plans used in this experiment are created in the BIM software to ensure real-world dimensional accuracy and compatibility with professional architectural workflows. The BIM models are exported into an open-source data exchange platform designed for exporting models, to seamlessly transition between design and simulation environments. Figure 2 shows the 3 office layouts this research was carried on.

In the game engine, a receiver script is embedded in the simulation scene, which automatically synchronizes changes made in Revit. This ensures that updates to the architectural layout (e.g., room geometry or furniture placement) are reflected in real-time during the simulation without the need for manual re-imports. Figure 000 shows the 3D model of the 3 office layouts quantified in this research.

4.2. Navigation Mesh Setup

To enable NPC movement, a NavMesh (Navigation Mesh) is baked onto all floor surfaces in the scene. A NavMesh is a simplified representation of the traversable areas of a floor plan, allowing AI agents to calculate viable paths from point A to point B. Meanwhile, all furniture objects and large obstacles are marked as NavMesh Obstacles, which are excluded from the traversable area and serve to dynamically block or redirect NPC navigation. Together, this system enables agents to simulate realistic walking behavior while avoiding collisions with spatial elements.

4.3. Needs-Based AI Implementation

Each NPC is controlled by a needs-based AI model, inspired by behavioral systems used in simulation games such as *The Sims*. This AI system is based on a GitHub project “UnityTutorial_SimsStyle” by Iain McManus [8]. NPCs maintain internal states such as hunger, fatigue, and productivity that fluctuate over time. The AI periodically selects the need with the highest priority and searches for the nearest Smart Object capable of satisfying that need. An example of the NPC’s search priority is shown in Figure 3**.**

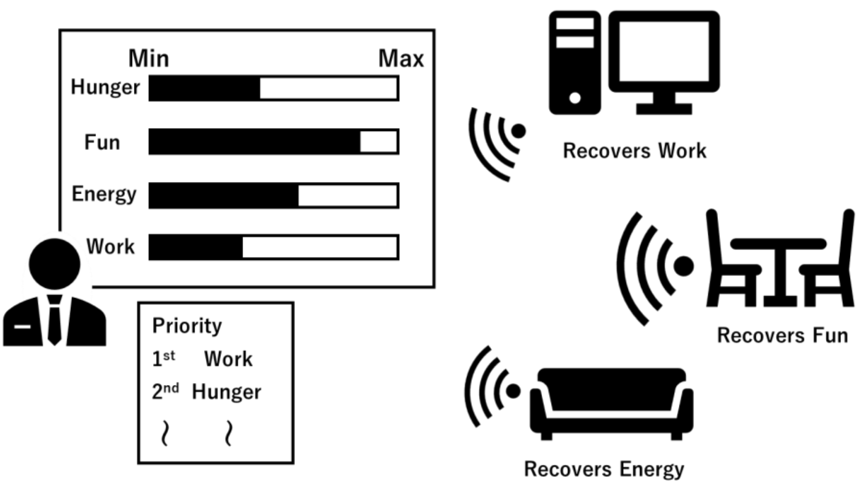

Fig 3 How Smart Objects Behave in the Simulation

4.4. Smart Object System

To reduce computational overhead, all interactable elements in the scene (e.g., furniture) are implemented as Smart Objects. A Smart Object contains metadata about available interactions, interaction points, and behavioural effects. By centralizing interaction logic within objects rather than within the agents, the system remains modular, scalable, and efficient for simulation across large layouts. When the Smart Object is interacted on, it restores the internal parameters according to its role. As a fridge or a sofa, it restores the corresponding parameters hunger and fatigue. The Smart Object also communicates to the NPC to appeal to their state, as shown in Figure 000.

4.5. NPC Behaviour Logging

Each NPC is equipped with a set of scripts to log behavioural data throughout the simulation. The following variables are tracked:

- Travel-to-Straight Distance Ratio Analysis

  This metric provides a basis for understanding the navigational complexity between furniture objects. This ratio is achieved by dividing the travel distance of the NPC from one furniture object to another, by the distance as the crow flies. High ratios may indicate bottlenecks or inefficient room connectivity. The equation is as follows.

$$\frac{Traveled\ Distance}{Actual\ Distance} = Travel\ to\ Straight\ Distance\ Ratio \tag{1}$$

- Visibility Log Analysis

  Visibility data quantify the exposure of objects during NPC navigation. Low visibility scores for specific rooms (e.g., restrooms, meeting rooms) suggest preserved privacy, while high visibility may imply insufficient spatial partitioning.

- Heatmap Analysis

  Heatmaps highlight areas with concentrated or sparse NPC activity. High-traffic zones may indicate functional bottlenecks, while underutilized areas may reveal wasted space.

Logs are saved in CSV format and linked to object pairs, forming the basis for evaluating layout efficiency. Example scenes from the simulations are shown in Figure 4.

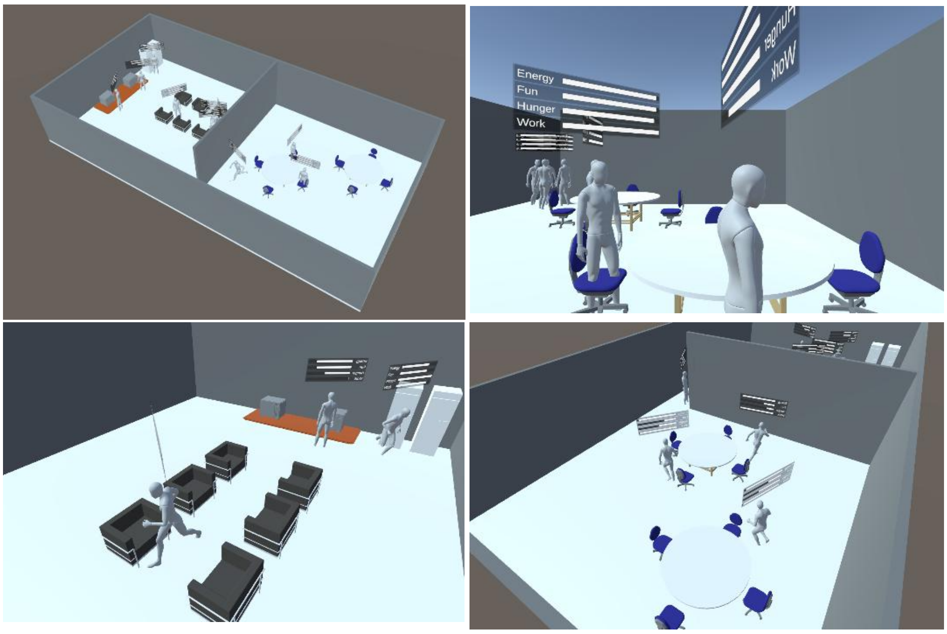

Fig. 4. Example of the NPC Simulation in Office Layout A

To summarize, the simulation is a Unity-based evaluation system designed to assess the spatial usability of architectural floor plans by using AI-driven agents (NPCs) that autonomously interact with environmental objects called SmartObjects. Each NPC selects interactions based on internal states such as hunger or fatigue. These SmartObjects represent furniture or appliances and offer context-specific interactions (e.g., sitting, eating), defined by their spatial coordinates and stat effects.

As NPCs navigate the environment, their travel paths are logged in detail. The system records both the actual traveled distance and the theoretical straight-line distance between SmartObjects. This data is used to compute the ratio of traveled to straight distance for each object pair. Visibility and Heatmap data are also logged to further quantify the floor plan into raw data.

In the future, this approach enables the automated, quantitative evaluation of layout efficiency, identifying spatial bottlenecks and informing iterative design improvements within simulated architectural environments.

5. Results and Findings

The quantification of the floor plans resulted in multiple behavioural data logs, which were retained in CSV format for each NPC. Specifically, both travel distance logs and visibility logs were recorded in this manner (see Figure 5 and Figure 6, respectively). Additionally, heatmap data representing spatial activity distribution was logged and visualized in a graph format (see Figure 7, Figure 8, Figure 9).

In addition to evaluating individual movement patterns, this study highlights the broader potential of floor plan quantification based on NPC behavioral data.

	A	B	C	D	E
1	Timestamp	NPC_ID	TargetName	ViewDuration(s)	Distance
2	2025/4/28 16:01	-21268	Office Chair -- efbca5d6046312743e0c22ff05f8b18f (43)	4.57	4.43
3	2025/4/28 16:01	-21268	Office Chair -- efbca5d6046312743e0c22ff05f8b18f (24)	1.81	8.19
4	2025/4/28 16:01	-21268	Office Chair -- efbca5d6046312743e0c22ff05f8b18f (21)	3.56	6.64
5	2025/4/28 16:01	-21268	Office Chair -- efbca5d6046312743e0c22ff05f8b18f (27)	0.38	2.65
6	2025/4/28 16:01	-21268	Office Chair -- efbca5d6046312743e0c22ff05f8b18f (21)	0.04	6.23
7	2025/4/28 16:01	-21268	Office Chair -- efbca5d6046312743e0c22ff05f8b18f (27)	0.64	1.98
8	2025/4/28 16:01	-21268	Office Chair -- efbca5d6046312743e0c22ff05f8b18f (21)	4.65	1.2
9	2025/4/28 16:01	-21268	Office Chair -- efbca5d6046312743e0c22ff05f8b18f (22)	23.83	2
10	2025/4/28 16:01	-21268	LargeObject_Bookshelf	0.08	5.5
11	2025/4/28 16:01	-21268	Office Chair -- efbca5d6046312743e0c22ff05f8b18f (22)	0.36	2.06
12	2025/4/28 16:01	-21268	Chair-Corbu (5)	0.08	8.03
13	2025/4/28 16:01	-21268	Chair-Corbu (9)	5.81	4.6
14	2025/4/28 16:01	-21268	Chair-Corbu (8)	2.43	2.37
15	2025/4/28 16:01	-21268	Chair-Corbu (15)	1.11	0.65

Fig. 5. Example of a Visibility Log from an NPC

	A	B	C	D
1	Start	Office Chair -- efbca5d6046312743e0	Traveled	4.924291
2	Office Chair -- efbca5d60463127	Chair-Corbu (9)	Traveled	8.680991
3	Office Chair -- efbca5d60463127	Chair-Corbu (9)	Total	8.680991
4	Office Chair -- efbca5d60463127	Chair-Corbu (9)	Average	8.680991
5	Chair-Corbu (9)	Office Chair -- efbca5d6046312743e0	Traveled	5.971019
6	Chair-Corbu (9)	Office Chair -- efbca5d6046312743e0	Total	5.971019
7	Chair-Corbu (9)	Office Chair -- efbca5d6046312743e0	Average	5.971019
8	Office Chair -- efbca5d60463127	Chair-Corbu (9)	Traveled	6.036232
9	Office Chair -- efbca5d60463127	Chair-Corbu (9)	Total	12.00725
10	Office Chair -- efbca5d60463127	Chair-Corbu (9)	Average	6.003626
11	Chair-Corbu (9)	Office Chair -- efbca5d6046312743e0	Traveled	11.09192
12	Chair-Corbu (9)	Office Chair -- efbca5d6046312743e0	Total	11.09192
13	Chair-Corbu (9)	Office Chair -- efbca5d6046312743e0	Average	11.09192

Fig. 6. Example of a Travel Log from an NPC

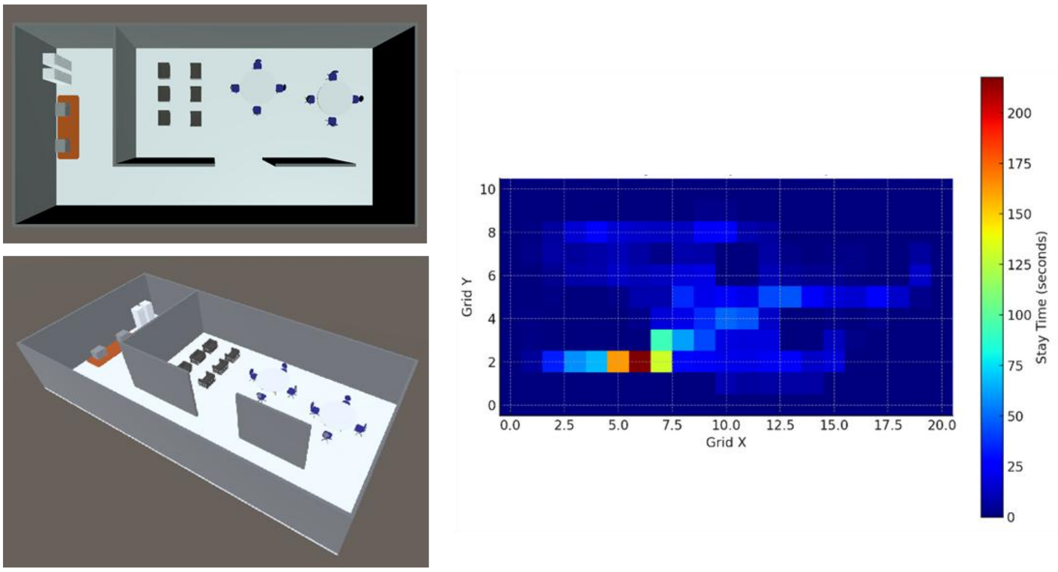

Fig. 7. Heatmap of NPC Stay Duration for Office Layout A

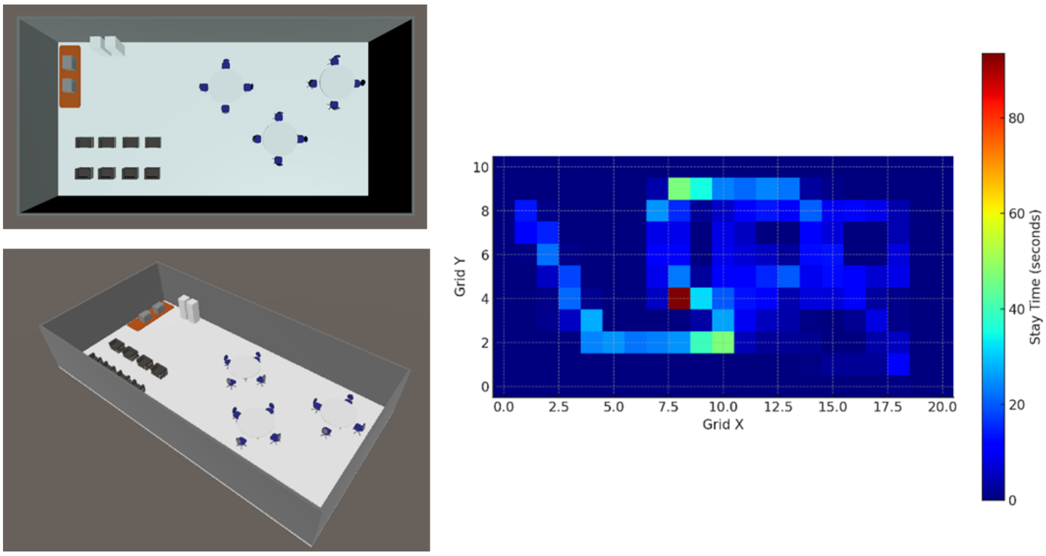

Fig. 8. Heatmap of NPC Stay Duration for Office Layout B

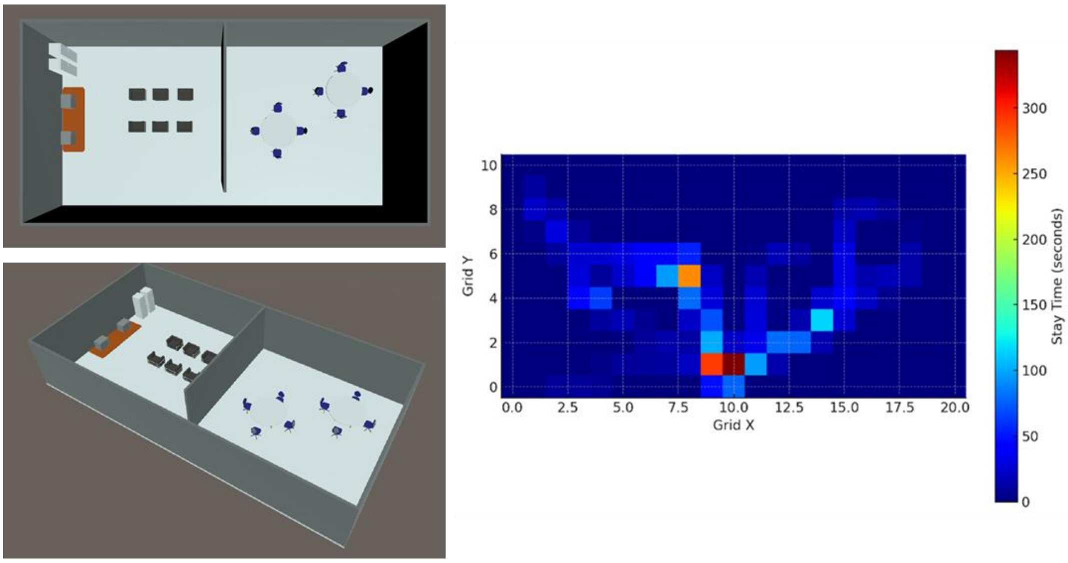

Fig. 9. Heatmap of NPC Stay Duration for Office Layout C

Firstly, the Travel-to-Straight Distance Ratio provides a numerical index of spatial navigability, enabling comparative evaluation across different layouts. High ratios systematically signal layout inefficiencies such as circuitous routes, dead-ends, or bottlenecked passageways. This metric, when aggregated across multiple NPCs and scenarios, offers a robust quantitative foundation for spatial optimization.

Secondly, the Visibility Logs introduce a method to objectively assess privacy levels within a floor plan. Unlike traditional methods reliant on designer intuition, visibility metrics allow for numerical benchmarking of how well private zones are shielded from public view. By adjusting thresholds for acceptable visibility levels, designers can fine-tune layouts to balance openness and seclusion according to intended space functions.

Thirdly, Heatmap Data transforms qualitative impressions of space usage into measurable activity distributions. By aggregating time-stamped location data, it becomes possible to statistically identify underutilized areas, traffic bottlenecks, and critical spatial intersections. This information supports data-driven spatial reconfiguration, optimizing not only functionality but also user experience.

From the 3 heatmap graphs, we can see that certain cells have a higher concentration of NPC stay duration than others. This, we can assume, is caused by a form of bottleneck or high use furniture placement in a limited area. For example, for Office Layout C, we can assume that a bottle neck has formed due to a small opening between the 2 rooms. This is proof that quantification of a floor plan can be useful in determining the characteristics of a floor plan simply from raw data. These data combined could be used to train AI to place furniture in a way that it won't cause these types of problems, simply by tweaking the reward system when machine learning, for example.

However, certain limitations must be acknowledged. The current quantification framework primarily measures physical accessibility, visual exposure, and occupancy density, but does not yet incorporate qualitative aspects such as user satisfaction, acoustic comfort, or emotional response. Furthermore, while the behavioural models approximate human movement, they do not fully replicate complex social behaviours, such as group dynamics or spontaneous collaboration.

Overall, this study demonstrates that floor plan quantification using needs-driven NPC simulations enables a multi-dimensional, empirical evaluation of spatial performance. Future research should aim to integrate additional behavioural, environmental, and subjective parameters to build a truly holistic, AI-supported layout assessment framework.

6. Discussion

This research demonstrates that floor plan quantification through needs-driven NPC simulation offers a new perspective on architectural evaluation. By moving beyond static spatial measurements, it enables dynamic, behavior-based insights into layout efficiency, privacy, and usability. However, there are several directions in which this framework can be extended to achieve even greater fidelity and utility.

Firstly, future versions of the system should expand the range of behavioural data logs. In addition to movement paths and visibility, logging elements such as interaction frequency, communication attempts between NPCs, time spent in collaborative versus individual activities, and even simulated emotional responses (e.g., frustration from congestion) could significantly enrich the dataset. This would enable a multi-dimensional analysis of not only spatial efficiency but also user experience quality within the environment.

Secondly, integrating machine learning and advanced AI techniques presents a promising pathway. Once a sufficiently large and diverse dataset of NPC behavioural patterns and corresponding layout characteristics is accumulated, supervised learning models could be trained to predict spatial performance metrics directly from floor plan features. Reinforcement learning algorithms could also be employed to iteratively adjust floor plans, optimizing them based on simulation feedback toward objectives such as minimizing congestion, maximizing accessibility, or enhancing user satisfaction.

Ultimately, this approach could lead to an autonomous layout refinement system: a closed feedback loop where floor plans are generated, simulated, evaluated, and iteratively improved with minimal human intervention. By combining simulation-based quantification with data-driven optimization, architectural design could become increasingly empirical, responsive, and user-centred.

Nonetheless, careful attention must be paid to preserving human design sensibilities and context-specific needs, ensuring that optimization does not compromise aesthetics, cultural appropriateness, or occupant well-being. Balancing quantitative efficiency with qualitative richness remains a critical challenge for the future of AI-assisted architectural design.

References

[1] Global Market Insights, AI in Construction Market Size, (2023), https://www.gminsights.com/industry-analysis/artificial-intelligence-in-construction-market

[2] Hillier B, Hanson J., The logic of space, The Social Logic of Space, Cambridge University Press; pp. 52-81, (1984), https://doi.org/10.1017/cbo9780511597237.004

[3] J. Michalek, R. Choudhary, P. Papalambros, Architectural Layout Design Optimization, Engineering Optimization, pp. 461–484, (2002), https://doi.org/10.1080/03052150214016

[4] P. Merrell, E. Schkufza, V. Koltun, Computer-Generated Residential Building Layouts, ACM Transactions on Graphics (TOG), Volume 29, Issue 6, no. 181, pp. 1-12, (2011), https://doi.org/10.1145/1866158.1866203

[5] N. Nauata, K. H. Chang, C. Y. Cheng, G. Mori, Y. Furukawa, House-GAN: Relational Generative Adversarial Networks for Graph-Constrained House Layout Generation. ACM Transactions on Graphics (TOG), 40(6), pp. 1–13, (2021), https://doi.org/10.1007/978-3-030-58452-8_10

[6] M. Ali, Use of Artificial Intelligence in Construction, Metropolia university of Applied Sciences, (2023), the referenced item does not yet have a DOI number

[7] E. F. Garcia, E. R. Zúñiga, J. Bruch, M. U. Moris, A. Syberfeldt, Simulation-based Optimization for Facility Layout Design in Conditions of High Uncertainty, Procedia CIRP, Volume 72, pp 334-339, ISSN 2212-8271, (2018), https://doi.org/10.1016/j.procir.2018.03.227

[8] I. McManus, UnityTutorial_SimsStyleAI, (2022), https://github.com/GameDevEducation/Unity Tutorial _SimsStyleAI.