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AI-Enhanced Emotional Prediction in Interior Design: Bridging Emotion and Architecture for Personalized Environments

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ABSTRACT

Artificial Intelligence can help in creating environments that adapt to users' emotional states and personal preferences. This paper proposes an Artificial Intelligence-based framework to predict and personalize emotional experiences in interior spaces, addressing the limitations of subjective emotional architecture. The proposed framework integrates Kansei Engineering, fuzzy analytic hierarchy process (FAHP), and the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) to translate users' emotional responses into weighted interior design parameters. These prioritized parameters are incorporated into an AI-based generative design model that produces personalized interior configurations. Emotional predictions are subsequently evaluated through immersive virtual reality (VR) environments by comparing AI-predicted emotional responses with physiological indicators and self-reported questionnaire data. The findings indicate that AI-assisted generative models effectively support participant-specific modifications to environmental design characteristics, including lighting, materials, color palettes, and biophilic integration. However, the framework demonstrated limited capability in generating coherent architectural floor plans, indicating that current AI systems are better suited to environmental personalization than comprehensive spatial planning.The research paper establishes a scalable model linking emotion prediction with adaptive, human-centered interior design to enhance well-being.

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1. Introduction

The built environment is widely recognized as an important mediator of human emotion, behavior, perception, and well-being. Within interior architecture, emotional and atmospheric approaches to design emphasize that environmental characteristics such as lighting, materiality, color, spatial organization, and multisensory perception can substantially influence how occupants perceive and experience space. Architectural perspectives associated with Barragán, Zumthor, and Pallasmaa have particularly emphasized atmosphere, sensory engagement, and embodied perception as fundamental components of spatial meaning, positioning interior environments not merely as passive physical containers but as active contributors to emotional and psychological experience (CEYLAN, 2025).

This understanding has gradually encouraged a shift from predominantly functional interpretations of interior space toward human-centered approaches in which emotional experience, comfort, perception, and psychological well-being constitute important dimensions of design quality.

Parallel to these theoretical developments, human-centered and neuroscience-informed design research has increasingly attempted to establish measurable relationships between environmental conditions and users' emotional and physiological responses. One important approach is Kansei Engineering (KE), developed by Professor Mitsuo Nagamachi in the 1980s, which provides a systematic means of translating human emotions, impressions, preferences, and subjective perceptions into measurable design parameters (Zongming Liu, 2025). By connecting affective responses with identifiable design characteristics, Kansei Engineering provides a methodological basis for incorporating subjective experience into structured design decision-making. At the same time, advances in digital technologies, including virtual environments, computational decision-support systems, generative design, and artificial intelligence (AI), have substantially expanded designers' capacity to simulate, evaluate, compare, and modify interior configurations before their physical implementation.

Recent advances in affective computing further extend these possibilities by enabling AI systems to recognize, interpret, predict, and potentially respond to human emotional states using multimodal information. Physiological signals, facial expressions, speech patterns, behavioral interactions, and self-reported assessments can increasingly be processed computationally to develop representations of emotional experience. Rather than considering emotion exclusively as a subjective outcome that can only be interpreted retrospectively, affective computing seeks to quantify emotional responses and incorporate them into intelligent prediction and decision-making systems. Such approaches have been increasingly adopted in human–computer interaction, healthcare, adaptive interfaces, and other human-centered technological applications; however, their systematic application within interior architecture remains comparatively limited. Integrating affective computing with architectural design therefore presents an opportunity to move toward evidence-based environments capable of responding more directly to occupants' emotional characteristics and individual preferences.

Machine learning and predictive modeling have already demonstrated their potential in areas including product design, automotive interiors (Zongming Liu, 2025), and human–computer interaction, where computational systems can be trained to anticipate preferences, perceptions, and emotional responses. Similar developments are increasingly influencing interior architecture and suggest a transition from static and predominantly intuition-based approaches toward adaptive, data-informed, and personalized environments (Zhang, Shen, & Li, 2025). Such a transition is particularly significant because conventional interior design processes commonly depend on generalized assumptions regarding users, whereas emotional reactions to environmental characteristics may vary considerably between individuals. AI-supported prediction therefore offers the potential to complement professional design judgment by identifying relationships between user-specific emotional responses and environmental variables and translating these relationships into personalized design recommendations.

Despite these developments, significant fragmentation remains between emotional architecture, affective computing, Kansei Engineering, physiological sensing, virtual reality, multi-criteria decision-making, and AI-assisted generative design. Existing studies commonly investigate these domains independently or combine only selected components of the overall design process. Research may, for example, examine emotion recognition without translating emotional information into spatial design decisions, apply Kansei Engineering without computational personalization, employ virtual reality to assess user experience without adapting the resulting design, or use generative AI primarily for formal visualization and design exploration. Consequently, comprehensive frameworks capable of integrating emotional data acquisition, affective interpretation, parameter prioritization, generative design adaptation, and subsequent user-centered validation within a continuous methodological process remain limited.

This fragmentation represents an important methodological challenge because emotional information alone does not necessarily lead to evidence-based design decisions. Many existing studies continue to rely predominantly on either subjective evaluations or isolated physiological measurements. Although both approaches can provide valuable information regarding users' emotional responses, they often lack mechanisms for integrating different forms of emotional information into a systematic design decision-making process. Emotional assessment in interior design therefore remains largely qualitative in many applications, making it difficult to translate emotional insights into consistent, reproducible, and evidence-based design decisions (Li, 2024). Consequently, emotional evaluation frequently remains descriptive rather than predictive, restricting its scalability and limiting the development of systematic personalization strategies.

A related limitation concerns the predominant orientation of AI applications in architecture. Current applications frequently emphasize performance optimization, energy efficiency, automation, formal exploration, image generation, or computational productivity. Comparatively fewer studies examine how AI might support emotionally responsive interior environments through multimodal emotional prediction and individualized design adaptation. Where emotional information is incorporated, it may remain disconnected from established architectural theories, human-centered design approaches, or systematic decision-making frameworks. This separation reduces its capacity to inform practical design decisions and highlights the need for methodological frameworks capable of translating emotional evidence directly into architectural parameters and personalized environmental interventions.

Virtual reality (VR) provides a particularly valuable environment for addressing this challenge because it enables users to experience and evaluate simulated architectural environments before physical implementation. VR-based studies can capture subjective assessments and potentially combine them with physiological measurements while users are immersed in controlled spatial scenarios. Nevertheless, relatively few studies integrate VR-based emotional evaluation simultaneously with physiological sensing, Kansei Engineering, multi-criteria decision-making, AI-based emotional prediction, and generative design within a unified computational workflow. Previous VR-based emotional studies often concentrate on evaluating user experience without establishing mechanisms through which the measured emotional responses subsequently modify the design itself. Similarly, previous AI-assisted architectural research has mainly emphasized formal exploration, automated generation, or performance optimization rather than participant-specific emotional personalization.

The research gap, therefore, does not arise from the absence of emotional architecture, Kansei Engineering, AI, physiological sensing, generative design, or VR as individual fields of investigation. Rather, it concerns the limited integration of these approaches into a sequential system capable of acquiring emotional information, converting that information into measurable parameters, prioritizing design variables, generating participant-specific environmental modifications, and validating the resulting design through further user assessment. Addressing this gap requires a framework in which emotional evaluation becomes directly connected with computational decision-making and design generation rather than remaining an independent analytical stage.

To respond to this need, the present study proposes an integrated AI-driven framework that combines multimodal physiological measurements, Kansei Engineering, fuzzy analytic hierarchy process (FAHP), the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), AI-assisted generative design, and immersive VR-based validation within a unified methodology for emotionally responsive interior design. The framework is intended to bridge emotional architecture and data-driven computational methodologies by positioning personalization as a fundamental component of the design process rather than as a secondary evaluation criterion. Multimodal emotional information—including electroencephalography (EEG), heart rate variability (HRV), behavioral responses, and self-reported Kansei evaluations—is translated into measurable emotional representations. Relevant interior design variables are subsequently prioritized through FAHP and TOPSIS, after which the resulting parameters are incorporated into an AI-driven generative design process. The generated alternatives are then evaluated within immersive VR environments by comparing AI-predicted emotional responses with physiological indicators and self-reported emotional evaluations.

The originality of the proposed framework consequently extends beyond the isolated application of AI or emotional prediction. Previous studies have independently examined emotional architecture, Kansei Engineering, AI-assisted design, physiological emotion recognition, and VR-based evaluation; however, these approaches generally treat emotion recognition, design decision-making, spatial generation, and user validation as separate processes. In contrast, the present framework establishes a continuous methodological pipeline connecting emotional measurement, computational prioritization, generative design, and participant-specific validation. This integration is intended to transform human emotional responses from descriptive observations into evidence that can directly inform spatial design decisions and personalized environmental modifications.

The study pursues five interconnected objectives. First, it develops an AI-enhanced emotional prediction framework integrating Kansei Engineering to quantify emotional responses associated with interior environments. Second, it identifies and prioritizes key spatial variables influencing emotional experience through multi-criteria decision-making techniques. Third, it incorporates these prioritized emotional and environmental parameters into an AI-assisted generative design process to produce alternative interior configurations. Fourth, it evaluates the performance of the proposed framework by comparing AI-predicted emotional responses with physiological measurements and self-reported emotional evaluations obtained within immersive VR environments. Fifth, it examines the framework's capacity to generate personalized interior design recommendations based on individual emotional and physiological profiles. These objectives form a sequential methodological process in which emotional information is first acquired and interpreted, influential environmental variables are prioritized, design alternatives are computationally generated, and the resulting environments are subsequently evaluated using multimodal evidence.

The contribution of the study can be understood through three complementary dimensions. Theoretically, the research extends emotional architecture by integrating affective design theories with computational intelligence and decision-making, thereby moving beyond the interpretation of emotional experience solely as a qualitative design concept. Personalization is instead conceptualized as a measurable and operational design objective that can be informed by user-specific emotional evidence. Methodologically, the study combines multimodal physiological assessment, Kansei Engineering, FAHP, TOPSIS, AI-based emotional prediction, AI-assisted generative design, and immersive VR validation within a single structured workflow. This integration provides a systematic process through which emotional responses can influence subsequent design decisions rather than remaining independent evaluation outcomes. Practically, the framework is intended to assist interior designers in developing personalized and emotionally responsive environments capable of supporting comfort, well-being, user satisfaction, and cognitive performance. This application may be particularly relevant to workplace environments, where the emotional qualities of interior settings can influence occupants' experiences and performance (Jialing Xiang N. M., 2024).

Accordingly, the principal contribution of the study lies not in proposing AI as an autonomous replacement for architectural design expertise, but in investigating its potential as a human-centered decision-support mechanism capable of connecting emotional evidence with environmental personalization. The framework establishes three hierarchical contributions: an AI-enhanced conceptual framework integrating emotional data with interior design decision-making; an experimental exploration of the framework through VR-based multimodal emotional assessment; and an evaluation of the capabilities and limitations of generative AI in translating emotional information into personalized spatial design outcomes. The research therefore considers AI-generated outputs in relation to their capacity to modify environmental characteristics such as lighting, materials, color palettes, and biophilic integration rather than assuming that contemporary generative systems can independently resolve the full complexity of architectural planning.

This distinction is important to the scope of the investigation. The proposed approach should be understood as an exploratory framework validation rather than a complete autonomous architectural generation system. Its purpose is to examine whether multimodal emotional evidence can be systematically translated into prioritized design parameters and whether AI-assisted generative methods can subsequently use these parameters to support participant-specific environmental personalization. In this way, the study seeks to establish a scalable connection between emotional prediction, evidence-based decision-making, adaptive design, and human-centered interior environments while simultaneously recognizing the present limitations of AI in comprehensive spatial planning.

The remainder of the paper develops and evaluates this framework systematically. Following the introduction, Section 2 describes the research methodology, including the mixed-methods approach, case study design, multimodal data collection, and immersive VR validation procedures. Section 3 presents the proposed AI-driven emotional prediction framework and explains the integration of Kansei Engineering, FAHP, TOPSIS, and AI-assisted generative design. Section 4 reports the case study findings, AI-generated design outcomes, and validation results. Section 5 discusses the principal findings together with their theoretical implications, methodological contributions, practical significance, and limitations. Finally, Section 6 summarizes the major conclusions and identifies directions for future research.

2. Materials and Methods

This paper adopts a mixed-methods approach combining theoretical modeling, AI-based prediction, and experimental validation. Multimodal emotional data are integrated into predictive models, while the Fuzzy Analytic Hierarchy Process (FAHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) are employed to prioritize interior design parameters (Zhang, Shen, & Li, 2025).

FAHP was employed to determine the relative importance of interior design variables influencing users' emotional experience. The evaluation criteria were derived from the Kansei Engineering analysis and included lighting quality, materiality, color, spatial organization, biophilic design, furniture arrangement, and visual complexity. Pairwise comparisons were performed using linguistic judgments converted into triangular fuzzy numbers according to the standard FAHP procedure. Consistency of the comparison matrix was verified using the conventional consistency ratio (CR), with acceptable consistency defined as $CR < 0.10$. The resulting normalized weights were subsequently used as inputs for the TOPSIS analysis.

TOPSIS was then applied to rank alternative design strategies according to their overall contribution to emotional well-being. Each design alternative was evaluated against the weighted emotional design criteria, and a relative closeness coefficient was calculated to determine its proximity to the ideal emotional design solution. The highest-ranked alternatives were subsequently incorporated into the AI-assisted generative design framework to produce personalized interior design recommendations.

This approach is particularly effective in complex contexts where precise quantitative data may be limited. In parallel, TOPSIS is utilized as a multi-criteria decision-making method that ranks alternatives based on their relative distance to an ideal solution, defined by optimal performance across all criteria, and a negative ideal solution, representing the least desirable outcomes. The consistency of FAHP pairwise comparisons was verified using standard consistency ratio thresholds, while TOPSIS rankings were evaluated based on relative closeness coefficients. Generative design techniques further support the development of personalized interior configurations, and validation is conducted by comparing AI-predicted emotional outcomes with empirical user responses in virtual reality (VR) environments (Salingaros, Jul2025).

The study begins with Case Study A, which is derived from prior research and serves as a conceptual foundation. Subsequently, Case Study B was developed by the author based on established design theories and principles.

Participants experienced the space using an immersive virtual reality simulation through a Meta Quest 3S headset. Physiological and neurological data were collected using the Muse 2 headband to record heart rate variability and electroencephalography (EEG) throughout the VR sessions.
The collected multimodal data were subsequently used as inputs to the proposed AI-assisted generative design framework.
Additional inputs for the AI generative model, used for editing the design, will include KE (Kansei Engineering) principles, as well as FAHP and TOPSIS for decision-making.
This process resulted in a personalized interior space based not only on users' preferences but also on their spatial perception and physiological responses.

The study included 13 participants, with each participant representing an individual case study within the proposed AI-driven framework. This sample size was selected because the research was designed as an exploratory proof-of-concept study intended to evaluate the feasibility of integrating multimodal physiological measurements, self-reported emotional responses, Kansei Engineering, multi-criteria decision-making, and AI-assisted generative design within a unified methodological framework. Rather than developing a population-level predictive model, the objective was to investigate whether participant-specific multimodal data could be successfully translated into personalized interior design recommendations.
The study included 13 participants who evaluated the VR-based office environment. Each participant represented an individual emotional response dataset. Case Studies C and D present two representative examples selected from the participant dataset to demonstrate how different emotional profiles generated different AI-assisted design outcomes.
Each participant contributed a complete multimodal dataset consisting of electroencephalography (EEG), heart rate variability (HRV), behavioral data obtained during immersive virtual reality interaction, and structured questionnaire responses. Consequently, the analysis emphasized within-participant emotional prediction and personalized design generation rather than statistical generalization to larger populations. Although the sample size limits external validity, it is considered appropriate for demonstrating the feasibility of the proposed framework and establishing a foundation for future large-scale validation studies.

Because the primary objective of this research was methodological development rather than population-level prediction, emphasis was placed on collecting rich multimodal observations from each participant rather than recruiting a large sample. Similar exploratory studies involving physiological sensing, virtual reality, and human-centered AI frequently employ relatively small participant groups due to the complexity of data acquisition, experimental control, and sensor-based measurements. Future research should validate the proposed framework using larger and more diverse participant populations to improve statistical generalizability and model robustness.

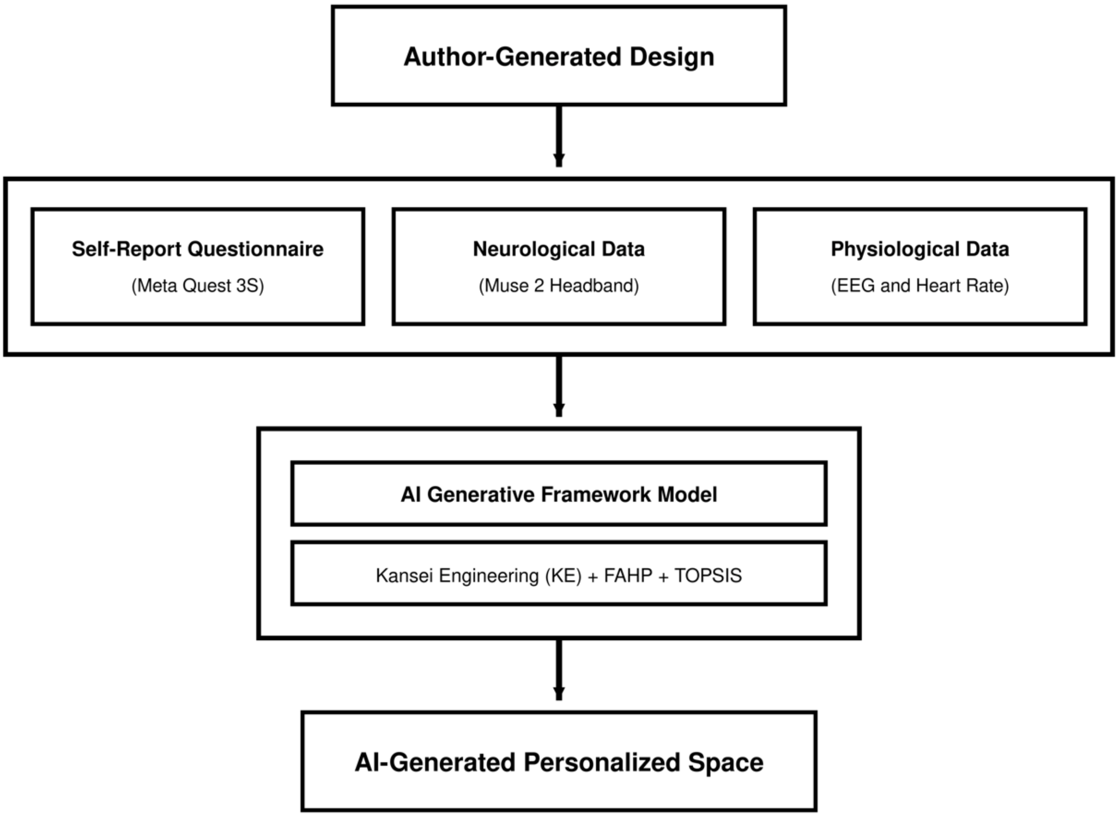

Figure 1. used methodology steps.

The proposed framework was evaluated by comparing AI-generated emotional design recommendations with participants' physiological measurements and self-reported emotional evaluations collected during immersive virtual reality sessions. This evaluation focused on examining the consistency between multimodal emotional information and the resulting design recommendations rather than measuring predictive accuracy using conventional machine learning performance metrics.

The consistency between predicted and observed emotional responses was used as a measure of model reliability.
Descriptive statistical analysis was performed to evaluate central tendency and variability across emotional and physiological measures. Correlation analysis was also used to assess relationships between physiological signals and reported emotional states.

The FAHP–TOPSIS workflow consisted of four sequential stages. First, Kansei Engineering analysis identified the principal emotional design criteria. Second, FAHP was applied to determine the relative importance of each criterion using fuzzy pairwise comparisons. Third, TOPSIS ranked alternative design strategies according to their weighted emotional performance. Finally, the highest-ranked design parameters were supplied to the AI-assisted generative design module as constraints for personalized interior generation. Figure 2 summarizes the overall decision-making workflow.

2.1 Case Study A: University Department Building (Reference Case Study Conceptual Benchmark)

Unlike Cases B–D, Case Study A does not represent an empirical participant-based experiment. Instead, it functions as a conceptual benchmark illustrating previous attempts to integrate AI and human-centered design principles. It is included only for theoretical comparison and is not included in the experimental validation dataset.

Case Study A examines a university department building developed through a hybrid design framework that combines Christopher Alexander's pattern language with generative artificial intelligence, as presented by Postle and Salingaros (2024). The case study was conducted in China and focused on exploring how AI-generated narratives can embed emotional, psychological, and human-centered design principles within architectural and interior environments. A subset of 253 design patterns was selected through a web-based interface and input into a large language model, which generated descriptive outputs related to spatial organization, material expression, ornamentation, and experiential qualities of the building.

The design emphasized clustered building wings of limited height, interconnected courtyards, abundant natural lighting, and human-scaled spatial proportions. Material choices and ornamental strategies were informed by neuroscience and psychology research, aiming to support comfort, well-being, and cognitive ease. While the case study demonstrates the conceptual potential of integrating generative AI with pattern-based design to produce emotionally resonant environments, its outcomes remain largely narrative and theoretical, lacking direct physiological measurements or empirical user-response data. This case study therefore serves as a foundational reference for human-centered, emotion-aware design approaches prior to empirical validation and AI-driven emotional prediction. (MichaelW. Mehaffy, 2023)

2.2 Case Study B: Research Case Study – Office Interior Environment (Pre-AI Generative Model)

Case Study 2 represents the primary empirical case study of this research and examines an office interior environment prior to the application of AI generative design models. This case study focuses on a digitally simulated office space designed to evaluate users' emotional, physiological, and behavioral responses under controlled and repeatable conditions using immersive Virtual Reality (VR). The interior environment consists of an office space with a total interior surface area of 36,517 sq ft and includes an open-plan office cluster, a meeting room, a reception area, and a manager's office. The office is characterized by large exterior-facing windows to examine the influence of the external environment on user perception and comfort, while indoor plants are distributed throughout the interior to assess the impact of biophilic design elements on emotional response and spatial preference. Architectural floor plans for case study B Figure B:

Figure 2. Case Study B Architectural floor plan.

The spatial layout and architectural plans were generated using AutoCAD, followed by three-dimensional modeling in SketchUp and rendered using Lumion. The finalized digital model was imported into SimLab to develop a fully immersive VR environment compatible with the Meta Quest 3S, and muse 2 headband was used to collected physiological data.
This workflow enabled accurate representation of spatial proportions, circulation, lighting conditions, material finishes, color schemes, and biophilic components, while allowing systematic control of design parameters.
Participants explored the virtual office environment using immersive virtual reality. The duration of exposure ranged between approximately 10 and 40 minutes, depending on each participant's level of comfort and completion of the experimental tasks. This flexible exposure period was adopted to minimize discomfort, reduce the likelihood of simulator sickness, and allow participants to interact naturally with the virtual environment. Although exposure duration varied between participants, the same experimental protocol, virtual environment, questionnaire, and physiological data collection procedures were applied consistently across all sessions.

Emotional data were collected using a multimodal measurement framework. Physiological measurements were obtained using the Muse 2 headband throughout each virtual reality session. Electroencephalography (EEG) signals and heart rate variability (HRV) measurements were continuously recorded to capture objective indicators of emotional arousal, cognitive engagement, and stress responses while participants interacted with the virtual environment. Prior to analysis, raw physiological signals underwent standardized preprocessing to improve signal quality. This preprocessing included noise filtering, normalization, and the removal of obvious motion-related artifacts associated with participant movement during immersive VR interaction.

Behavioral data were obtained through the VR system, including navigation patterns, dwell time, interaction duration, and spatial preference indicators. In parallel, self-reported emotional responses were collected using structured questionnaires based on Kansei-based perceptual scales, capturing participants' subjective evaluations of comfort, calmness, stimulation, stress, satisfaction, and overall emotional valence. Shots from Case study illustrated in picture 1.

Emotional Response and Cognitive Support
Descriptive statistics for the emotional response variables can be summarized as follow Participants reported generally positive emotional valence, with mean scores above the neutral midpoint for all emotional items. Low standard deviations indicate consistency across respondents, particularly for comfort and calmness, which emerged as the most salient emotional responses.
Cognitive support metrics showed that participants perceived the environment as strongly conducive to focus and productivity, whereas perceptions of collaboration encouragement were comparatively lower. This outcome suggests a design effect favoring task-oriented zones over interactive spaces.

Picture 1. Case Study B Office Design.

Analysis of the Kansei semantic differential data revealed that participants predominantly associated the tested environment with pleasant, relaxing, natural, and organized qualities. Mean responses were clustered toward the positive end of the semantic scale, and low dispersion suggests perceptual agreement among participants. Such convergent perceptual weighting supports the robustness of these measures as stable indicators of qualitative spatial experience. These represent the inputs for the AI generative model. Data for KE and cognition for AI model shown in figure 3.

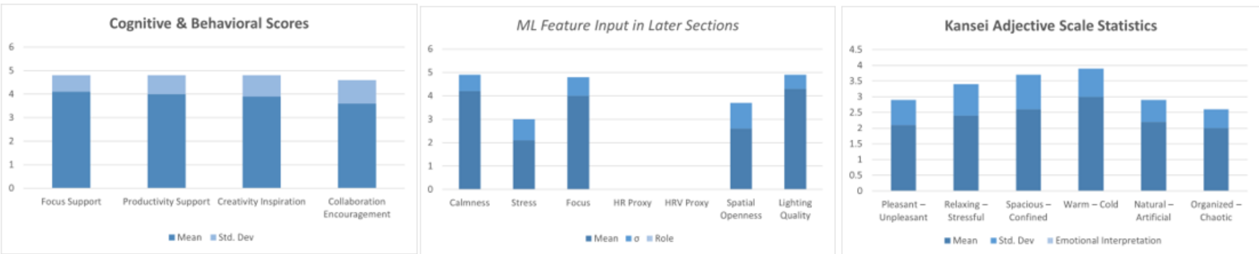

Figure 3. KE and cognition data used as inputs for the AI Generative Model.

Key Interpretive Insights

The integrated descriptive results indicate that:

- Emotional variables align positively with aesthetic and comfort perceptions, reinforcing theoretical expectations about environmental influence on affective states.
- Cognitive dimensions favor individual engagement, which is consistent with the design's spatial zoning logic.
- Kansei adjective outcomes reflect cohesive user perceptions that can reliably inform downstream multi-criteria modeling (e.g., Kansei–FAHP).

These interpretations form the basis for subsequent analytical stages in this research, where these quantified perceptual scores will be integrated into predictive and optimization models.

3 Emotion-Conditioned Interior Image Generation (AI Model Architecture)

This research proposes a multimodal emotion-informed generative model designed to translate users' emotional experience of interior environments into emotionally adapted visual design representations. The model integrates physiological responses and questionnaire-based emotional evaluations as complementary inputs, which are transformed through linguistic mediation and used to condition a diffusion-based image generation process.

The architecture is intentionally structured to separate emotional characterization, semantic representation, and visual synthesis, ensuring interpretability and methodological clarity as shown in figure 4. Generative AI is employed strictly as a visual synthesis mechanism, while emotional interpretation remains grounded in human-derived data.

The proposed framework does not involve training a new artificial intelligence model. Instead, it employs pretrained AI models as computational components within a structured design workflow. The role of AI is divided into three sequential operations: (1) emotional data abstraction, where physiological and questionnaire data are transformed into symbolic emotional representations; (2) semantic translation, where emotional states are converted into textual descriptions using a pretrained language model; and (3) visual synthesis, where a pretrained diffusion model generates emotionally conditioned interior design images based on emotional descriptions and architectural references.

Model evaluation in this study focuses on the correspondence between emotional inputs and generated design characteristics rather than conventional machine-learning accuracy metrics. The generated outputs were assessed according to their alignment with participant emotional profiles, Kansei-derived descriptors, and predefined interior design parameters. Therefore, the framework represents an exploratory AI-assisted design methodology rather than a fully trained predictive model.

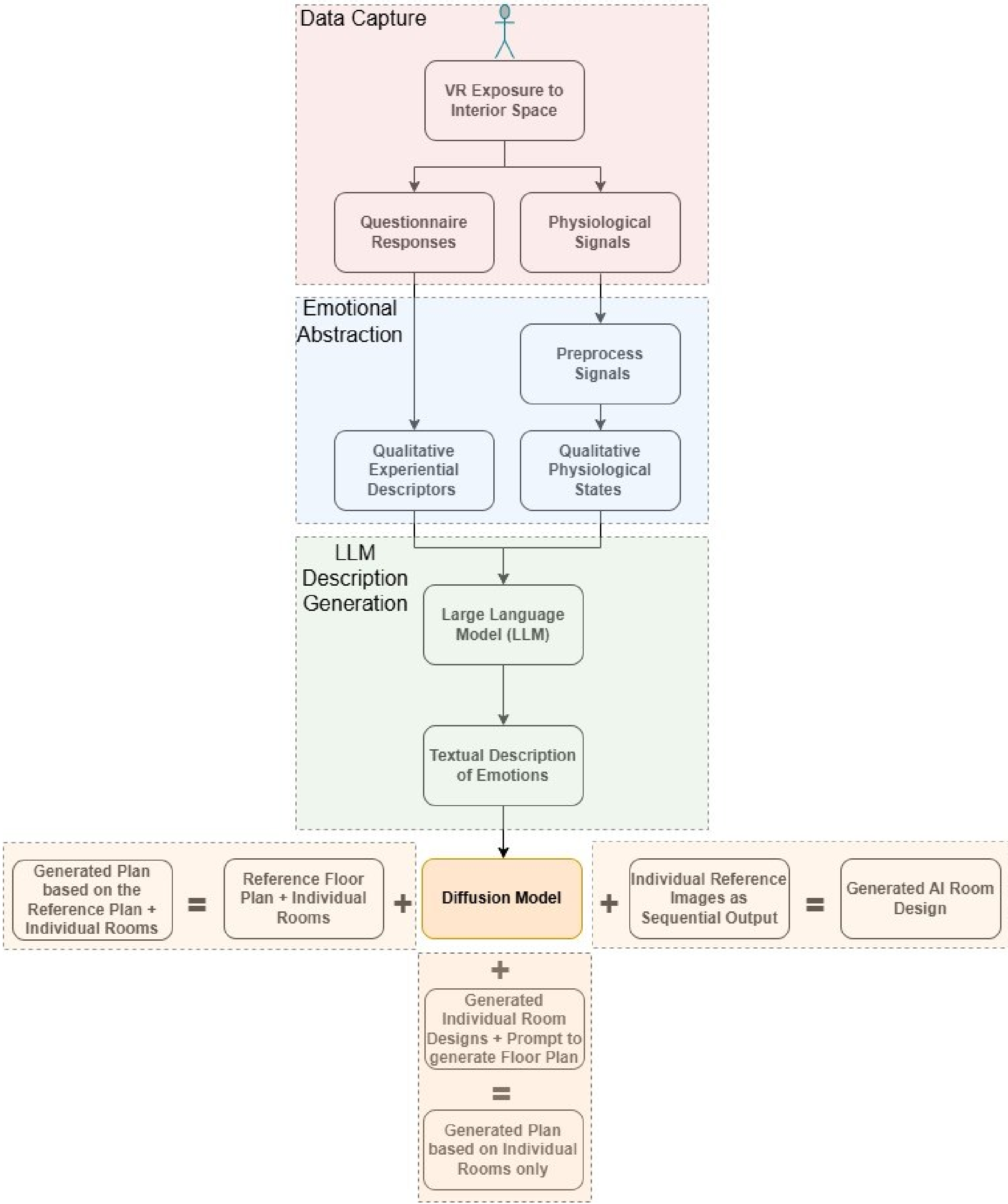

Figure 4. Generative AI Model with 3 visual outputs for the generated design.

The emotional representation process consists of three sequential stages: physiological feature extraction, subjective emotional evaluation, and multimodal integration. Physiological signals obtained from EEG and heart-rate variability were transformed into normalized response features representing activation and stability patterns. Questionnaire responses based on Kansei semantic scales were converted into qualitative emotional descriptors. Behavioural indicators from VR interaction were used as supporting contextual information. These three data streams were integrated to generate a participant-specific emotional profile used as input for the generative design process.

3.1 Physiological Data Processing and Abstraction

Physiological measurements collected during immersive spatial exposure are represented as multivariate time-series data:

$$\mathrm{X}(t) = \{x_1(t), x_2(t), \ldots, x_n(t)\}, t \in [0, T]$$

where $x_i(t)$ denotes the i-th physiological signal channel recorded continuously over the duration of the VR session, and t represents time.
These signals capture participants' bodily responses to the interior environment as it is experienced, reflecting temporal fluctuations of physiological activity rather than discrete or labelled emotional events.
To ensure data quality and comparability across participants, each signal undergoes deterministic preprocessing:

$$\tilde{x}_i(t) = \mathcal{P}(x_i(t))$$

where $\mathcal{P}(\cdot)$ represents standardized signal-processing and $\tilde{x}_i(t)$ denotes the preprocessed signal.
From the pre-processed signals, summary physiological features are extracted:

$$\mathrm{f}^{\mathrm{phys}} = \Phi(\widetilde{\mathrm{X}}(t))$$

where $\Phi(\cdot)$ denotes a feature-extraction function, and $\mathrm{f}^{\mathrm{phys}}$ is a vector of scalar descriptors representing relative physiological activation intensity, variability, and temporal stability over the exposure period. These features provide a compact representation of bodily response patterns without assigning explicit emotional labels.
To enable integration with other components of the model, continuous physiological features are abstracted into qualitative physiological states:

$$\mathrm{s}^{\mathrm{phys}} = \mathcal{M}^{\mathrm{phys}}(\mathrm{f}^{\mathrm{phys}})$$

where $\mathcal{M}^{\mathrm{phys}}(\cdot)$ maps numerical features to qualitative categories (e.g., low, moderate, high activation), and $\mathrm{s}^{\mathrm{phys}}$ represents the participant's physiological response profile. This abstraction supports interpretability and reduces sensitivity to individual baseline differences.

3.2 Questionnaire-Based Emotional Representation

Alongside physiological measurements, participants' conscious emotional and perceptual evaluations are collected using structured questionnaires and Kansei-based perceptual scales. These responses are represented as:

$$\mathrm{q} = \{q_1, q_2, \dots, q_m\}$$

where each response q_j corresponds to a Likert-scale assessment of experiential dimensions such as comfort, calmness, focus, stimulation, or overall satisfaction.
These responses capture how participants consciously interpret and evaluate the interior space, complementing the bodily responses captured physiologically.
To align questionnaire data with the symbolic representation used in the model, responses are transformed into qualitative experiential descriptors:

$$\mathrm{s}^{\mathrm{quest}} = \mathcal{M}^{\mathrm{quest}}(\mathrm{q})$$

where $\mathcal{M}^{\mathrm{quest}}(\cdot)$ groups questionnaire responses into qualitative states (e.g., low/medium/high comfort), and $\mathrm{s}^{\mathrm{quest}}$ represents the participant's self-reported emotional evaluation.

3.3 Integrated Emotional State Representation

Physiological and questionnaire-based symbolic representations are combined into a unified emotional state:

$$\mathrm{S}^{\mathrm{emo}} = \mathcal{I}(\mathrm{s}^{\mathrm{phys}}, \mathrm{s}^{\mathrm{quest}})$$

where $\mathcal{I}(\cdot)$ denotes an integration function, and $\mathrm{S}^{\mathrm{emo}}$ represents the participant's overall emotional experience of the interior environment.

This integrated emotional state reflects both objective bodily response patterns and subjective experiential evaluations, without encoding architectural rules, design strategies, or visual prescriptions.

3.4 Language-Mediated Emotional Description

The integrated emotional state is converted into a textual description using Large Language Models:

$$\mathrm{d} = \mathcal{L}(\mathrm{S}^{\mathrm{emo}})$$

where $\mathcal{L}(\cdot)$denotes the instruction-tuned language model operating strictly in verbalization mode, and dis a textual representation of emotional tendencies such as calmness, alertness, comfort, or stimulation.

The role of the language model is purely semantic: it expresses emotional information in natural language without reinterpretation, inference, or optimization. Semantic equivalence is maintained such that:

$$\mathrm{Semantics}(\mathrm{d}) \equiv \mathrm{Semantics}(S^{\mathrm{emo}})$$

This ensures that linguistic mediation does not alter the underlying emotional content and prepares the representation for downstream generative conditioning.

3.5 Diffusion-Based Image Generation

Visual synthesis is performed using a pre-trained diffusion model, which serves as the visual generation component of the framework. The diffusion model is conditioned on:

the textual emotional description d, and

original reference images $\mathrm{I}_{\mathrm{ref}}$representing the initial architectural design context.

Image generation is defined as:

$$\mathrm{I} \sim p_\theta(\mathrm{I} \mid \mathrm{d}, \mathrm{I}_{\mathrm{ref}})$$

where $p_\theta(\cdot)$denotes the diffusion model with fixed parameters θ, and I is the generated interior image. The emotional text guides atmospheric and experiential qualities, while the reference images anchor spatial proportions, layout continuity, and architectural plausibility.

Individual functional interior spaces are first generated independently, resulting in:

$$\{\mathrm{I}_1, \mathrm{I}_2, \dots, \mathrm{I}_k\}$$

where each $\mathrm{I}_i$represents a generated image corresponding to a specific interior function (e.g., reception, workspace, meeting room).

These images are jointly provided to the diffusion model to generate a coherent floor-plan-level representation:

$$\mathrm{F}_1 \sim p_\theta\left(\mathrm{F} \mid \{\mathrm{I}_i\}_{i=1}^{k}\right)$$

where F_1represents a synthesized three-dimensional floor plan emerging from spatial relationships between the generated interior spaces.

In the second stage, floor-plan-level generation is simultaneously conditioned on:

the generated interior space images $\{\mathrm{I}_i\}$,

the designer's original floor plan $\mathrm{F}_{\mathrm{orig}}$, and

the emotional textual description d.

$$\mathrm{F}_2 \sim p_\theta\left(\mathrm{F} \mid \{\mathrm{I}_i\}_{i=1}^{k}, \mathrm{F}_{\mathrm{orig}}, \mathrm{d}\right)$$

Here, F_{orig}preserves architectural geometry, circulation, and adjacency, while emotional conditioning influences spatial atmosphere, material expression, and experiential coherence. This ensures emotional adaptation without violating architectural intent.

4 Office Interior Environment (Post-AI Generative Model)

4.1 Case Study C: Research Case Study

Case study C represents the result of integration of questionnaire-based emotional profiling and physiological time-series analysis, the AI generative model produced an optimized spatial configuration for one of the participants. The design output reflects a data-driven translation of subjective perception and objective biometric indicators into human-centered spatial parameters.

Time-series physiological analysis revealed strong coherence between heart rate–related signals ($r \approx 0.95–0.98$), moderate variance, and minimal outlier presence (<4%). These indicators suggest stable emotional regulation and the absence of stress-driven arousal patterns. The data implies a user profile that benefits from emotionally balanced, low-stimulation environments rather than dynamic or high-contrast settings.

In response, the generative model prioritized smooth sensory transitions and reduced physiological triggers. The resulting configuration incorporates diffuse, evenly distributed lighting without glare, matte and low-reflectance surfaces, and a restrained material palette. Sharp contrasts, abrupt color transitions, and visually aggressive forms were systematically eliminated.

These adjustments were intended to support environments associated with lower physiological arousal and greater emotional stability.

and maintain the physiological stability observed in the biometric data.

Self-reported measures indicated high levels of calmness and comfort ($\mu \approx 4.2–4.5$), alongside strong support for focus and productivity ($\mu \approx 4.0–4.1$). Stress reduction scores were consistently above the neutral midpoint, and Kansei semantic differential results clustered toward relaxing, natural, organized, spacious, and familiar descriptors.

The AI model interpreted these patterns as indicative of a focus-dominant work preference with sensitivity to environmental chaos and visual complexity. Consequently, the optimized layout emphasizes spatial legibility and predictable organization.

Workstations are arranged in linear or symmetrically ordered configurations, maintaining clear separation to support sustained concentration. Visual openness is preserved without enforcing interaction, balancing psychological spaciousness with task-oriented privacy. Kansei descriptors identified through semantic differential analysis including pleasant, natural, warm, and familiar, were computationally mapped to design parameters within the generative system. This explicit Kansei-to-geometry and Kansei-to-material translation constitutes a central methodological component of the framework.

Natural wood surfaces were selected as the dominant tactile and visual language, reinforcing familiarity and emotional warmth. Muted green accents were introduced to align with biophilic emotional associations, while neutral base tones maintain perceptual stability. Rounded edges and softened geometries were favored over sharp orthogonal interruptions to reduce cognitive tension. Repetition and rhythmic ordering elements were incorporated to enhance perceived organization and predictability.

Both physiological coherence and self-reported comfort measures indicated improved emotional regulation in environments with visual access to nature. However, the data suggest a preference for controlled, non-immersive biophilia rather than dense or visually complex planting.

Accordingly, the AI model positioned biophilic elements as emotional regulators rather than decorative components. Desks were oriented toward glazed openings where possible, ensuring visual continuity with exterior greenery. Indoor plants were strategically distributed as peripheral anchors

rather than concentrated clusters, preventing visual overload. Daylight exposure was maximized while controlling glare, reinforcing psychological openness without increasing sensory intensity.
The AI-optimized configuration for Case Study C demonstrates how multimodal data integration combining physiological coherence metrics and quantified emotional perception can inform spatial decisions during the design phase.
The resulting environment is characterized by low-arousal sensory conditions, high spatial legibility, controlled biophilic integration, and material selections aligned with Kansei-derived emotional vocabulary. This case illustrates the capacity of AI-driven emotional prediction to translate human affective and physiological patterns into structured interior design parameters, advancing predictive and preventative spatial optimization methodologies.
Collectively, these findings substantiate the capacity of AI-driven emotional prediction and generative design modeling to optimize interior environments by aligning spatial configurations with users' affective and physiological needs prior to physical implementation. The results further reinforce the methodological validity of integrating subjective perception, physiological coherence, and predictive modeling within an emotional architecture framework. Scenes from the generated designed illustrated in picture 2.

Picture 2. AI Generated design Case Study C.

4.2 Observation of the design change (Multimodal Emotional–Physiological–Spatial Design Framework)

The integrated analysis of physiological signals, questionnaire responses, and Kansei Engineering mapping demonstrates a consistent and convergent pattern across all datasets. The findings indicate a user profile characterized by high emotional stability, sensitivity to overstimulation, preference for low cognitive load environments, and strong affinity toward natural, organized, and familiar spatial conditions.
These results collectively inform a unified AI-driven emotional design framework that translates multimodal human data into spatial, material, and environmental parameters.

This resulted in a more personalized spatial configuration that demonstrated alignment with identified emotional preferences and physiological patterns; however, direct measurement of emotional improvement after implementation was beyond the scope of this study.However, spatial organization remained inconsistent with the existing layout. There was no significant difference observed in the design of the manager's office. Design Changes illustrated in Table 1. The AI-assisted framework generated participant-specific modifications to environmental design parameters that were associated with improved self-reported comfort and favorable physiological trends. Nevertheless, the generated architectural layouts frequently lacked coherent spatial organization and did not consistently preserve functional relationships, highlighting the current limitations of generative AI in large-scale architectural planning.

Therefore, the current framework should be understood as an emotional design optimization system rather than an autonomous architectural planning system. AI demonstrates stronger capability in modifying atmospheric, material, and perceptual qualities than in generating complete architectural layouts that satisfy functional and spatial constraints. While the system improves user-centered spatial quality, its current limitations reduce its practical applicability for architectural planning.

Table 1: Design transformation before and after the AI Model.

Category	Case Study B Before (Raw Multimodal Interpretation)	Case Study C After (Integrated AI-Driven Design Outcome)
Physiological Data Interpretation	High coherence signals (r ≈ 0.95–0.98), moderate variance, low stress indicators identified separately per space	Unified baseline: environment consistently optimized for low arousal, emotional stability, and smooth transitions across all spaces
Emotional Regulation Strategy	Emotional stability identified per individual dataset (work, meeting, waiting, etc.)	System-wide emotional regulation model applied across entire spatial ecosystem
Lighting Strategy	Adequate lighting used in the space based on workspace needs.	Standardized warm, diffuse, low-glare lighting strategy across all zones
Material Strategy	Wood finishes and natural materials applied per space based on stress reduction needs	Global material system: matte, natural, non-reflective surfaces applied consistently across all environments
Color Strategy (Kansei)	Colors used are natural and neutral.	Unified emotional palette: warm neutrals + earthy tones + consistent soft green biophilic accent
Spatial Organization	Each zone designed independently in relationship to the whole space.	Emotionally sequenced spatial system (focus → collaboration → meeting → transition)
Furniture Layout	Context-specific layouts (desk focus, lounge comfort, meeting structure)	soft geometry, symmetry, psychological safety across all zones
Biophilic Strategy	symbolic, immersive greenery depending on space	Controlled distributed anchored plants + framed greenery + daylight continuity across all spaces
Nature Integration	Some spaces use plants, others use nature references	biophilia becomes a functional emotional regulator, not decorative element
Cognitive Load Management	Addressed separately in each environment (focus, meeting, transition zones)	System-wide cognitive load reduction via clarity, predictability, and elimination of visual noise
Circulation & Navigation	Individual circulation logic per space type	Single orthogonal, legible circulation system across entire layout
Spatial Zoning Logic	Function-based zoning (work, meeting, lounge, etc.)	Emotion-based zoning (low arousal → focus → interaction → transition)
Visual Complexity Control	Reduced locally depending on user needs per space	General reduction of visual complexity and elimination of competing focal points
Kansei Application	Direct mapping of function to each space	Integrated Kansei-to-design translation system applied consistently across all environments
Observed Outcome	Separate insights per dataset	Single coherent adaptive spatial system optimizing emotional regulation, cognition, and behavior

4.3 Case study D:

Case Study D represents the result of edits made for another participant with different inputs. Based on the self-reported questionnaire results, this participant consistently emphasized the importance of comfort, visual clarity, perceived safety, sustained focus, and reduced stress. Lighting quality and spatial legibility were identified as the primary emotional drivers influencing their overall experience. In response to these findings, the AI-guided redesign increased uniform ambient illumination, simplified material expression, and minimized visual clutter to support cognitive ease and enhance emotional stability. The integrated analysis of self-reported questionnaire data and continuous physiological time series signals demonstrates a consistent convergence toward environments characterized by high comfort, visual clarity, perceived safety, and reduced stress.

The findings indicate a user profile that is highly sensitive to spatial legibility, lighting conditions, and perceptual order, with emotional stability strongly dependent on low visual complexity and stable sensory input. These results inform an AI-guided design framework that translates multimodal behavioral and physiological indicators into spatial, lighting, and material strategies aimed at enhancing cognitive ease and emotional regulation. Scenes from Case study D illustrated in picture 3.

Analysis of the physiological data for this case study D, derived from continuous time-series signals, indicated improved emotional regulation in environments characterized by stable sensory input and minimal fluctuations in arousal, rather than in settings defined by high contrast or strongly atmospheric conditions. Accordingly, the proposed design interventions prioritized realistic daytime lighting conditions, neutral color palettes, symmetrical spatial compositions, and interface-based furniture configurations. These strategies were implemented to reduce sensory dominance and enhance perceptual predictability.

Overall, the AI-generated modifications made the interior space object-driven compositions toward functionally abstract, technology-oriented spaces that regulate emotional responses through clarity, brightness, and spatial order. This approach aligns subjective emotional preferences with objective physiological responses, reinforcing the integration of perceptual experience and biometric evidence within the design process.

Picture 3. Case Study D Design.

Although for this case study the Architectural floor plan was given to the AI generative Model with different formats, but the generated layouts were insufficient, failing to maintain spatial organization or align with the intended design scenes.

Picture 4. Generated Layout with defects.

Across the 13 participant case studies included in this exploratory investigation, a consistent trend was observed in which environments characterized by reduced sensory complexity, greater spatial clarity, and organized layouts were associated with more favorable emotional responses. These observations should be interpreted within the context of the present sample rather than as universal design principles. Illustrated in table 4. The final AI-driven design system operates as a functionally abstract emotional architecture model.

Table 2: Representing the transformation for the AI Framework.

Category	Before	After
Physiological Data Interpretation	Stability linked to low arousal environments with minimal fluctuation; sensitivity to high contrast conditions identified	Unified system prioritizing stable sensory input, low arousal fluctuation, and consistent physiological regulation
Emotional Regulation Mechanism	Improved regulation observed in specific low-stimulation environments	System-wide emotional stability achieved through uniform environmental control
Lighting Strategy	Preference for stable, non-dynamic lighting; sensitivity to contrast and atmospheric effects	Daylight-referenced, uniform ambient illumination with no high-contrast or dramatic lighting
Material Strategy	Reduced stress in environments with low sensory complexity	Simplified, neutral, low-texture materials applied consistently across all spaces
Color Strategy	Neutral environments linked to higher comfort and lower stress	Standardized neutral and desaturated palette ensuring perceptual predictability
Spatial Organization	Preference for clarity, legibility, and reduced complexity	Symmetrical, highly legible layouts with minimized spatial ambiguity
Furniture Configuration	Comfort and clarity prioritized in self-report data	Interface-like, functional furniture arrangements supporting cognitive ease
Cognitive Load Management	Sensitivity to clutter and visual complexity	System-wide reduction of visual hierarchy and environmental noise
Biophilic Strategy	Low reliance on immersive nature; preference for stable environments	Minimal or abstracted biophilic integration embedded into color and balance systems
Environmental Logic	Emotion influenced by clarity, brightness, and spatial order	Fully abstracted functional system prioritizing predictability and clarity over decoration
Final Outcome	Separate physiological and questionnaire-based insights	Unified AI-driven abstract emotional architecture prioritizing clarity, stability, and cognitive efficiency

5. Results

This section presents the outcomes of the AI-generated design and emotional validation across the case studies. The results of this research demonstrate consistent relationships between interior spatial design, physiological responses, behavioral patterns, and self-reported emotional evaluations across all 13 case studies. However, a key finding is that emotional responses are person-specific, particularly in AI-optimized environments same to what happened in (Case Study C and Case Study D), where design outputs were personalized based on individual physiological and questionnaire data. Across all case studies,

Lighting, spatial clarity, material complexity, and biophilic distribution were consistently identified as environmental factors associated with participants' reported emotional comfort and perceived cognitive load.

A general trend was observed in which Environments characterized by higher spatial legibility and reduced sensory complexity were consistently associated with more favorable emotional responses and lower physiological stress indicators among the participants. Although similar trends were observed across several participants, the findings should be interpreted as participant-specific observations rather than universally applicable design rules.

Across all datasets, convergence between physiological, behavioral, and self-reported data confirms that emotional experience is shaped by both environmental design and individual differences.

Noticing changes in design for Participant 1 in case study C whose responses were more strongly to biophilic and restorative environments and for Participant 2 in Case study D whose responses were more strongly to clarity-based + cognitively simplified environments, This demonstrates that emotional optimization in interior design cannot be generalized universally, but must be adaptively personalized using multimodal AI systems. Psychological, Cognitive, and Emotional Design Intent Across Case Studies are compared in table 2 with total observational results of the main role of the generative AI framework.

Table 3: Psychological, Cognitive, and Emotional Design Intent Across Case Studies.

Category	Case Study A	Case Study B	Case Study C	Case Study D	Summary of Observations
Psychological Intent	Human-centered emotional enrichment	Measure baseline emotional experience	Enhance comfort and emotional balance	Enhance comfort and emotional balance	Shift toward cognitive simplification
Cognitive Focus	Exploratory + narrative cognition	Mixed focus + distraction sensitivity	Structured attention and reduced load	High clarity, minimal cognitive effort	Cognitive load continuously decreases
Emotional Objective	Restorative + experiential richness	Comfort	Calmness + stress reduction	Safety + stability + predictability	Greater consistency between physiological indicators and self-reported emotional responses
Spatial Perception	Symbolic + narrative richness	Variable perception	Highly predictable + simplified perception	Highly predictable + simplified perception	Perception shifts toward clarity
Stress Response	Conceptual low stress	Different levels in each zone	Reduced stress levels+ stable regulation	Reduced stress levels+ stable regulation	Overall trend toward lower reported stress across the illustrated case studies
Emotional Regulation	Theoretical regulation via design narrative	Theoretical regulation via design narrative	Physiologically aligned regulation via simplicity	Physiologically aligned regulation via simplicity	Regulation becomes increasingly data-driven

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The findings suggest that emotional responses to interior environments are dynamic, multimodal, and highly individualized within the participant group examined in this study. However, the nature of optimization differs by individual as follow: Emotional well-being can be enhanced through either biophilic richness (Participant 1) or spatial simplification and clarity (Participant 2). This highlights the importance of adaptive, user-specific AI models in interior architecture. Overall, the study indicates that AI-assisted design has the potential to support personalized emotional calibration of interior environments when integrated with multimodal physiological and subjective data Table 4 summarizes the principal observations across the four case studies. The comparison is intended to illustrate qualitative differences in design characteristics and participant responses rather than provide statistical comparisons.

Table 4: Design parameters differences from the previous studies showing the resulted impacts.

Category	**Case Study A (Conceptual AI–Pattern Design)**	**Case Study B (Pre-AI VR Baseline)**	**Case Study C (Post-AI Optimized Design)**	**Case Study D Post-AI Optimized Design)**	**Total Observation**
Interior Type	University department building	Office environment (baseline)	office (AI-optimized version)	office (AI-optimized version)	N/A
Total Interior Area	Not specified (conceptual scale)	36,517 sq ft	Generated Pictures shows different dimensions with defects	Generated Pictures shows different dimensions with defects	AI Framework cannot make edits for floor plans or layouts.
Spatial Strategy	Narrative + adaptive geometry + courtyards	Standard open-plan office layout	Simplified, symmetrical layouts	symmetrical layouts	Progressive simplification + clarity increase
Lighting Strategy	Conceptual daylight + natural modulation	Mixed lighting conditions	Controlled diffuse lighting	Uniform ambient illumination + brightness stability	Shift toward controlled lighting (more personalized)
Material Strategy	Natural + ornamental + fractal-inspired	Mixed conventional materials (Wood, Marble, Carpets,…)	Natural wood + muted green tones	Simplified, neutral, low-complexity materials	Reduction of material complexity (more personalized)
Physiological Measures	Not measured	HRV + EEG (Muse 2)	interviews	interviews	Strong correlation: stability increas
Behavioral Measures	Not applicable	Navigation variability	Structured movement, reduced hesitation	High predictability, reduced cognitive effort	Participants demonstrated more consistent navigation patterns within AI-modified environments
Emotional Comfort	Theoretical high comfort	Theoretical high comfort	Higher self-reported comfort scores compared with the baseline virtual environment	Higher self-reported comfort scores compared with the baseline virtual environment	Higher participant-reported comfort levels were observed
Stress Level	Theoretical low stress	Moderate stress in complex zones	Minimal stress due to sensory simplification	Minimal stress due to sensory simplification	Lower self-reported stress scores and more stable physiological indicators within the participant sample

Key Emotional Drivers	Atmosphere + ornamentation	Lighting + spatial crowding	Lighting + biophilia + organization	Lighting + clarity + spatial legibility	Lighting consistently dominant factor
Biophilic Strategy	Narrative biophilia (courtyards, greenery)	Distributed plants+outdoor greenery	Controlled AI-optimized biophilia	Minimal / symbolic biophilia (reduced dominance)	Biophilia becomes less dense, more functional
Main Observed Design Change	Conceptual emotional design	Baseline human response	AI emotional optimization	AI emotional optimization	Shift: expressive → optimized → abstract-functional

To get more clarification about the exact role of the generative AI model alongside with the emotional validation. In table 3 compared all of the case studies with total observation results.

Figure 5. Methodological Evolution of AI Utilization Across the Case Studies

Category	**Case Study A**	**Case Study B**	**Case Study C**	**Total Observation**
AI Role	LLM + pattern language generation	No AI intervention	Transformer–LSTM–SVR + AI-generative optimization	AI evolves from a conceptual → predictive → regulatory system
Data Sources	Textual	Design Theories	Neurological Physiological + questionnaire-driven optimization	Multimodal depth increases progressively
Emotional Modeling	Narrative emotional inference	Empirical emotional measurement	Predictive emotional modeling+Physiological alignment + perceptual simplification model	Shift from descriptive → predictive → adaptive → regulatory
Validation Type	Theoretical validation	VR-based human response validation	AI-driven physiological-emotional alignment validation	Stronger validation
AI Function	Concept generator	None	Emotional prediction + spatial optimization	AI-assisted framework progressively integrates emotional prediction into the interior design workflow
Multimodal Integration	None	None	Full + real-time physiological coherence alignment	Full multimodal integration implemented within the proposed framework
Output Type	Conceptual design framework	Designer Work	Optimized spatial design	Increasing optimization
Key Contribution	Foundational emotional architecture model	Baseline human response dataset	Validated AI emotional prediction model	emotion integrated design

Table 5 synthesizes the methodological evolution of AI utilization across the case studies and highlights the progression from conceptual design support to participant-specific emotional personalization. The comparisons are interpretive and should be considered within the exploratory scope of the present research.

Although the proposed AI-enhanced emotional prediction framework was effective in generating personalized interior design modifications aligned with users' emotional, physiological, and behavioral profiles. Across all Case Studies, which were developed for 13 different participants, the AI-generated design outcomes exhibited clear variation based on individual multimodal inputs, including questionnaire responses, EEG signals, and heart rate variability data.
the integration of self-reported emotional data and physiological indicators resulted in design configurations that supported increased comfort, reduced stress, and improved emotional regulation. These modifications supported cognitive ease, perceived safety, and focus, reflecting both subjective

preferences and physiological indicators favoring stable sensory input and minimal arousal fluctuation.

Overall, the findings confirm that the framework successfully translates multimodal emotional data into targeted spatial design interventions, enabling a personalized and human-centered approach to interior environment optimization. The consistency between physiological stability indicators and self-reported comfort measures further validates the effectiveness of integrating objective and subjective data within the design process.

However, while the framework proved effective in generating localized design edits and environmental modifications, it was less successful in producing coherent overall spatial layouts or floor plan configurations. The AI-generated layouts did not consistently align with the original spatial context or the implemented design modifications, and in several instances included spatial inconsistencies and inaccuracies. This highlights a current limitation of the framework in handling large-scale spatial organization, indicating that while AI can effectively optimize environmental and perceptual parameters, it remains less reliable in holistic spatial planning tasks.

6. Discussion and Policy level implication

The findings presented in this study should be interpreted as evidence of observed associations rather than definitive causal relationships. Because the analysis primarily relied on descriptive statistics within an exploratory proof-of-concept framework, the reported relationships between environmental characteristics, physiological responses, and emotional perceptions indicate meaningful trends that warrant further investigation through larger-scale studies employing inferential statistical analyses.

The findings of this study demonstrate that emotional responses to interior environments can be effectively modeled as a function of multimodal inputs, including physiological signals (heart rate variability and EEG), self-reported questionnaire data, and spatial design parameters. Across the 13 case studies,

The proposed AI-driven framework demonstrated the feasibility of translating participant-specific emotional and cognitive information into measurable design recommendations.

Within the context of this exploratory investigation, the findings suggest that emotional experience is influenced by the interaction between environmental characteristics and individual participant profiles.

This was particularly evident in Case Studies C and D, where the same AI model and generative workflow were applied, yet produced different spatial outcomes due to differences in participant-specific physiological and psychological data. While both cases followed identical computational procedures, the resulting environments differed in lighting balance, spatial density, and material expression, confirming that emotional prediction is highly personalized rather than deterministic.

The findings provide preliminary support for the hypothesis that AI-assisted emotional prediction may enhance interior design personalization by integrating multimodal physiological and subjective information.

The observed agreement between physiological indicators and self-reported comfort measures suggests that integrating objective and subjective data may provide a useful basis for supporting emotionally responsive interior design. However, the findings also indicate that emotional prediction is more effective at the level of environmental parameters than at the level of complete spatial generation. While the system successfully optimized lighting, material selection, and perceptual qualities, it showed inconsistencies in generating coherent full floor plans across cases. This partially supports the hypothesis but also suggests that emotional intelligence in design systems is currently more robust at the micro-spatial (detail) level than at the macro-spatial (layout) level. The findings are generally consistent with previous research in emotional architecture and Kansei Engineering, which has demonstrated the influence of lighting, color, materiality, spatial organization, and biophilic elements on emotional perception. However, whereas many earlier studies relied primarily on subjective questionnaires or expert evaluations, the present study integrates physiological measurements, self-reported emotional responses, immersive virtual reality, and AI-assisted generative design within a unified exploratory framework. This integration represents a methodological advancement by linking emotion recognition with personalized environmental design recommendations.

From a smart design policy perspective, the proposed framework contributes to the development of human-centered criteria for future intelligent built environments. Current smart building approaches frequently prioritize energy efficiency, automation, and operational performance, while emotional well-being remains difficult to measure and incorporate into decision-making processes. By introducing measurable emotional and physiological indicators, this framework suggests a pathway toward evidence-based standards for evaluating human-centered environmental quality.

Future implementation requires collaboration between designers, policymakers, technology developers, and researchers to establish ethical guidelines, data governance frameworks, and evaluation standards for AI-assisted emotional design systems. Rather than replacing conventional design regulations, emotionally responsive AI systems may complement existing frameworks by introducing human experience as an additional measurable design consideration.

This distinction highlights an important conceptual boundary within the proposed framework. The AI-assisted workflow demonstrated strong capability in translating participant-specific emotional and physiological information into localized design recommendations, including material selection, lighting strategies, color palettes, furniture organization, and biophilic integration. In contrast, the generation of complete architectural floor plans remained constrained by the model's limited representation of spatial relationships, circulation logic, and functional adjacency requirements. Therefore, the framework is best understood as augmenting the designer's decision-making process at the environmental and experiential level rather than replacing architectural planning.

This exploratory study contributes preliminary evidence supporting the integration of physiological and subjective emotional data into AI-assisted interior design workflows.

Unlike earlier studies that relied primarily on subjective rating scales or expert-driven weighting systems, this research integrates objective biometric signals with subjective perception data. This multimodal approach aligns with recent advancements in AI-assisted design but further contributes by demonstrating participant-specific variability across multiple case studies using the same generative pipeline.

An important unexpected outcome was the limited ability of the AI system to maintain spatial coherence when generating full layout configurations. Although localized design edits were highly consistent with emotional and physiological inputs, large-scale spatial organization sometimes diverged from the original architectural constraints or introduced structural inconsistencies. This suggests that while emotional prediction models are effective in guiding environmental optimization, they do not yet fully capture architectural logic or spatial constraint systems. A possible explanation is that the current model prioritizes emotional minimization and comfort maximization without sufficiently encoding geometric or functional constraints required for architectural planning.

This limitation illustrates a distinction between emotional intelligence and spatial intelligence within current generative AI systems. While the model successfully interprets multimodal emotional information and converts it into experiential design attributes, it does not yet adequately encode architectural rules governing circulation, structural constraints, spatial hierarchy, and functional relationships. Future research should integrate constraint-based architectural reasoning and building information modeling (BIM) principles to bridge this gap.

7. Limitations

The study evaluated AI-generated design outcomes based on their alignment with emotional indicators and design principles; however, post-generation user testing was not conducted. Therefore, improvements in emotional well-being should be interpreted as design potential rather than experimentally confirmed outcomes.

First, although the study included thirteen participants representing individual case studies, the sample size remains relatively small and therefore limits statistical generalizability. Because this research was designed as an exploratory proof-of-concept investigation focusing on methodological integration rather than population-level prediction, the findings should be interpreted as preliminary evidence supporting the feasibility of the proposed framework. Future research involving substantially larger and more diverse participant groups will be necessary to evaluate predictive accuracy, improve model robustness, and examine the framework across different demographic groups, building types, and cultural contexts. So, the present study should be interpreted as an exploratory proof-of-concept rather than a fully validated predictive AI framework. Although the findings demonstrate the feasibility of integrating multimodal emotional information into interior design workflows, the proposed methodology requires further validation using larger participant samples, diverse building typologies, and independent datasets.

Second, VR-based evaluation, while immersive, does not fully replicate long-term interaction with physical environments. So, the analytical approach relied primarily on descriptive statistical interpretation. Because inferential statistical analyses and predictive performance metrics were not employed, the reported relationships should be interpreted as observed associations rather than definitive causal effects.

Third, the investigation was limited to office interior environments and a relatively homogeneous participant sample. Consequently, the findings cannot be generalized to other architectural typologies or broader populations without additional validation.

Fourth, although the proposed AI-assisted workflow effectively generated participant-specific environmental recommendations, it demonstrated limited capability in producing coherent architectural layouts. This highlights the current distinction between emotional personalization and architectural spatial reasoning within contemporary generative AI systems.

Additionally, physiological measurements obtained during immersive VR exposure are inherently sensitive to movement artifacts, individual physiological variability, fatigue, and external environmental influences. Although standardized preprocessing procedures were applied to reduce noise and improve signal consistency, these factors may still have affected the measured physiological responses. Future research should incorporate more advanced artifact-removal techniques and larger datasets to further improve signal reliability and model robustness. Because predictive accuracy metrics were not calculated, the current study should be interpreted as an exploratory validation of framework feasibility rather than a complete predictive model evaluation.

Despite these limitations, the findings have significant implications for emotional architecture and AI-assisted design. The study demonstrates that emotional experience can be operationalized as a measurable and design-actionable system, enabling a shift toward predictive and personalized interior environments.

From a practical perspective, the framework provides designers with a structured methodology for aligning spatial decisions with emotional and physiological user data. From a theoretical perspective, the study supports the view that interior environments should be understood as adaptive systems shaped by continuous interaction between humans and space.

Overall, the research confirms that AI-enhanced emotional prediction can effectively guide interior design decisions at a granular level, particularly in relation to environmental comfort, emotional regulation, and cognitive support. However, limitations in large-scale spatial generation indicate that further development is required to bridge the gap between emotional modeling and architectural planning systems. The integration of multimodal data, AI prediction models, and immersive evaluation represents a significant step toward emotionally intelligent interior environments.

Furthermore, although two representative case studies (Case Studies C and D) are discussed in detail to illustrate the operation of the proposed framework, they should not be interpreted as representing all participants or all possible emotional responses. The remaining participant cases exhibited individual variability that reinforces the exploratory nature of the proposed framework. Future research involving larger and more diverse populations across multiple building typologies is necessary before broader design recommendations can be established.

Finally, broader issues related to privacy, algorithmic fairness, and long-term governance of physiological and emotional data were beyond the scope of the present investigation. These topics should form an integral part of future research before large-scale practical implementation.

8. Conclusion

This study developed and explored an AI-enhanced framework for emotional prediction and personalization in interior architecture by integrating multimodal data, including physiological signals such as electroencephalography (EEG) and heart rate variability (HRV), self-reported emotional evaluations, and spatial design parameters. Across 13 case studies, the framework demonstrated the feasibility of translating participant-specific emotional and cognitive information into targeted interior design recommendations within the experimental conditions of the study. The results provide preliminary evidence that multimodal AI-supported methods can contribute to the development of personalized and emotionally responsive interior environments.

A central finding was the highly individualized and context-dependent nature of emotional responses to interior environments. This was particularly evident in Case Studies C and D, where the application of identical AI models resulted in different spatial outcomes because of variations in participants' physiological and psychological profiles. These observations indicate that emotionally responsive design cannot be adequately addressed through generalized assumptions about user preferences and instead requires approaches capable of accounting for individual differences. Within the examined cases, environmental variables including lighting, spatial legibility, materiality, color, and related spatial characteristics were repeatedly associated with variations in participants' reported emotional responses.

The findings further suggest that the proposed framework is more effective as a system for participant-specific environmental modification than as an autonomous architectural generation mechanism. Within the scope of the present investigation, AI-assisted generative processes were capable of supporting modifications to environmental characteristics in response to emotional information; however, they demonstrated more limited capability in producing coherent and architecturally resolved spatial layouts. This distinction indicates that current generative AI systems may be more appropriately positioned as decision-support and personalization tools that complement professional design expertise rather than as substitutes for comprehensive architectural reasoning.

The study contributes to emotional architecture by providing a computational pathway through which subjective and physiological information can be systematically incorporated into design decision-making. Rather than treating emotional experience solely as a qualitative or post-occupancy consideration, the proposed framework explores how emotional information may be translated into measurable variables and subsequently incorporated into AI-supported design adaptation. In this respect, the research extends conventional intuition-based approaches toward a more predictive, evidence-informed, and user-centered design process. Methodologically, the integration of multimodal physiological assessment, subjective evaluation, AI-based prediction, and immersive virtual environments provides a structured approach for examining relationships between user responses and interior design characteristics.

From a practical perspective, the framework demonstrates the potential of AI-assisted emotional prediction to support designers in developing interior environments that are more responsive to individual differences in comfort, emotional regulation, perception, and cognitive experience. Such an approach may have future relevance for workplaces, educational environments, healthcare settings, and other human-centered building typologies in which users' emotional and cognitive responses constitute important dimensions of environmental performance. Nevertheless, these potential applications should be interpreted cautiously because the present research represents an exploratory proof-of-concept rather than a validated design system ready for broad professional implementation.

Several limitations must therefore be acknowledged. First, the exploratory nature of the study and the limited participant sample restrict the generalizability of the findings. Second, the use of immersive VR environments provides controlled conditions for evaluating alternative designs but may not fully reproduce long-term behavioral, social, sensory, and environmental interactions occurring in real-world interior spaces. Third, physiological indicators such as EEG and HRV may be influenced by factors unrelated to spatial design, including participant fatigue, prior emotional state, individual health conditions, environmental distractions, and experimental conditions. Consequently, physiological responses should not be interpreted as direct or exclusive indicators of architectural causality. In addition, the interpretability of hybrid AI models remains limited, which can reduce transparency regarding how particular emotional indicators are translated into specific design recommendations. The framework also demonstrated limitations in generating coherent architectural layouts, emphasizing the continuing importance of architectural constraints and professional design reasoning.

Future research should therefore validate the proposed framework using substantially larger and more diverse participant samples, standardized experimental protocols, repeated measurements, and additional architectural typologies. Quantitative measures of AI prediction performance should be incorporated alongside inferential statistical analyses to determine the strength, consistency, and statistical significance of relationships between physiological responses, subjective evaluations, and spatial variables. Longitudinal and real-world studies would also be valuable for determining whether emotional responses observed in immersive simulations remain consistent during prolonged occupation of physical environments. Furthermore, integrating constraint-based architectural reasoning, spatial-performance requirements, explainable artificial intelligence (XAI), and more transparent decision-support mechanisms may improve both the architectural coherence and interpretability of future AI-generated recommendations.

Overall, this exploratory investigation provides preliminary evidence that AI-assisted emotional prediction can support the development of more personalized approaches to interior design by integrating physiological, subjective, and spatial information within a unified computational framework. The findings support the feasibility of moving from generalized interpretations of emotional architecture toward participant-specific environmental adaptation while also demonstrating important limitations in current AI-based spatial generation. The proposed framework should therefore be considered an initial methodological foundation rather than definitive validation of predictive performance. Further empirical validation, larger participant samples, quantitative model assessment, and real-world experimentation are required before its broader reliability and practical applicability can be established. Nevertheless, the study contributes to the emerging intersection of emotional architecture, neuroarchitecture, affective computing, immersive environmental evaluation, and human-centered artificial intelligence by establishing a structured pathway through which human emotional responses may inform evidence-based and personalized interior design decisions.

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Conflicts of Interest

The author(s) report no conflicts of interest.

Data availability statement

All data generated or analyzed during this study are included in this published article and its supplementary files.

Institutional Review Board Statement

The study was approved by the IRB Committee of Southeast Missouri State University (Approval No 20260028, 23 January 2026).
Written informed consent was obtained from all participants prior to data collection.

CRediT author statement

Conceptualisation: R.M.; Methodology: R.M.; AI Model Description: Z.E.; Writing – original draft: R.M.; Writing – review & editing: R.M.; Visualisation: R.M.; Supervision: R.M.
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