Optimal Transport-based Affective User Requirements Realignment for Automated Spatial Design Revision

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Abstract

Modern residential occupants require their affective intents to be reflected in spatial design to achieve satisfaction. However, current generative architectural design studies focus on morphological and functional requirements, overlooking affective intent. This study proposes an affective user requirements realignment framework for automated, minimally disruptive spatial design revision based on Optimal Transport. The proposed BIM-integrated framework (i) represents spatial experience as a multidimensional affective distribution derived from 1,638 annotated responses across 54 parametric configurations, (ii) predicts the distribution from discrete design parameters using a lightweight Transformer regressor, and (iii) selects a minimally disruptive revision via entropic-regularized Wasserstein distance to a user-specified target affect across 6,480 candidate configurations. The selected parameter set is automatically applied through a Revit C# add-in to support closed-loop design review. Results demonstrated consistent convergence toward target affects (reduction: 0.036–0.290) with positive directional alignment across all ten affective dimensions (mean cosine similarity = 0.502), demonstrating the feasibility of affect-preserving revision in BIM workflows as a proof-of-concept.

Keywords –

Design Review, User-Centered Design, Automation, Affective Design, User Requirements.

1 Introduction

Residential architecture has moved beyond meeting morphological and functional needs to accommodate the psychological and emotional expectations [1]. Homes are now considered as personal environments that shape routines, well-being, and identity [2], which increases the pressure to improve the collection and integration of emotional requirements into design workflows. However, most residents lack architectural vocabulary and spatial literacy; therefore, they express their needs through narratives and subjective impressions rather than parametric terms [3]. Feedback such as “the room feels too small” conveys a strong experiential meaning, but is difficult to translate into quantifiable interventions, creating a persistent interpretive gap and risking the loss of user intent [4,5]. Although environmental psychology and neuroarchitecture link built features to emotional responses, real spaces involve tightly interdependent relationships between geometry, materiality, lighting, and atmosphere, making single-variable interpretations unreliable [6,7].

Recent advances in generative Artificial Intelligence (AI) have improved early stage option generation and communication [8]. However, most studies emphasize generation, rather than the more practically critical problem of revision. Revisions require interpreting feedback, preserving design intent, respecting constraints, and maintaining coupled spatial relationships [9]. This is economically important because early design phases account for a large share of the total design/documentation effort; thus, emotional misalignments discovered later can trigger costly rework or discourage necessary changes.

Accordingly, this study focused on affective design revisions in Building Information Modeling (BIM) environments by formulating emotional requirements as explicit affective targets. Rework has been shown to contribute to over 50% of total cost growth in construction project [10], and economic analysis of BIM-based high-rise project have directly quantified design errors as causing 5–20% rework overhead [11]. Those phenomena underscore the economic importance of addressing design intent misalignments early in the review process. To ensure clarity and reproducibility in design review contexts, user input is operationalized as the selection of a predefined affective dimension, allowing the revision process to concentrate on distribution-aware optimization and minimal design modification, rather than linguistic interpretation.

2 Related Studies

2.1 AI Application in Architectural Design Alternatives

The integration of generative AI into architectural workflows transforms traditional decision-making processes. Notably, generative design introduces an AI-powered approach that combines engineering design principles with cloud computing to automatically generate and optimize options based on parameters such as materials, dimensions, and cost constraints. In architectural designs, this approach has been extended to generate reference imagery [8], photorealistic interior visuals [12], and exterior façade designs guided by layout sketches and prompts [13].

The deep learning models employed in these efforts include generative adversarial networks (GANs), diffusion models, and transformers. GANs and diffusion models are particularly effective in image-to-image generation tasks such as diagram alterations and style transfer [14], with diffusion models suited to high-resolution rendering via platforms such as Dream Studio [15]. Transformer-based models, such as generative pre-trained Transformer, specialize in text processing for code generation, design documentation, and javascript object notation BIM object creation [16].

Generative modeling techniques are frequently used in BIM-based research. Studies including computer aided design-to-BIM automation [17] and conversational BIM agents coupled-GAN [18] have demonstrated the efficiency of generating certain objects or resources in BIM-based workflows. These studies highlight the need for multimodal inputs and a semantic pipeline to derive architectural variables for integration into structured BIM. However, generative models focus on generating outputs from zero-based scenarios; therefore, examining the efficiency of revising BIM-based workflows is required.

2.2 User Requirements Realignment

Architectural design is a tightly coupled system. Changing one element (e.g., window size, and ceiling height) can trigger cascading and unintended effects elsewhere; therefore, revision cannot be treated as a wholesale replacement without risking damage to the already successful aspects of the design [4]. Preserving design intent, including both explicit architectural decisions and implicit experiential coherence, is therefore essential because even small edits can disturb spatial harmony, function, and emotional responses [19]. Neuroarchitecture and environmental psychology further demonstrate that affective experiences emerge from multifeatured interactions (e.g., geometry, materiality, lighting, and enclosure), implying that selective change while maintaining stability in other dimensions is generally necessary [20].

This motivates distribution-aware revision. Instead of optimizing a single scalar target, the goal is to move the predicted affective distribution toward the user's intended distribution with minimal collateral displacement [21]. Information-theoretic divergences such as Kullback-Leibler and Jenson-Shannon [22] and overlap-based metrics such as Hellinger and Bhattacharyya [23,24] can quantify mismatch; however, they consider probability shifts as pointwise differences and do not encode how "far" mass moves between affect categories. This is a key limitation of minimal-change design control, in which only a subset of attributes should shift.

Optimal transport (OT) addresses this problem by endowing distributions with geometry. The Wasserstein (Earth Mover's) distance measures the minimum "work" required to transport probability mass between distributions given a ground-cost matrix capturing inter-label distances, making it well suited to small, selective, and cost-aware revisions [25]. Entropic regularization and Sinkhorn-based approximations enable fast and differentiable computation inside iterative optimization loops [26], with theoretical support for stability and sample behavior [27]. Overall, although classical divergences are lightweight, OT-based metrics model label-space transitions more directly, providing a stronger foundation for revision systems that adjust target affects while preserving the other components.

3 Proposed Methods

3.1 Research Framework

The framework began by allowing the user to select a target affective dimension encoded as a target affective distribution. A transformer regressor predicted the affective distributions for candidate spatial configurations, and an OT) module evaluated all 6,480 parametric design vectors (Ceiling Height:8 × WWR:10 × CCT:9 × Floor:3 × Color:3), by computing the Wasserstein distance (WD) from the target. A design with the minimum transport cost was selected, providing a distance-based ordering of alternatives and quantifying the minimal parameter change required to align the predicted affect with the user's intent.

3.2 Design of Experiment

3.2.1 Design Variable Selection

Emotional responses to architectural space originate from the combined effects of multiple spatial features, rather than isolated parameters. Previous studies in environmental psychology, interior architecture, and neuroarchitecture have consistently identified lighting conditions, materiality, openness, and enclosure-related variables as dominant contributors to affective experiences in residential interiors. In particular, lighting attributes such as correlated color temperature (CCT) and luminance balance regulate arousal and comfort, whereas window-to-wall ratio (WWR) and ceiling height influence perceived openness and spaciousness. The material and surface color further modulate warmth, calmness, and overall valence.

Based on accumulated evidence, five interior design variables were selected for this study: ceiling height, WWR, CCT, room color, and floor material. These variables are strongly associated with emotional evaluations in residential spaces, making them suitable for controlled affective design experiments [28–30].

3.2.2 Affective Annotation

A systematic affective annotation procedure was conducted to construct a dataset linking spatial design parameters to human affective responses. The process began with the development of domain-grounded affective vocabulary. Drawing on environmental psychology, interior architecture, and neuroarchitecture, 22 affective adjectives were initially extracted from previous empirical studies [29–31].

Using four thesaurus expansion steps, synonyms and near-synonyms (e.g., happy-pleasant) were grouped, and semantically redundant terms were merged. Subsequently, the KJ clustering method was applied to identify conceptual clusters and remove ambiguous or overly broad terms. This process resulted in a final set of ten affective vocabularies closely aligned with the spatial experience: pleasant, exciting, cozy, spacious, attractive, simple, bright, open, calm, and comfortable.

3.2.3 Experimental Design

A parametric BIM environment was constructed using Autodesk Revit 2023 to generate the controlled interior design stimuli. The model represented a typical urban apartment living unit common in high-density residential developments with base dimensions of 4380 × 7440 × 2300 mm. The geometry was intentionally simplified to isolate the perceptually salient variables and minimize confounding architectural factors.

Full factorial combinations of the variables yielded 243 possible configurations. An L27 fractional factorial design was adopted to reduce redundancy, while preserving orthogonality. An additional 27 configurations were selected using the cyclic shift method to ensure uniform coverage of the multidimensional design space. In total, 54 interior design stimuli were labeled with their corresponding design vectors.

3.3 Inference Module: Affect-Spatial Elements Mapping

Each design configuration x_i was defined using five parameters: ceiling height, WWR, CCT, floor material, and room color. To ensure compatibility with the learning model $f_\theta(x)$, the data were encoded and normalized as follows. The continuous variables (ceiling height, WWR, CCT) were standardized using a StandardScaler, and the categorical variables (floor material, room color) were one-hot encoded with the first category dropped, yielding a 7-dimensional input vector.

For each configuration, the affective response vector α_i consisted of 10 ratings normalized to [0, 1]. To support OT-based computation, the ratings were further normalized into a probability distribution.

$$\alpha_i' = \frac{\alpha_i}{\sum_{k=1}^{K} \alpha_{i,k}}, K = 10, \sum_{k=1}^{K} \alpha_{i,k}' = 1 \quad (1)$$

A lightweight Transformer regressor was trained on all 54 design configurations to predict multidimensional affective responses from spatial design variables. Model selection and performance estimation were conducted using Leave-One-Out Cross-Validation (LOOCV), the statistically appropriate method for the design-level dataset size. The one-hot encoded design vector was projected onto a 64-dimensional embedding space. Learnable positional encoding was added and treated as a single-token sequence for the transformer processing. The embedding was then passed through a three-layer transformer encoder, where each layer included four-head self-attention, a 128-dimensional feed-forward network, and residual connections with layer normalization, enabling the model to learn nonlinear interactions among the design attributes.

Finally, a two-layer regression head (64→128→10) output continuous scores for the ten affective dimensions. Overall, the model mapped discrete design parameters onto a compact latent space, captured their interdependencies via stacked self-attention, and predicted the affective distribution of each configuration.

3.4 Optimizer Module: Entropic-Regularized Wasserstein Distance

The affective intent selected by the user determines the affective distribution of the target (P^*). When a user expresses a desire to increase or decrease a specific affective dimension, the corresponding component of the distribution is adjusted proportionally, followed by normalization.

$$P^* = \mathrm{Normalize}(P + \Delta) \quad (2)$$

where Δ denotes the user-intended directional change. This normalized vector is the optimization objective of an OT-based search.

For each spatial design vector x in the Space-Affect database, the transformer regression model $f_\theta(x)$ predicts its affective distribution.

$$Q_x = f_\theta \tag{3}$$

Thus, each candidate design produced a probability distribution over the same 10 affective dimensions as the target.

To quantify the discrepancy between the target affect distribution P^* and each predicted distribution Q_x, the WD was computed using the entropy-regularized Sinkhorn divergence [25].

$$W_\varepsilon(P^*, Q_x) = \min_{\Gamma \in U(P^*, Q_x)} \langle \Gamma, M \rangle + \varepsilon \mathrm{KL}(\Gamma \parallel P^{*\otimes Q_x}) \tag{4}$$

where $U(P^*, Q_x)$ denotes the set of admissible transport plans, M is the ground cost matrix and ε controls the entropy regularization strength. A uniform ground metric ($M_{ij} = 0$ and $M_{ij} = 1$ for $i \neq j$) was adopted as no validated psychometric distance exists for the architectural affective space and inter-affect correlations are uniformly high (mean r = 0.799), making the uniform metric the most conservative prior. The Frobenius inner product formulation enables linear-time Sinkhorn iterations and stable gradient propagation through $f_\theta(x)$.

Because the design space contained all 6,480 possible combinations, the optimizer evaluated the Sinkhorn distance for every candidate x.

$$\mathrm{x}^* = \arg\min_{x \in X} W_\varepsilon (P^8, Q_x) \tag{5}$$

where X denotes the full Cartesian product of all design variable attributes. This guarantees that the returned configuration is a globally optimal design vector with respect to the target affect.

3.5 Evaluation Metrics

3.5.1 Affect-Spatial Elements Mapping Evaluation

The proposed regression model was evaluated using metrics that captured the overall error magnitude, proportionality, and explanatory power. As a single metric can be misleading, particularly when targets differ in scale or when large errors are costly, we used five standard regression measures: mean absolute error (MAE) and R^2. MAE measures the average absolute error.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}| \tag{6}$$

It expresses errors as percentages, enabling comparisons across affective dimensions within different ranges. Finally, R^2 measures the proportion of variance explained by the model.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{7}$$

Higher values indicate a stronger overall fit. Together, these metrics provide a balanced assessment of multidimensional affective regression performance.

3.5.2 Optimization Evaluation

Two complementary success criteria were defined: (i) positive WD reduction, the optimized design achieves a lower WD to the target distribution than the initial design; and (ii) positive directional alignment, cosine similarity > 0 between the intended and actual affective shift direction. WD reduction measures how effectively optimization decreases the discrepancy between the target affective distribution P^* and the predicted distribution Q_x.

$$\mathrm{Reduction} = \frac{W_\varepsilon(P^*, Q_{init}) - W_\varepsilon(P^*, Q_{final})}{W_\varepsilon(P^*, Q_{init})} \tag{8}$$

where Q_{init} and Q_{final} denote the initial and optimized affective states, respectively. Values closer to 1 indicate stronger affective convergence toward the target [25,26].

To assess the directional consistency with user intention, a perceptual alignment score was defined using the cosine similarity between the intended affective shift and the predicted shift.

$$\mathrm{Alignment} = \cos\big((P^* - P), (Q_x - P)\big) \tag{9}$$

A value close to 1 indicates strong alignment with the target affect, whereas negative values indicate a deviation from the intended direction [32].These metrics ensure that optimized revisions are both affectively closer to the target state and directionally consistent with user intent.

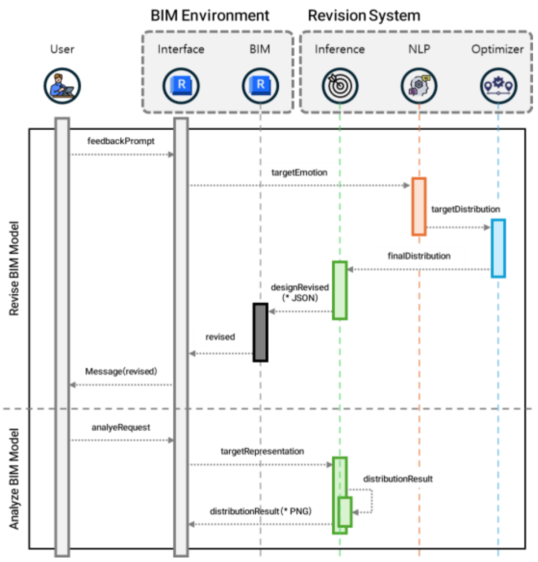

Figure 1. Proposed UML sequence diagram

3.6 BIM Add-in Application

The proposed system for affective design automation was fundamentally instantiated as a cohesive Revit add-in and entirely implemented using C# application programming interface (API) within the Visual Studio Environment. This integral implementation ensures seamless interaction with the BIM, minimizes data latency, and maximizes efficiency within the design workflow [18]. The comprehensive data flow and interlayer communication of this closed-loop system are precisely depicted using a Unified Modeling Language (UML) sequence diagram (Figure 1**Error! Reference source not found.**), which illustrates the sequential interactions among its modular components. This architectural approach directly integrates advanced computational modules into a commercial BIM platform.

4 Results

4.1 Inference Module Results

A total of 182 participants (male: 106, 58.2%, female: 76, 41.8%, age: 35.2±11.7, range 17–63) were recruited across architecture-related (n=70, 38.5%) and non-architecture (n=112, 61.5%) backgrounds, yielding 1,638 affective responses. The internal consistency of the ten affective scales was confirmed with Cronbach's α = 0.938. One-way analysis of variance confirmed statistically significant design condition effects across all ten affective dimensions (F=3.70–11.76, $p < .001$).

To justify the architectural choice of the Transformer regressor, 29 models across seven categories were systematically compared using LOOCV in Table 1. The Transformer (d = 32, nhead = 4, L = 1) achieved the highest overall LOOCV R^2 = 0.588 (MAE = 0.367), outperforming XGBoost (R^2 = 0.576), Gaussian Process-Matern (R^2 = 0.540), and MLP networks (R^2 = 0.352). Beyond predictive accuracy, tree-based XGBoost produced step-function prediction, collapsing to identical values for unseen parameter combinations. Since the OT optimizer searches intermediate values, smooth interpolation is structurally required, making the Transformer the appropriate model.

As shown in Table 1, the Transformer achieved LOOCV R^2 ranging from 0.483 (cozy) to 0.705 (open), with a mean of 0.588. Strong performance was observed for open (0.705), pleasant (0.685), spacious (0.640), attractive (0.636), and bright (0.593), indicating that these dimensions are well captured by the five spatial variables. Excitement (0.531), cozy (0.492), and calm (0.489) showed relatively lower explanatory power, attributable to high within-condition individual variance in these affective dimensions rather than model limitations.

Table 1. Top 10 model comparison using LOOCV.

Model	LOOCV R²	MAE	Style
TF (d=32, h=4, L=1)	**0.588**	**0.367**	**Smooth**
XGBoost (d=3, n=100)	0.576	0.368	Step
GP (Matérn 1.5)	0.560	0.384	Smooth
RF (n=50, d=5)	0.546	0.381	Step
GBR (n=50, d=3)	0.544	0.385	Step
Ridge (α=1)	0.540	0.392	Linear
Lasso (α=0.01)	0.536	0.392	Linear
GP (Matérn 2.5)	0.534	0.389	Smooth
BayesianRidge	0.534	0.395	Linear
SVR (rbf, C=10)	0.503	0.415	Kernel

4.2 Optimizer Module Results

Across the ten affective categories, the optimization framework consistently reduced the WD to the target distribution, indicating that it can adjust the design variables to decrease the overall affective mismatch. As reported in Table 2, the reduction values ranged from 0.036 to 0.290, indicating meaningful convergence, even within a discrete and limited design space.

Table 2. Performance of the optimizer module

No.	Initial	Target	Final	Red.	Align.
1	0.106	0.255	0.118	0.078	0.388
2	0.092	0.243	0.129	0.247	0.941
3	0.085	0.237	0.108	0.143	0.437
4	0.099	0.249	0.132	0.215	0.699
5	0.126	0.272	0.168	0.290	0.732
6	0.095	0.246	0.111	0.100	0.346
7	0.109	0.258	0.132	0.148	0.373
8	0.082	0.235	0.118	0.232	0.734
9	0.106	0.255	0.115	0.064	0.221
10	0.100	0.250	0.107	0.036	0.150

Note: 1=Cozy, 2=Bright, 3=Excitement, 4=Open, 5=Simple, 6=Pleasant, 7=Spacious, 8=Attractive, 9=Calm, 10=Comfortable

The largest reductions (Red.) were achieved for simple (0.290), bright (0.247), and attractive (0.232), suggesting that these affects were highly responsive to the available physical variables. Spacious (0.148), excitement (0.143), and pleasant (0.100) exhibited moderate improvements, whereas cozy (0.078), calm (0.064), and comfortable (0.036) showed smaller but still positive reductions. The variation in reduction magnitude reflects differences in how sensitively each affective dimension responds to the five design variables.

The directional change was further examined using the alignment metric (Align.), which measures the cosine similarity between the intended affective shift direction and the actual distributional change. Positive alignment was achieved across all ten affective dimensions (mean = 0.502), with particularly strong alignment for bright

(0.941), attractive (0.734), simple (0.732), and open (0.699), confirming that the optimizer reliably moved the affective distribution in the intended direction. Moderate alignment was observed for cozy (0.388), spacious (0.373), and pleasant (0.346), while calm (0.221) and comfortable (0.150) exhibited weaker directional consistency, reflecting the limited sensitivity of these dimensions to the five parametric variables considered. Notably, all alignment scores were positive, indicating that the optimization consistently produced directionally appropriate adjustments without counterproductive shifts.

4.3 Revit API-based Design Revision

This section describes the sequence of steps, target emotion selection, inference, optimization, and the final application of design changes. The efficacy of the add-in was demonstrated by comparing pre- and post-revision affective distributions. The initial spatial parameters of the design case study are listed in Table 3.

Table 3 Initial and revised design parameters

Variables	Initial Design	Revised Design
Ceiling Height	2.7m	2.8m
WWR	30%	90%
CCT	2700K	3500K
Room Color	Gray	White
Floor Material	Tile	Tile

4.3.1 Initial Design Analysis

The add-in performed an objective analysis of the current design state. This involved utilizing a pretrained affective prediction model to estimate the distribution of the 10 affective dimensions induced by the initial spatial configuration. This initial analysis served as the baseline for the design and was used to benchmark the improvement in the target affective dimension after revision. At this stage, the system primarily generated the current affective profile without setting a specific optimization goal. An example of the initial design analysis is shown in Figure 2.

4.3.2 Design Revision Optimization

This module employed a retrieval-based optimization algorithm using the affective prediction model as its objective function to explore new combinations of the five spatial variables. The evaluation of the optimization used an OT-based method to calculate the distance between the affective distributions. In this case, the search successfully identified a revised combination of parameters that achieved the required increase in ‘bright’ while maintaining the overall coherence of the affective distribution. Based on these, revised design parameters were retrieved from the inference layer and are presented in **Error! Reference source not found.**.

4.3.3 Apply and Reset

Finally, the optimized spatial parameters were automatically applied to the BIM parameters. Following this automatic modification, the system captures the viewpoint image of the revised design. The user is then presented with this rendering, along with the predicted affective distributions, to make a final decision.

The primary validation of the system was a comparison of the initial and revised affective distributions. As shown in Figure 3, the ‘bright’ score significantly increased in the revised design compared to the initial states. This improvement validated the proposed methodology. Based on the visualization of the rendering and affective data, the user can choose to apply or reset the revised design.

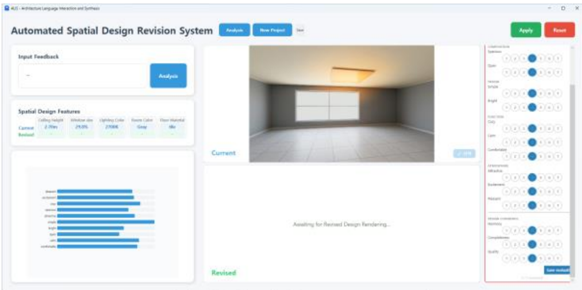

Figure 2. Revit API UI for initial BIM Analysis

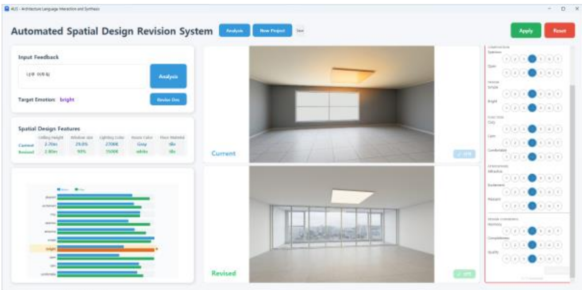

Figure 3. Revit API UI for Revised Design

5 Discussion

This study demonstrated the proof-of-concept that affective design revision can be formulated as a distribution-alignment problem rather than a single-variable optimization task. The use of OT provides a principled mechanism for reducing unintended affective shifts, with the degree of collateral affective displacement varying across dimensions. The revised results demonstrate consistent positive WD reduction and directional alignment across all ten affective dimensions, empirically supporting the framework's validity as a proof-of-concept.

The uniform ground metric was adopted because no validated psychometric distance exists for the architectural affective space, inter-affect correlations are uniformly high (mean r = 0.799), and the uniform metric constitutes the most conservative prior. A sensitivity analysis comparing three cost matrix formulations yielded 70% agreement in optimal design selection, with the uniform metric performing consistently in all discordant cases. Future work may explore empirically grounded cost matrices derived from affective space or psychometric scaling.

This work differentiates itself from three prior streams. BIM optimization studies have targeted structural or cost-based objectives, whereas this work introduces multidimensional affective distributions as the optimization criterion within an automated revision loop. Affective design studies characterize space–emotion relationships without closing the loop into parametric revision, which this work achieves end-to-end. OT applications in affective computing have used Wasserstein distance as a training loss, whereas here OT serves as a design search criterion over a smooth, interpolable 6,480 candidate landscape, made possible by the Transformer's continuous interpolation for unseen parameter combinations. The current exhaustive search guarantees global optimality at negligible computational cost (< 1 ms); scaling to continuous spaces will require Bayesian optimization, differentiable Sinkhorn layers, or reinforcement learning-based exploration.

Perceptual validation through user studies and open-ended natural language feedback interpretation remains critical directions for future work, alongside assessments of design coherence and system usability.

6 Conclusion

This paper presents a BIM-integrated framework for automating affective design revision using optimal transport theory. By linking parametric spatial variables with predicted affective distributions, the proposed method enables designers to enhance selected emotional qualities while reducing unintended distributional displacement in most affective dimensions. The framework was implemented as a Revit add-in, demonstrating its technical feasibility within existing BIM-based design workflows.

The results suggest that optimal transport provides a promising, mathematically grounded foundation for affective design revision, as demonstrated in this proof-of-concept implementation. Although the current framework operates on a discrete set of five spatial variables and ten affective dimensions, it establishes a proof-of-concept foundation for future user-centered design automation. The proposed approach bridges the gap between user affective requirements and parametric design operations, thereby real-world practice validation is required.

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