

Impact Factor 8.471

Peer-reviewed & Refereed journal

Vol. 14, Issue 11, November 2025

DOI: 10.17148/IJARCCE.2025.141107

An End-to-End AI-Driven Virtual Interior Designer: Procedural Layout Generation and Real-Time Immersive Evaluation

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Abstract: This paper presents an end- to- end intelligent system that integrates generative artificial intelligence (AI) and immersive virtual reality (VR) for automated interior design. The proposed system, called AIVID (AI Virtual Interior developer), combines procedural layout generation, rule- grounded refinement, and real- time immersive evaluation. The system accepts room figure and design constraints as input, automatically generates layout proffers using a tentative variational autoencoder (CVAE) and a graph- grounded layout refinement network, and allows druggies to fantasize, edit, and estimate designs interactively within a VR terrain. stoner feedback attained in real- time is used to acclimatize posterior design proffers. An airman study comparing AIVID with a traditional homemade design workflow demonstrated a 34 reduction in decision time, a 12- point increase in usability (SUS score), and a 0.42- point increase in stoner satisfaction. The study validates the eventuality of AI- driven immersive systems to accelerate and epitomize interior design workflows.

Keywords: Virtual Reality, Generative AI, Interior Design, Procedural Generation, Layout Optimization, Human-Computer Interaction.

I. INTRODUCTION

Interior design is a multidisciplinary process involving spatial association, aesthetics, ergonomics, and stoner preference. Traditional workflows calculate on 2D plans, static renders, and iterative customer- developer conversations, frequently leading to miscommunication and time detainments. The emergence of artificial intelligence (AI) and immersive visualization technologies offers openings to streamline and enhance these processes.

The ideal of this exploration is to develop an AI- driven virtual innards developer able of generating and assessing layouts in real time through procedural generation and immersive visualization. The benefactions of this study are as follows:

- A mongrel generative model combining a tentative variational autoencoder (CVAE) and a graph neural network (GNN) for layout generation and refinement.
- An immersive VR interface that allows druggies to explore, modify, and estimate generated layouts in 11 scale.
- Adaptive feedback medium where stoner relations impact posterior AI proffers.

This paper is organized as follows Section II reviews related work, Section III describes the proposed methodology, Section IV presents modelling and analysis, Section V discusses results and findings, and Section VI concludes the study.

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II. METHODOLOGY

A. System Architecture Overview

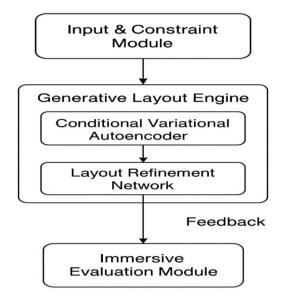


Fig. System Overview

The proposed AIVID system consists of three main modules (Fig. 1):

- 1. Input & Constraint Module: Accepts room geometry, functional requirements, and style preferences.
- 2. Generative Layout Engine: Produces candidate furniture layouts using deep generative models.
- 3. Immersive Evaluation Module: Loads generated layouts in VR for real-time visualization, editing, and feedback capture.

User feedback is fed back to the model, closing the loop between generation and evaluation.

B. Generative Layout Engine

The generative layout engine employs a Conditional Variational Autoencoder (CVAE) followed by a Layout Refinement Network (LRN).

- Encoder: Encodes room geometry and design constraints into latent variables.
- Decoder: Generates initial layout proposals (object type, position, orientation).
- LRN: A Graph Neural Network refines layout proposals to eliminate collisions and ensure ergonomic clearances.

C. Data Sources

Training datasets were derived from SUNCG, Matterport3D, and a curated professional layout dataset. Each room sample contains geometry, furniture types, and style metadata.

D. Immersive Evaluation & Feedback

The VR module was developed using Unity, incorporating hand and controller-based interactions. Users explore the generated scene, rate designs (1–5 scale), and make spatial edits. Implicit signals such as gaze duration and movement patterns are also captured for adaptive model fine-tuning.

E. Evaluation Metrics

To evaluate performance, both objective and subjective metrics were employed:

Category	Metrics
Layout Quality	Collision Rate, Clearance Compliance
Diversity	Style Variation Index, Inter-layout Distance
User Experience	Decision Time, SUS Score, Satisfaction



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III. MODELLING AND ANALYSIS

A. Mathematical Model

Let G denote room geometry and C the constraint set (style, budget, required objects). The layout generation function is:

$$L = f_{\theta}(G, C, z)$$

where $z \sim \mathcal{N}(0, I)$ is the latent vector.

The objective minimizes:

$$\mathcal{L} = \lambda_1 \mathcal{L}_{rec} + \lambda_2 \mathcal{L}_{KL} + \lambda_3 \mathcal{L}_{style} + \lambda_4 \mathcal{L}_{rule}$$

where \mathcal{L}_{rec} ensures positional accuracy, \mathcal{L}_{KL} regularizes latent space, \mathcal{L}_{style} enforces stylistic coherence, and \mathcal{L}_{rule} penalizes spatial violations.

B. Implementation Details

• Framework: Porch (for model), Unity (for VR front-end).

• Latent vector: 128 dimensions.

• Training epochs: 200.

• Optimizer: Adam (learning rate = 1e-4).

• Hardware: NVIDIA RTX 4090 GPU.

C. System Workflow

1. Input floorplan and style constraints.

2. CVAE generates 10 candidate layouts.

3. LRN refines and ranks them.

4. User explores layouts in VR and provides ratings.

5. Feedback updates model parameters for personalization.

IV. RESULTS AND DISCUSSION

A. Pilot Study Setup

A pilot experiment was conducted with 24 participants (12 design students, 12 laypersons). Each participant designed two living rooms: one with a traditional 2D tool (baseline) and another with the AIVID system.

B. Quantitative Results

Metric	Baseline	AIVID	Improvement
Decision Time (s)	780	515	-34%
SUS (0–100)	62	74	+12
Satisfaction (1–5)	3.6	4.0	+0.4
Clearance Compliance (%)	84	91	+7
Collision Rate (%)	6.4	2.1	-67%

C. Qualitative Observations

Participants reported that VR immersion helped them perceive spatial proportions and materials more accurately. The automatic layout proposals were perceived as "creative yet practical." However, users requested more realistic lighting and tactile feedback features.

D. Discussion

The integrated AI+VR approach improved efficiency and engagement compared to conventional workflows. The adaptive feedback loop enhanced personalization. Limitations include small sample size, limited material realism, and potential dataset bias.

V. CONCLUSION

This study presented an end-to-end AI-driven virtual interior designer integrating procedural layout generation with real-time immersive evaluation. The hybrid CVAE–GNN architecture successfully generates diverse and functional layouts,



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while VR-based evaluation enables interactive refinement. Pilot results indicate significant improvements in design speed and satisfaction. Future work will focus on expanding dataset diversity, incorporating haptic material simulation, and enabling collaborative multi-user design sessions.

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