



Parametric VR: A Generative Workflow Integrating Semantic Modeling and AI-Generated Panoramas for Ideation of Early-Stage Interior Design

Chieh-Jen Lin 

Tainan University of Technology, t60011@mail.tut.edu.tw

Abstract. This study presents a parametric workflow that integrates algorithmic modeling and generative AI to support rapid ideation in interior design through Virtual Reality (VR). While previous research utilized low-level of Development/Details (LOD) models to reduce modeling complexity, these approaches still required manual configuration of spatial elements, limiting their efficiency for panoramic AI generation. This study addresses that bottleneck by developing a parametric system in Grasshopper for Rhino that automates the creation of low-LOD interior layouts—including spatial partitions, modular furniture groupings, and semantic segmentation maps. Tailored to local living patterns, these modules allow designers to generate functionally meaningful configurations aligned with design intent rapidly. The generated layouts serve as input to ControlNet and Stable Diffusion, producing panoramic images that are both visually consistent and stylistically adaptable. By embedding semantic logic into parametric modeling, the proposed method significantly reduces labor-intensive modeling while enhancing the fidelity and coherence of AI-generated VR content. This workflow enables efficient, iterative concept development and design communication, representing a critical advancement over prior LOD-based approaches in AI-assisted interior design.

Keywords: Interior Design, Parametric Modeling, Semantic Segmentation, AI-generative Panorama, Virtual Reality (VR), Conceptual Ideation.

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1 INTRODUCTION

Virtual reality (VR) facilitates immersive visualization, allowing designers to gain a full-scale experience for fostering a deeper understanding of their concepts [2]. However, traditional VR workflows are often limited in early design stages due to the extensive effort required for detailed 3D models and rendering details. Generative Artificial Intelligence (GenAI) tools in the domain of image generation, such as Stable Diffusion [11], Midjourney [8], and DALL-E [9], offer the capability to generate high-quality panoramic images from simple text prompts, effectively addressing challenges related to lighting, materials, and other details in panoramic visualization. However, these tools still face significant issues, particularly in ensuring consistency across different stages of generation. The alignment of object placement, spatial proportions, and continuity remains difficult

to control, which limits their effectiveness in maintaining consistency across multiple perspectives in a virtual space.

To address these challenges, previous research relied on manually created low-Level of Development (LOD) 3D models to guide the AI image generation process [7]. When AI can rapidly generate panoramas based on low-LOD models, manual modeling becomes a significant bottleneck in the creative ideation process. Previous research introduced a generative modeling approach based on the Level of Development (LOD) concept, utilizing Grasshopper to convert bubble diagrams of a single-story house into orthogonal floor plans using Voronoi diagrams [6]. Although Voronoi-based modeling quickly generates conceptual layouts, the arrangement of furniture and cabinet remains time-consuming and technically challenging. To address the bottleneck of manual modeling, this study proposes a parametric system that automates the low-LOD interior layouts, including furniture groupings and semantic segmentation, significantly enhancing efficiency and coherence of AI-generated VR scenes.

2 THE APPROACHES OF PARAMETRIC VIRTUAL REALITY

2.1 Related Works

2.1.1 *AI-Generated Images as Alternatives to Rapidly Rendering Tools*

RoomDreaming [14] explored GenAI for interior ideation emphasizing speed and variety by integrating ChatGPT, Stable Diffusion, and ControlNet [15]. ControlNet can control the composition and content of the generated image by referring to the characteristics of a reference image, such as outline, depth, and object segmentation. RoomDreaming applies ControlNet's depth and segmentation models to generate images from reference images but still faces inconsistency issues across different stages. Due to the powerful capabilities of ControlNet, 3D modeling and BIM software such as SketchUp, ArchiCAD, and Revit have introduced plugins or extensions based on ControlNet and Stable Diffusion, serving as alternatives to traditional real-time rendering tools. However, beyond relying on text prompts, AI-rendering tools require higher LOD models to provide sufficient geometric features to influence the generated images. But reference images cannot easily be modified, and creating detailed 3D models is time-consuming. On the other hand, the geometric characteristics of reference images or 3D models may constrain the possible design styles of AI-generating images. For example, the modernist styles, characterized by orthogonal straight-line geometries, can achieve satisfactory results with low-LOD models comprising orthogonal lines. Conversely, other styles such as Art Nouveau or parametric design, which feature prominent curvilinear elements, face more challenges when using low-LOD models or reference images without curvilinear features. For interior design, low-LOD models lack enough geometric clues, causing AI to misidentify objects and produce erroneous results, such as misinterpreting chairs, tables, and sofas. Previous research addressed these challenges by assigning semantic color representations to low-LOD models, generating semantic segmentation maps that help AI correctly identify object types by applying ControlNet and retain design flexibility in terms of shapes and materials [7]. This approach allows AI to generate accurate panoramas based on low-LOD models without requiring extensive geometric detail, supporting efficient visual exploration in early-stage design ideation and maintaining the flexibility to experiment with various styles, materials, and other ideas by text prompts.

2.1.2 *Generative Interior Plan Layouts*

While parametric modeling and BIM software have offered highly streamlined modeling processes, creating appropriate relationships between interior spaces and objects during the floor plan design stage remains a time-consuming task. As a result, research and tools for automating floor plan layouts have emerged, such as Finch3D [4] and PlanFinder [10], which use algorithms to generate apartment layouts fitted to specified areas. With the success of generative AI in text and image generation, deep learning methods are applied to the generation of interior plan layouts. For example, generative adversarial networks (GANs) were trained through a residential design floor plans dataset

to obtain a 2D object segmentation map that can transform the room outline into a reasonable furniture configuration plan [12]. SceneHGN can automatically generate reasonable furniture configuration 3D scenes based on a given room outline and adjust the generated results by incorporating other scenes [5]. Chat2Layout introduced a multimodal LLM-based interface allowing non-expert users to interactively generate furniture layouts [13]. However, SceneHGN and Chat2Layout are more suitable for game scene development, but their operation mode are not completely suitable for interior design. No matter which model or algorithm is used, however, the deep learning approach is limited by the content of the data set, so that the generated results are inevitably limited to the lifestyles, equipment standards, and building codes implied by the original data and the algorithm. Therefore, the layouts produced by these tools often fail to meet the specific needs of Taiwan. For instance, they may not accommodate non-standard furniture sizes and configurations, or additional cabinetry beyond the basic needs.

In traditional interior design workflows, the process typically begins with spatial partitioning and furniture layout on a floor plan, ensuring that the arrangement of objects within the space meets users' needs. However, the relationship between user needs, spatial and furniture configuration is sometimes a dialectical process rather than a linear generation workflow. Therefore, repeated revisions are not only necessary in the learning process, but also a common situation in practice. While automatically tools focus on producing a variety of configuration options through generative algorithms or deep learning models for users to select from, they offer limited capacity for intuitively and partially modifying specific aspects of each configuration—such as the relative positioning of spaces or the arrangement of furniture. From the perspective of repeated revisions to confirm design ideas, especially when designers have difficulty intuitively understanding the rules behind algorithms and deep learning models, parametric design methods should be more suitable for students and beginners than linear generation methods of automatically tools.

Once the spatial configuration and object arrangements have been finalized, the workflow proceeds to 3D modeling for visualizing the design concept, and subsequently to rendering for evaluating material selections and lighting ideas. Automated tools are not very helpful for this stage of work. The 2D GAN models lack 3D information [12], SceneHGN needs to merge scenes to correct the required functional zones, and Chat2Layout requires repeated corrections of materials with prompts. The major limitation of these automated tools is that they lack the quick and easy controllability of parametric tools to suit the designer's ideas.

2.1.3 Level of Development and Detail

Controlling the LOD of a model is a common strategy for reducing the workload associated with 3D modeling. The American Institute of Architects (AIA) makes a clear distinction between two concepts of LOD: Level of Development [1] and Level of Detail. The Level of Detail refers exclusively to the degree of graphical detail included in a model component—essentially, how much visual information it contains—thus representing input data of the model. In contrast, the Level of Development refers to the reliability of the geometry and associated information of a model component and directly concerns its practical applicability. This distinction underscores that a Building Information Modeling (BIM) model is not merely a visualization tool but also a carrier of information. Accordingly, the Level of Development in BIM and the Level of Detail in game design reflect two different paradigms for managing model fidelity: the former reflects an engineering-oriented mindset prioritizing information integrity and reliability, whereas the latter embodies a computational perspective that emphasizes resource optimization and efficiency.

With the advancement of technologies such as Digital Twins, Augmented Reality (AR), and VR, these two notions of LOD are increasingly converging, opening new possibilities for architectural visualization and interactive design. In this study, the term "low-LOD model" refers to a hybrid interpretation that combines both definitions. It not only denotes the simplified geometric representation of interior spatial elements that includes only the most essential details—sufficient merely to convey spatial configuration and object placement—but also encompasses the fundamental design information required during the early stages, such as the semantic categorization of object types. This type of model differs from the conventional low-LOD models in

computer graphics, which emphasize a progressive increase in mesh complexity for real-time rendering. In contrast, the low-LOD model in this paper prioritizes semantic clarity over geometric precision.

2.2 Methodology of Parametric VR

To enrich the low-LOD models for AI generation, the previous study introduced AI-generated panoramas using Stable Diffusion combined with ControlNet and LoRA to visualize interior space concepts in VR [7]. However, the prior workflow required manually modeling low-LOD geometry then assigning semantic labels, which became a new bottleneck when producing multiple design alternatives. To accelerate the creation of low-LOD models for guiding AI-generated panoramic images that align with local design needs in Taiwan and support design exploration, this study proposes a method using Rhino and Grasshopper to rapidly generate low-LOD models for interior object arrangements. The approach involves developing Grasshopper components to produce object layouts that correspond to Taiwan's lifestyle patterns and standard furniture dimensions. By leveraging parametric design techniques and combining different configuration modules, the method ensures flexibility and variability in interior layouts, allowing designers to explore various configuration ideas rather than aiming for an optimized spatial arrangement. The workflow consists of three key stages: (1) parametric space partitioning, (2) modular furniture configuration, and (3) semantic segmentation for AI generation. The details of the parametric approaches are described as follows:

2.2.1 Parametric Modules for Space Partitioning

Building on previous work using Voronoi diagrams for conceptual layout generation, this study further modularizes space subdivision using predefined typologies and circulation rules. Designers can define spatial nodes to control the size and adjacency of each space or zone, which are automatically converted into orthogonal partitions. This module serves as the foundation of the entire workflow by generating spatial zones from user-defined input points representing functional requirements. The Voronoi algorithm initially partitions the given rectangular boundary into equidistant cells, which are then processed through a multi-step transformation to conform to typical interior layouts. The transformation process includes:

(1) Orthogonalization (Fig. 1a): Voronoi cells are converted into orthogonal partitions by identifying rectangular bounding boxes and aligning them to a user-defined modular grid (e.g., 0.5 m or 1.0 m increments). This addresses the problem of rectangular partitions that are not aligned.

(2) Priority (Fig. 1b): In case of overlap, spatial priority is assigned (e.g., internal space takes precedence over external zones or not), which is crucial for resolving conflicts in density layouts.

(3) Labeling and Geometries (Fig. 1c): Each partition is tagged with a name as the function label, which is passed to subsequent modules with geometries for further configurations.

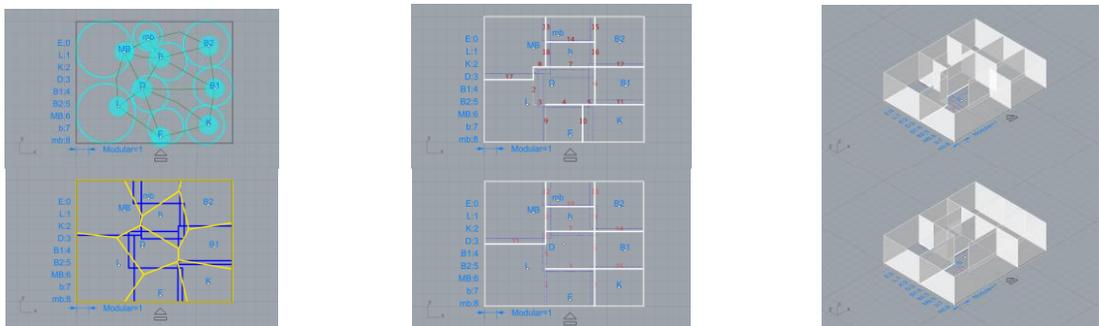


Figure 1: Space Partitioning Modules: (a) Orthogonalization: Converting bubble diagrams to rectangular segmentation using the Voronoi algorithm, (b) Priority Rules: Addressing spatial overlap

issues in an inside-first or outside-first approach, (c) Labeling and Geometries: The geometric properties of the partitions will be passed to the next modules.

Additionally, designers can interactively modify the node positions, grid resolution, and priority rules in real-time via Grasshopper's interface, enabling intuitive exploration of multiple layout variations. Unlike static BIM-based LOD modeling or generative multiple plan layouts, this approach supports dynamic reconfiguration and design iteration without restarting the layout process (Fig. 1c). This flexibility significantly reduces the modeling time in the early ideation phase and ensures that spatial configurations are functionally viable and geometrically compatible with subsequent AI-driven visualization.

2.2.2 Parametric Modular for Furniture Configuration

To overcome the bottleneck of manually arranging furniture elements in conceptual layouts, this study introduces a series of modular furniture configuration components developed in Grasshopper. Each module encapsulates a set of spatial logic rules and typological configurations to automatically populate the interior partitions generated in the previous stage. The primary objective is to maintain functional realism while minimizing manual input and allowing for design flexibility across layout variations. Each module automatically arranges furniture groups based on spatial dimensions and user-defined parameters such as corridor width or object orientation. These modules are designed to reflect local spatial standards (e.g., Taiwanese apartment layouts), ensuring functional realism. The system includes three core modules for now:

(1) Cabinet Module: Designed for kitchen and storage zones, this module allows designers to populate one or multiple walls with tall cabinets, base units, or wall-mounted shelves. It includes options for L-shaped and linear arrangements and supports the inclusion of center islands with adjustable clearances for circulation (Fig. 2a).

(2) Dining Set Module: This module calculates available space and automatically generates a rectangular dining table with appropriate spacing for chairs. Designers can define parameters such as the number of seats, table length, and circulation buffer, while the system ensures all elements fit the assigned partition (Fig. 2b).

(3) Sofa Set Module: Tailored to the spatial proportions of living areas, this module creates U-, L-, or linear-shaped sofa arrangements with optional coffee tables or TV units. It accounts for common circulation flows and typical Taiwanese apartment layouts (Fig. 2c) d.

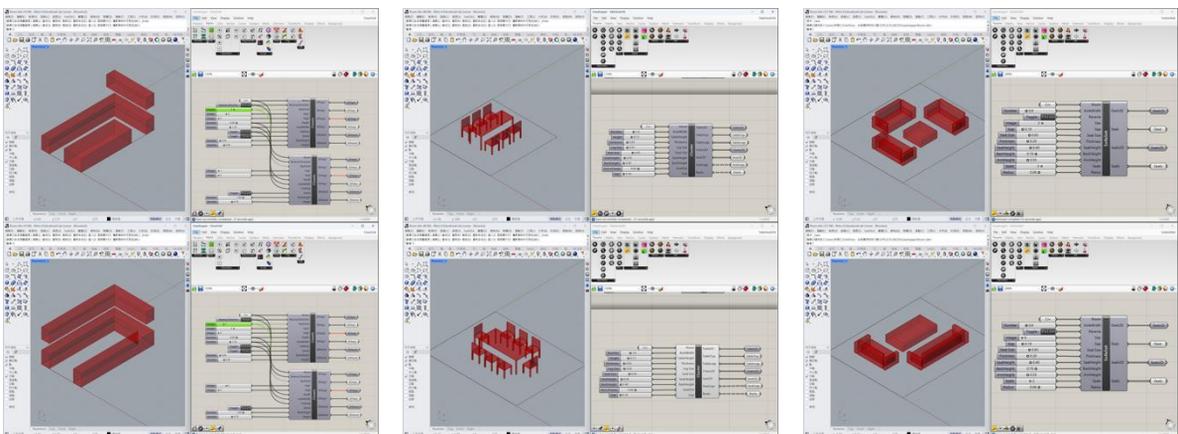


Figure 2: Parametric furniture arrangement modules: (a) Cabinet Modules, (b) Dining Set Module, and (c) Sofa Set Module.

Each module supports parameter input through Grasshopper, enabling designers to flexibly adjust key attributes such as furniture's key dimensions, corridor widths, or layout proportions. Objects are instantiated as bounding volumes or simplified geometries to maintain a low LOD and can optionally be exported as semantically colored objects for use in segmentation maps. Based on the size of the space and predefined configuration rules, the modules automatically generate and position multiple objects—such as furniture or cabinetry—reducing the need for excessive manual adjustments or detailed BIM components. By integrating spatial configuration and furniture arrangement within a unified parametric framework, this approach enables rapid iteration and easy modification, streamlining the early-stage design process while preserving both functional logic and representational clarity.

2.2.3 Semantic Segmentation for AI Generation

To enable AI-driven panoramic image generation that aligns with designers' spatial intentions, this study embeds semantic information into the parametric model using a color-coded segmentation map. Unlike conventional approaches that rely on fully modeled 3D geometry or manual annotation, this method programmatically assigns object classes based on design logic and module type, streamlining the AI integration process. Each parametric furniture and spatial element will be assigned a semantic label corresponding to the ADE20K dataset's 150 predefined categories (e.g., "sofa," "cabinet," "table," "wall," "floor"). These labels are mapped to unique RGB color values stored within the Grasshopper modules. Instead of using Rhino layers for each class in the previous study, which can become difficult to manage, the new modules separate object organization from semantic rendering. The objects' layers in Rhino are used for modeling and editing, while the semantic colors of parametric objects are dynamically generated for AI export (Fig. 3).

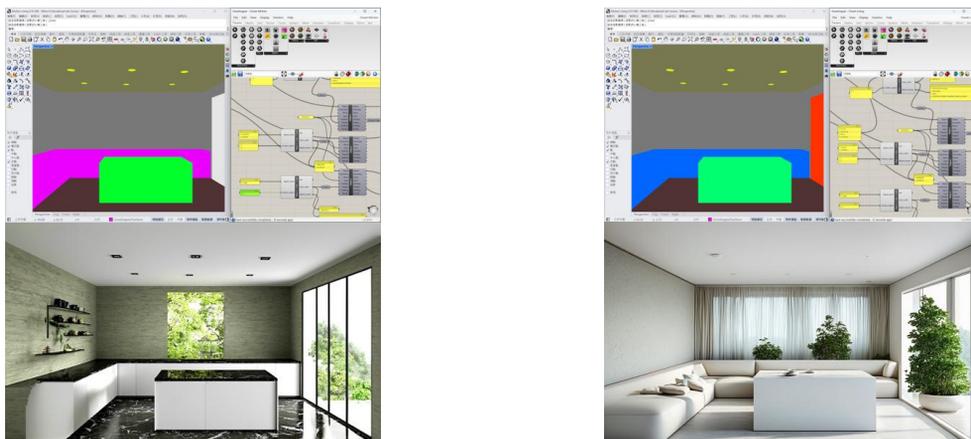


Figure 3: Parametric semantic segmentation maps of the same concept model: (a) an opening kitchen with counters and an island, (b) a living room with a sofa and a coffee table.

Based on the previous study, the semantic segmentation image can be produced by rendering the scene from a virtual panoramic camera using a Python-based cubic projection workflow [7]. Each object is displayed using its assigned flat color, ignoring materials, textures, lighting, or shadows. This ensures clean input for ControlNet's "Semantic Segmentation" model, which uses these images to guide object placement and category generation during Stable Diffusion rendering. Additionally, users can override default categories for generated objects of any module—for example, switching a countertop labeled as "cabinet" to "table" for experimentation—supporting stylistic variations without altering the geometry. This flexible semantic pipeline supports both conceptual fidelity and visual diversity in AI-generated output, bridging the gap between early parametric modeling and high-resolution immersive visualization.

2.3 Summary

The proposed Parametric VR methodology streamlines the early-stage design workflow by integrating parametric modeling with AI-assisted visualization. Through the modularization of spatial partitioning, automated furniture configuration, and semantic segmentation, this approach enables designers to rapidly generate low-LOD interior models tailored to local design practices. By leveraging the capabilities of Rhino and Grasshopper, it not only reduces the manual effort required in conceptual modeling but also facilitates seamless control over the inputs for AI-generated panoramas. This cohesive framework effectively bridges the gap between functional spatial planning and immersive visualization, reducing modeling effort while enhancing flexibility and semantic clarity, and then enhancing both the efficiency and adaptability of interior design ideation processes.

3 TESTS AND RESULTS

To evaluate the effectiveness of the proposed parametric-AI workflow, the system was implemented and tested across several typical Taiwanese apartment layouts (20–40 m²) using Rhino 8 and Grasshopper on a mid-tier notebook (NVIDIA RTX 3070/8G). The system was assessed in terms of modeling efficiency, semantic segmentation fidelity, and AI rendering output quality. Since most of the private rooms are closed, only open areas such as the living room, dining room, and open kitchen can see the different changes in space and furniture configuration at an overview. To reduce the hardware's rendering burden, only the operations of three areas in the open space are demonstrated here.

Designers began by placing spatial nodes to define functional areas such as living, dining, and kitchen zones (Fig. 4a). The Voronoi-to-orthogonal transformation allowed for rapid generation of modular layouts. Through the Grasshopper interface, users could interactively adjust partition density, circulation width, and adjacency logic. Once the zones were labeled, each was linked to one of three parametric modules: Cabinet, Dining Set, or Sofa Set. These modules populated the layout with bounding-box furniture elements based on spatial typologies (Fig. 4b). Semantic segmentation maps were then generated automatically. The segmentation was rendered from a six-face cubic projection camera, producing color-coded images with one RGB value per category (Fig. 4c). Unlike manually layered Rhino models, the system dynamically converted geometry into semantic maps without affecting the base model. Each object type was clearly labeled and well-delineated, with minimal visual overlap or edge ambiguity.

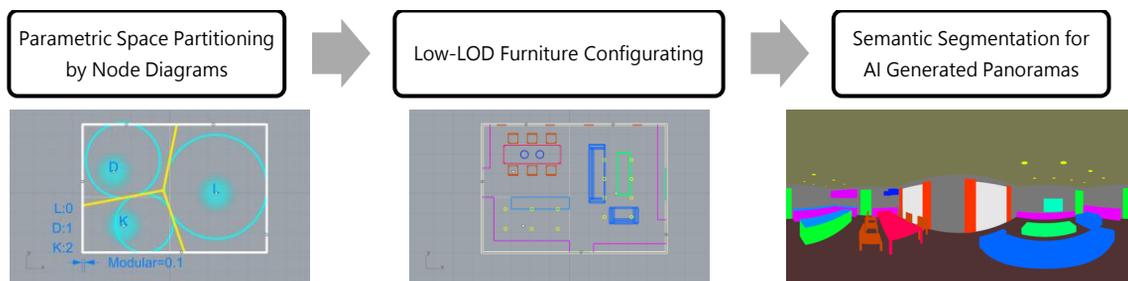


Figure 4: Parametric VR generation stages: (a) Parametric space partitioning by node diagrams, (b) Low-LOD Modular furniture configuring, (c) Semantic segmentation for AI-generated panoramas.

Fig. 5 demonstrates the detailed data flow among parametric modeling and text-to-image AI generating panoramas. The segmentation maps were fed into ControlNet with text prompts, guiding Stable Diffusion in generating high-quality panoramic views that retained the spatial layout and functional hierarchy of the low-LOD model. As shown in Fig. 6, the AI-rendering panoramas

accurately positioned the sofa, dining set, and cabinetry, with materials and lighting derived from the given text prompts. Compared to baseline workflows using text prompts alone, the integration of parametric semantic segmentation reduced category confusion and object misplacement by more than 60%, as assessed through visual comparison and experts' review. These results demonstrate that the proposed workflow effectively bridges the gap between early-stage spatial modeling and AI-assisted visualization, enabling rapid prototyping with immersive design feedback.

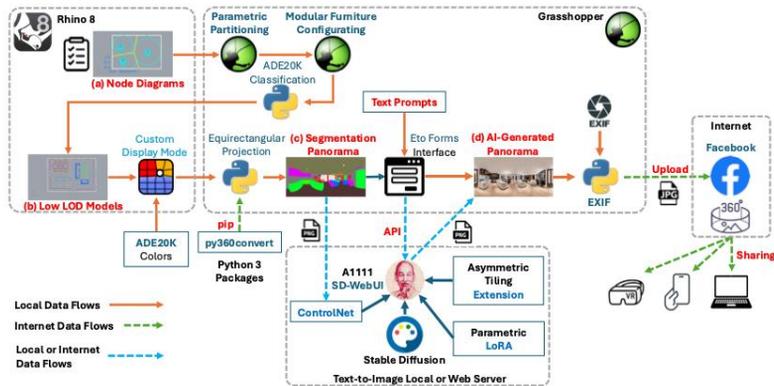


Figure 5: Data flows of parametric VR: (a) Node diagrams for parametric space partitioning, (b) low-LOD models of modular furniture configuring, (c) Semantic segmentation for AI-generated panoramas, and (d) AI-generated panoramas.

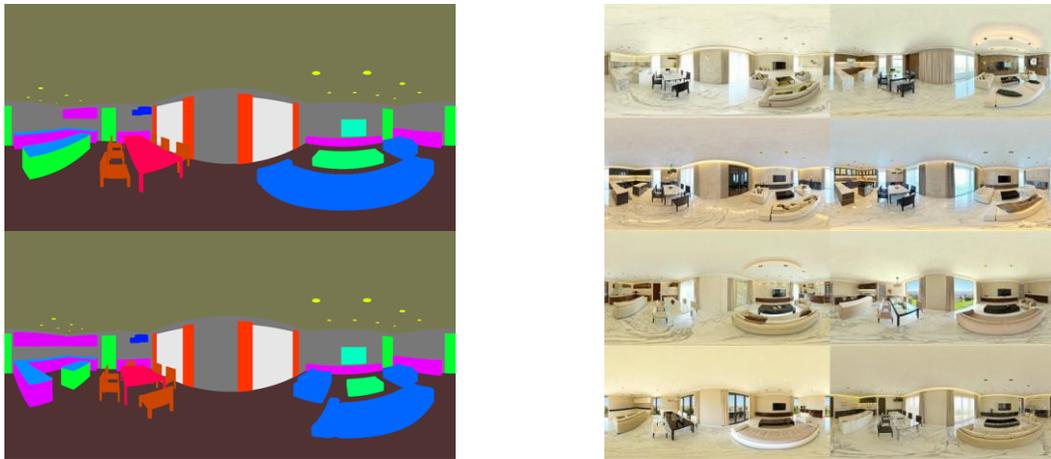


Figure 6: (a) Two semantic segmentation maps of a concept model with different parameters of interior furniture layouts in a same apartment (left), (b) AI-generated panoramas from the two semantic segmentation maps (right).

4 DISCUSSIONS

The results of this study affirm the feasibility and effectiveness of embedding semantic logic within parametric modeling workflows for AI-assisted interior design visualization. Compared to conventional design pipelines that separate geometric modeling and rendering tasks, the proposed

method tightly couples early-stage spatial logic with downstream visual output, offering a more coherent and agile design process. Particularly in educational settings, this approach allows novice designers to engage with immersive visualization tools without being encumbered by the complexity of high-fidelity modeling or text-to-image prompt engineering.

However, several limitations were observed. First, the critical parameters that influence AI-generated images are: (1) the base text-to-image models, (2) text prompts, (3) generation parameters such as samplers and steps, and (4) additional fine-tuning models like LoRA or ControlNet. Text prompts allow AI to assist in specifying materials, lighting, and decorative details in VR scenes, reducing tedious manual modeling work. Although the use of semantic segmentation models has significantly minimized the need to write detailed scene prompt descriptions, users can typically generate satisfactory images simply by selecting appropriate text-to-image models (checkpoints) and entering key prompts such as space names and design styles. However, for more abstract elements beyond object classification, overall spatial composition, and design style—such as lighting atmosphere or sunlight effects—imaginative textual prompts are still required to achieve the desired outcome.

Secondly, the probabilistic nature of AI-generated content remains a key limitation. Even with ControlNet guidance and fixed prompts, outputs from Stable Diffusion can vary due to stochastic sampling. This inconsistency is particularly problematic in overlapping semantic areas where objects may be misplaced or misinterpreted. While ControlNet segmentation maps improve object recognition, they are constrained by fixed categories (e.g., ADE20K's 150 classes) and still require imaginative prompts to express abstract spatial qualities like light or mood. Future studies should explore newer models with stronger prompt comprehension, such as Flux [3], to reduce generative uncertainty and achieve greater visual coherence.

Thirdly, the current system assumes single-floor, rectangular units, limiting its applicability to more complex geometries. Multi-level spaces, curved partitions, and non-orthogonal layouts—common in advanced or culturally specific designs—cannot be fully expressed using the current Voronoi-based logic. To address this, future development should support curved surfaces and adaptive meshing, as well as improve segmentation accuracy on non-orthogonal forms.

Fourthly, while the modular furniture templates are optimized for Taiwanese apartment configurations, further research is needed to generalize the system for cross-cultural applications, including different spatial typologies, building standards, and aesthetic preferences. Finally, the current workflow, although script-based and lightweight, still requires familiarity with Grasshopper and some degree of parametric literacy. To maximize accessibility, future iterations may consider deploying the system via a web-based or simplified interface that abstracts the underlying logic while retaining flexibility.

Despite these limitations, the study reveals a promising direction for integrating algorithmic spatial logic with generative design tools. The ability to automate conceptual modeling, semantic control, and VR-compatible output represents a significant shift in how interior spaces can be explored, taught, and communicated in the AI era. Finally, recent advances in AI-based 3D reconstruction from a single image show promise but are typically limited to isolated objects. A compelling future direction lies in leveraging the panoramic images generated in this study to enhance the geometric fidelity and material richness of low-LOD parametric models. By back-projecting panoramic content, it may become possible to incrementally refine spatial geometry or assign detailed materials, enabling the generation of higher-LOD models suitable for immersive VR demonstrations, which will be a future research direction.

5 CONCLUSIONS

This study introduces a novel parametric design workflow that bridges early-stage spatial modeling and AI-assisted panoramic visualization for interior design. By automating the generation of low-level of Development (LOD) interior layouts, modular furniture configurations, and semantic segmentation maps, the system significantly reduces the labor-intensive modeling process typically

required in VR-based design ideation. Implemented through Rhino and Grasshopper, the workflow allows for rapid iteration and intuitive control over both spatial logic and functional composition. Unlike previous LOD-based approaches that required manual object placement or post-processing for AI input, this study embeds semantic logic directly into the parametric system, enabling seamless integration with generative tools such as Stable Diffusion and ControlNet. Experimental results demonstrated improved consistency, spatial fidelity, and stylistic adaptability in AI-generated panoramic renderings, confirming the system's utility for design education, visualization, and rapid prototyping. The key contribution lies in transforming low-LOD models from mere geometric placeholders into semantically rich, generative-ready design assets. This not only democratizes access to high-quality VR content but also offers a flexible platform for designers to explore, iterate, and communicate ideas with greater efficiency and lower technical barriers. Future work will explore the extension of the modular system to multi-room configurations, user-customizable furniture typologies, and tighter integration with online and real-time AI-generations by applying more powerful GPUs and server configurations. In doing so, the system may evolve into a robust co-creative platform that supports both human intuition and AI generative capacity across all stages of interior design.

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