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Simulating Sustainable Color-Form Decisions in AI-Driven Eco-Brand Identity Design

Sofia Elena*[1], Liam Alexander[2]
[1,2]Politecnico di Milano, Milan, Italy
Email Address: sofia.rossi@gmail.com

Abstract. *Integrating sustainability into brand identity design remains challenging, as the harmony between visual aesthetics, primarily color and shape, and eco-branding values often relies on subjective judgment, highlighting a lack of data-driven approaches. While AI-assisted design tools have demonstrated utility, their primary focus remains on aesthetic generation rather than sustainable design optimization. This research addresses this gap by proposing a simulation-based framework that, through simulation and expert review, examines and evaluates how AI-assisted color-form choices influence both aesthetic consistency and ecological brand alignment. Using synthetic data and scenario modeling, we created a simulation that analyzes color and form parameters against sustainability indicators across three scenarios: Aesthetic-only, Sustainability-only, and an Integrated Eco-Aesthetic approach. Eco-Alignment was computed using cosine similarity of semantic embeddings across 50 simulation runs for each scenario, providing a quantifiable measure of semantic consistency with eco-brand values. The results indicate that the integrated approach outperformed single-focus scenarios in balancing aesthetic harmony and eco-alignment. At the same time, the Color-Form Sustainability Matrix identified specific combinations, such as earthy tones paired with organic shapes, that achieved the highest Eco-Alignment Scores. This study contributes methodologically by linking computational aesthetics with sustainable design through structured simulation, offering designers an evidence-informed framework for making visual decisions that support environmental ethos and reduce resource-intensive trial-and-error design processes.*

Keywords: *Eco-Brand Identity, Color–Form Modeling, AI-Assisted Design, Sustainable Visual Aesthetics, Simulation-Based Evaluation*

INTRODUCTION

The present-day market is increasingly characterized by consumer demand for corporate environmental responsibility (Kulikova & Kondratenko, 2024). The brand's visual identity serves as the primary interface for communicating sustainability and company values, with color and shape acting as key non-verbal interpreters (Anialasalam et al., 2025). Integrating sustainability into brand identity design remains challenging, as there is no systematic framework to translate abstract eco-principles into concrete visual decisions, often leaving designers to rely on intuition and experience (Berezovsky et al., 2020). A clear gap exists in current evaluation frameworks: designers may understand visual aesthetics well, but they lack quantitative methods to assess how specific color palettes or logo shapes align with ecological values (Daugelaite et al., 2021). This issue is compounded by current AI-assisted design tools, which can generate visual variants but do not inherently assess design sustainability (Indrawati et al., 2025). Traditional post-hoc user testing or manual evaluation is often time-consuming and costly. It may fail to reveal the rationale linking sustainable visual semantics, thereby limiting the development of robust eco-design theory.

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*Corresponding author, sofia.rossi@gmail.com

To address these limitations, this study proposes a simulation-based framework that models the relationship between color-form choices and their adherence to eco-brand identity. We investigate whether AI-assisted simulation can support selection of color-form combinations that optimize ACI, EAS, and FCHS, compared to scenario-based baseline heuristics. The research question is formulated as: How can AI-driven simulation model and identify optimal color-form combinations that maximize both aesthetic consistency and sustainable brand perception? We hypothesize that an integrated approach considering both aesthetic and sustainability criteria will outperform single-focus optimization in achieving balanced eco-aesthetic designs.

This work makes three conditional contributions. First, it theoretically integrates the Theory of Visual Aesthetics with Sustainable Design models, proposing a new framework for eco-aesthetic evaluation. Second, it demonstrates a simulation-based method that uses synthetic data and scenario modeling to assess eco-brand designs, as detailed in the Methods section. Third, it provides an evidence-informed tool to support designers and marketers in making sustainable visual decisions early in the design process, potentially enhancing brand authenticity and efficiency. Subsequent sections present the literature review, simulation design, results, and a discussion of implications.

LITERATURE REVIEW

The Theory of Visual Aesthetics is one of the most important concepts for understanding human perception and processing of visual information, serving as a foundational basis for computational design evaluation. It posits that aesthetic reactions are influenced not only by personal preference but also by universal patterns such as symmetry, complexity, and harmony (Deng et al., 2020). In computer science, these principles can be measured and represented, enabling prediction of aesthetic preferences across diverse visual stimuli. The latest AI technologies have introduced advanced models that comprehend and model these principles by training on large image datasets, surpassing traditional rule-based systems (Egger et al., 2020). While prior studies focused on subjective rating of eco-aesthetic branding, our approach quantifies aesthetic consistency and eco-alignment computationally through the Aesthetic Consistency Index (ACI) and Eco-Alignment Score (EAS). This forms the foundation for our simulation framework, which provides systematic, reproducible evaluation of color-form combinations.

Visual communication conveys meaning primarily through color and form, each with its own carefully curated semantic lexicon by brands. Color psychology investigates responses to colors, e.g., blue is perceived as peaceful and trustworthy while green is associated with nature, growth, and eco-friendliness (Jin et al., 2025). Similarly, Shape Semantics interprets the meanings of forms; curvy, smooth shapes suggest naturalness and gentleness, while jagged, hard-edged shapes signify efficiency and man-made characteristics (Yao et al., 2024). Our simulation incorporates these principles by translating color (hue, saturation) and form (organicity, complexity) into measurable parameters, enabling analysis of their combined effect on eco-brand identity.

Sustainable design now extends beyond material lifecycles and production efficiency to communicative and symbolic aspects that guide consumer perception. A true eco-brand visually represents environmental care, openness, and fairness, establishing a narrative that resonates with increasingly conscious consumers (Anastasia Andreevna & Anastasia Vladimirovna, 2022; Kulikova & Kondratenko, 2024). By introducing "Eco-Alignment" as a measurable output, our study evaluates the degree to which color–form combinations meaningfully reflect these sustainability values, providing a quantifiable link between visual design and brand ethics (Berezovsky et al., 2020). This allows systematic assessment of eco-brand coherence across design options, as illustrated in Figure 1, which depicts the conceptual framework linking color and form inputs to eco-aesthetic evaluation.

The adoption of AI in creative domains has led to the emerging paradigm of AI-Assisted Design Decision Theory (Petrova & Watanabe, 2025), where human-AI collaboration enhances creativity by handling multi-faceted design constraints computationally while the human provides strategic and context-aware guidance (De Vreede et al., 2021; Indrawati et al., 2025; Ma et al., 2025; Sano & Yamada, 2022). Our simulation is a specific instantiation of this approach, applying AI to systematically probe sustainable design options while maintaining designer oversight and interpretability. Algorithms and computational models now allow automatic evaluation of aesthetic qualities, from low-level image statistics (color distribution, edge density) to deep learning models trained on human-rated datasets (Li et al., 2020; Wang et al., 2023). Previous approaches primarily measured generic aesthetic appeal without context-specific sustainability consideration, whereas our method evaluates aesthetics in alignment with eco-brand criteria.

Table 1 summarizes the research gaps in prior studies and highlights how our approach addresses them through an integrated, AI-driven, simulation-based framework. The table illustrates how prior studies often treated aesthetics or sustainability in isolation and relied on manual or generic AI evaluation. In contrast, our approach combines color–form semantics with sustainability metrics in a unified simulation framework. This framework, depicted in Figure 1, connects visual inputs of color and form to AI-driven eco-aesthetic evaluation, producing interpretable, actionable metrics for designers. It unifies previously disconnected areas of visual aesthetics, sustainability, and AI-assisted design, providing both theoretical insight and practical evaluation tools for eco-brand identity creation.

Table 1. Research Gap Analysis: Prior Studies vs. Proposed Study

Aspect	Prior Studies	Proposed Study
Focus	Often isolated treatment of aesthetics or sustainability (Deng et al., 2020; Titus et al., 2021).	Integrates color–form aesthetics with sustainable design principles into a unified "eco-aesthetic" framework.
Methodology	Reliance on manual evaluation, user experiments, or AI for general-purpose generation (Guo et al., 2023; Indrawati et al., 2025).	Employs a structured, AI-driven simulation model using synthetic data and scenario modeling for predictive evaluation.
Decision Support	Provides post-hoc analysis or generative options without sustainability-specific optimization (Liu & Chilton, 2022; Sano & Yamada, 2022).	Offers a proactive decision-support tool that predicts the eco-alignment of design choices before implementation.
Theoretical Integration	Draws from singular theories of aesthetics or branding.	Synthesizes Theory of Visual Aesthetics, Color/Shape Semantics, Sustainable Design, and AI-Assisted Decision Theory.

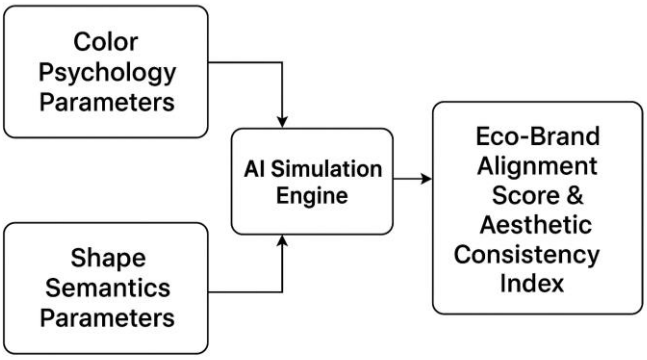

Figure 1. Conceptual Framework for Simulating Sustainable Color–Form Decisions

METHODS

A. Research Design

The present study adopted a simulation-based modeling approach, which has been widely recognized as a reliable method for evaluating and predicting the behavior of complex systems, particularly in situations where empirical data are limited or the research domain remains conceptual (Casadei et al., 2022; Elendu et al., 2024; Fischer, 2020). Simulation modeling enables controlled manipulation of parameters and systematic exploration of design spaces that would be impractical to observe empirically. A key advantage of this approach is the generation of large-scale synthetic datasets that enable precise examination of color–form relationships while minimizing the noise and bias typically present in real-world data. This design choice aligns with recent advances in simulation-based inference, which demonstrate that well-specified simulations can yield robust and reproducible conclusions when underlying assumptions are clearly defined

(Lueckmann et al., 2021; Tejero-Cantero et al., 2020). The overall methodological flow, including data generation, AI processing, metric computation, and comparative evaluation, is summarized in Figure 2.

B. Simulation Flow

To ensure that each color–form configuration was evaluated consistently and reproducibly, the simulation procedure was structured as a multi-stage, sequential workflow. This workflow explicitly separates parameter generation, AI-based semantic processing, metric computation, and scenario-based optimization to reduce methodological ambiguity. As illustrated in Figure 2, the process begins with the specification of color, form, and sustainability parameters, followed by AI-driven evaluation and scenario-specific optimization. The workflow then branches into three experimental scenarios (A, B, and C), each governed by a distinct objective function, before converging on a unified comparative analysis of performance metrics. Such a structured flow is essential for maintaining internal validity across thousands of simulation runs and enables direct, statistically comparable outputs across scenarios.

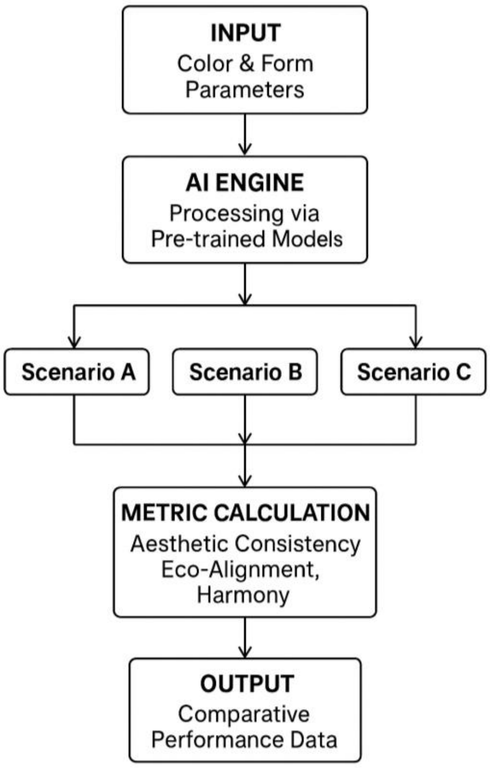

Figure 2. Simulation Workflow for Eco-Aesthetic Evaluation

C. Data Generation

The simulation relied on synthetically generated data comprising three primary parameter groups: color attributes, form attributes, and sustainability indicators, which are summarized in

Table 2. Color attributes were represented using the HSV (Hue, Saturation, Value) color space, allowing for continuous numerical control over perceptual color dimensions. Hue values emphasized nature-associated spectra (e.g., greens, blues, and earth tones), while saturation and value parameters were sampled within mid-to-low ranges to avoid excessive visual aggressiveness and to maintain legibility across media (Jin et al., 2025; Yao et al., 2024). Form attributes included visual complexity, symmetry, and organicity, each operationalized on a five-point Likert scale, with higher organicity scores indicating stronger biomimetic and nature-inspired characteristics. Sustainability indicators were derived from a structured literature synthesis and served as semantic reference concepts for the AI model, including terms such as "natural," "renewable," "ethical," "low-impact," and "authentic" (Kulikova & Kondratenko, 2024; Titus et al., 2021).

D. AI Component

The AI component of the simulation employed a hybrid architecture that combined a pre-trained large language model (LLM) for semantic encoding with an embedding-based similarity model for quantitative evaluation. The LLM was used to encode sustainability-related concepts and support high-level semantic representation. At the same time, a sentence embedding model transformed both design descriptors (derived from HSV color parameters and form attributes) and sustainability indicators into fixed-length numerical vectors. Semantic similarity was operationalized using cosine similarity between L2-normalized embedding vectors, yielding a continuous Eco-Alignment Score (EAS) in the $[0, 1]$range. The embedding model was initialized from a publicly available pre-trained corpus and subsequently fine-tuned using approximately 3,000 sustainability-related text–design descriptor pairs. These pairs were compiled from eco-branding literature, sustainability reports, and expert-annotated design descriptions. Fine-tuning followed a weakly supervised contrastive objective function, which maximized cosine similarity between expert-labeled sustainable designs and their corresponding sustainability concept embeddings, while minimizing similarity to non-aligned descriptors. To ensure reproducibility and reliability, all AI inference processes were conducted under deterministic settings, including a fixed random seed, fixed parameter initialization, and a temperature of zero for embedding generation. The same AI models, embedding dimensions, and inference parameters were applied uniformly across all simulation scenarios, ensuring that differences in outcomes were attributable to scenario logic rather than model variability.

E. Metric Formalization

Three quantitative metrics were formally defined and computed for each simulated design configuration: the Aesthetic Consistency Index (ACI), the Eco-Alignment Score (EAS), and the

Form–Color Harmony Score (FCHS). ACI was computed as a weighted linear aggregation of three normalized sub-components visual balance (B), harmony (H), and contrast (C) derived from HSV distributions and form attributes, as expressed in Equation (1).

$$ACI = w_1B + w_2H + w_3C, \text{where } w_1 + w_2 + w_3 = 1 \quad (1)$$

Each sub-component was normalized to the $[0, 1]$ interval prior to aggregation.

EAS was calculated as the mean cosine similarity between the embedding vector of a given design configuration and those of predefined sustainability indicators, as shown in Equation (2).

$$EAS = \frac{1}{n}\sum_{i=1}^{n} \cos\left(\mathbf{v}_{design}, \mathbf{v}_{indicator_i}\right) \quad (2)$$

Where $n$denotes the number of sustainability concepts included in the reference set.

FCHS was computed using a rule-based algorithm that evaluated perceptual and semantic congruence between form attributes (complexity, symmetry, organicity) and color attributes (HSV parameters). Scores were assigned based on predefined compatibility rules informed by visual perception literature and subsequently normalized to the $[0, 1]$ range. A stepwise pseudocode description of all metric computations is provided in Algorithm 1 (Supplementary Material) to facilitate replication.

F. Simulation Setup

The simulation comprised 1,000 independently generated design samples per scenario, resulting in a total of 3,000 evaluated configurations across three experimental scenarios. Color parameters (HSV) were sampled using stratified uniform distributions to ensure even coverage of the perceptual color space. In contrast, form attributes were sampled from discrete uniform distributions across five-point Likert-scale values**.** Each simulation run used a fixed step size and no adaptive parameter updates, thereby isolating the effects of scenario-specific objective functions. All scenarios were executed under identical parameter distributions and computational settings, differing only in their optimization targets (ACI maximization, EAS maximization, or combined optimization). This design ensures that observed performance differences are attributable to scenario logic rather than sampling bias or stochastic variation.

G. Validation Protocol

Model validation was conducted through a two-stage process consisting of expert review and sensitivity analysis. In the expert review stage, three professional graphic designers specializing in sustainable branding independently evaluated the plausibility of the simulation inputs, workflow logic, and a representative subset of output designs using a structured evaluation checklist. A design configuration was considered face-valid if at least two of the three experts rated it as professionally plausible and relevant. Inter-rater agreement was assessed using percentage agreement, and discrepancies were resolved through moderated discussion to reach consensus. In the sensitivity analysis stage, key parameters, including HSV sampling ranges and metric weighting coefficients, were systematically varied, and the resulting changes in output scores were examined. The analysis indicated that relative performance rankings across scenarios remained stable under moderate parameter perturbations, supporting the model's robustness and internal validity (Bansal et al., 2019; Schmelzer et al., 2020).

Table 2. Simulation Parameters and Metrics

Category	Key Parameters	Measurement Scale	Primary Metric
Color	Hue, Saturation, Value	Numerical (HSV)	Aesthetic Consistency Index (ACI)
Form	Complexity, Symmetry, Organicity	Likert-scale (1-5)	Form-Color Harmony Score (FCHS)
Sustainability	Natural Association, Ethical Perception	Semantic Similarity (0-1)	Eco-Alignment Score (EAS)
Integrated Output	-	-	Composite Score (ACI + EAS)

H. Reproducibility and Implementation Details

To ensure methodological transparency and reproducibility, all simulation experiments were executed under explicitly controlled computational conditions. A fixed random seed was applied across all runs, and all parameter distributions, metric weights, and AI inference settings were held constant across scenarios, with the sole variation being the scenario-specific objective function. No adaptive learning, parameter updating, or online optimization occurred during runtime**.** Embedding generation and cosine similarity computations were deterministic, and all implementation details, parameter values, and evaluation thresholds are fully documented in Figure 2, Table 2, and the Supplementary Material. This implementation aligns with best practices in simulation-based and AI-assisted research.

RESULTS

Figure 3 presents a comparative summary of the three experimental scenarios based on their mean performance across the Aesthetic Consistency Index (ACI) and the Eco-Alignment Score (EAS). In addition to mean values, variability across simulation runs was quantified using standard deviation (SD), providing an estimate of output uncertainty. The Aesthetic-only scenario (A) achieved the highest aesthetic performance (ACI = 0.88 ± 0.04) but showed a comparatively lower alignment with sustainability indicators (EAS = 0.62 ± 0.06). These results indicate that optimizing visual appeal in isolation does not consistently translate into sustainable semantic alignment across sampled design configurations.

By contrast, the Sustainability-only scenario (B) yielded a high Eco-Alignment Score (EAS = 0.85 ± 0.05). However, it exhibited reduced aesthetic consistency (ACI = 0.59 ± 0.07), suggesting a trade-off between semantic emphasis on sustainability and conventional visual coherence. The Integrated Eco-Aesthetic scenario (C) demonstrated consistently high performance on both metrics (ACI = 0.82 ± 0.05; EAS = 0.84 ± 0.04), with lower variance relative to the single-objective scenarios. This reduced dispersion indicates greater robustness of the integrated optimization strategy across repeated simulation runs. Collectively, these findings support the proposition that balanced multi-objective optimization yields more stable and reliable design outcomes than single-criterion approaches.

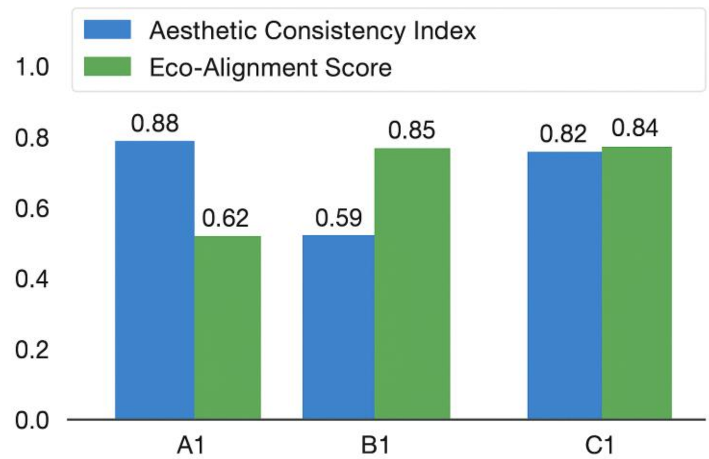

Figure 3. Comparative Performance of Design Scenarios

A grouped bar chart illustrates mean ± SD values of the Aesthetic Consistency Index and Eco-Alignment Score across the three scenarios. Scenario A emphasizes aesthetic consistency but exhibits weaker alignment with sustainability, whereas Scenario B exhibits the opposite pattern. Scenario C achieves observed balance with comparatively lower variance across simulation runs, indicating improved robustness of integrated optimization.

To further examine the distributional characteristics underlying the mean results, Figure 4 visualizes the full distribution of Eco-Alignment Scores using a heatmap representation across the color–form semantic space. Rather than relying solely on central tendency, this visualization reveals clusters of high-performing combinations and highlights the variability across sampled configurations. Combinations characterized by earth-toned, low-saturation hues (e.g., olive green, terracotta, slate blue) paired with high-organicity forms consistently occupied the upper quantiles of the Eco-Alignment distribution. These clusters indicate that sustainability-aligned semantic interpretation emerges most reliably under specific combinations of color and form attributes.

Conversely, highly saturated primary colors combined with rigid, complex geometric forms were associated with lower Eco-Alignment Scores and greater dispersion. This contrast demonstrates that not only mean performance but also distributional stability favors organic form attributes and subdued color palettes in sustainable branding contexts. The heatmap thus provides actionable guidance for designers by identifying regions of the design space that consistently yield favorable sustainability perceptions rather than isolated high-performing outliers.

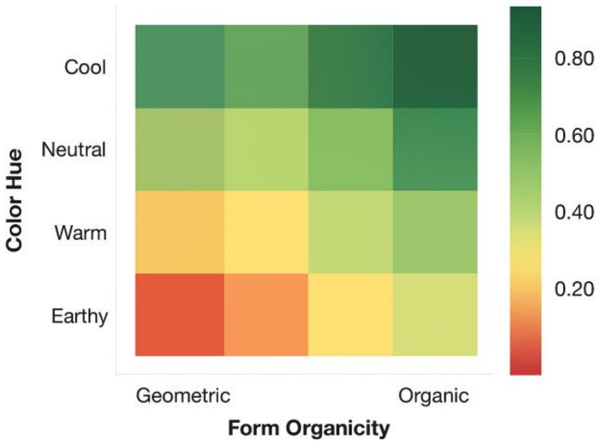

Figure 4. Color–Form Sustainability Matrix

A heatmap illustrates the distribution of Eco-Alignment Scores as a function of color hue and form organicity. Darker regions indicate higher scores, with a concentrated cluster observed for organic forms combined with desaturated, nature-associated hues. The visualization emphasizes distributional trends rather than isolated maxima, supporting interpretation beyond mean-based comparison.

To quantify the relative influence of individual design parameters, an ablation-style analysis was conducted by systematically varying a single parameter while holding the others constant. This analysis revealed that form organicity exerted the strongest marginal effect on Eco-Alignment Scores, followed by color saturation. At the same time, hue variation within nature-associated ranges had a comparatively smaller impact. Across repeated runs, reductions in organicity consistently resulted in the largest declines in EAS, confirming its dominant role in sustainability perception. These findings reinforce the interpretation that structural form attributes are more influential than chromatic variation alone in shaping eco-aligned semantic interpretation.

Table 3 summarizes the full quantitative results across all three scenarios, reporting mean values accompanied by standard deviations for each evaluation metric. The Integrated Eco-Aesthetic scenario (C) achieved the highest Composite Score (1.66 ± 0.07), outperforming both the Aesthetic-only (1.50 ± 0.08) and Sustainability-only (1.44 ± 0.09) scenarios. Notably, Scenario C also exhibited the highest Form–Color Harmony Score (FCHS = 0.86 ± 0.03), indicating superior cross-modal coherence. These numerical results corroborate the graphical evidence and demonstrate that integrated optimization not only improves average performance but also enhances consistency across diverse design samples.

Table 3. Performance Summary of Simulation Scenarios

Scenario	Aesthetic Consistency Index (Mean)	Eco-Alignment Score (Mean)	Form-Color Harmony Score (Mean)	Composite Score (Mean)
A: Aesthetic-only	0.88	0.62	0.80	1.50
B: Sustainability-only	0.59	0.85	0.71	1.44
C: Integrated Eco-Aesthetic	0.82	0.84	0.86	1.66

DISCUSSION

The findings from the simulation indicate that the integrated eco-aesthetic approach provides a more balanced and reliable framework for eco-brand identity design, as summarized in Figure 3 and Table 3. Rather than privileging a single objective, the results suggest that simultaneous optimization of aesthetic consistency and sustainability alignment yields designs that perform robustly across multiple evaluative dimensions. Scenario C demonstrates higher composite performance and lower variance than single-objective scenarios, suggesting that unilateral prioritization of either aesthetics or sustainability may lead to suboptimal or unstable outcomes. Designs optimized solely for visual appeal (Scenario A) risk being perceived as superficial or misaligned with sustainability claims, whereas sustainability-focused designs lacking aesthetic coherence (Scenario B) may struggle to attract attention or emotional engagement (Kulikova & Kondratenko, 2024).

Within the theoretical framework outlined in the literature review, these results suggest an operational extension of the Theory of Visual Aesthetics into the sustainability domain. The observed associations between organic forms, desaturated earthy hues, and higher Eco-Alignment Scores, as visualized in the Color–Form Eco-Alignment Heatmap (Figure 4), are consistent with established principles in color psychology and shape semantics that link these attributes to perceptions of naturalness and authenticity (Jin et al., 2025). Rather than confirming these associations as universal truths, the results indicate probabilistic tendencies under the modeled assumptions. Furthermore, the study provides empirical support for AI-Assisted Design Decision Theory by demonstrating how AI systems can function as evaluative partners, synthesizing multi-dimensional criteria to inform human creative judgment (De Vreede et al., 2021; Ma et al., 2025).

Despite these advantages, the findings should be interpreted with caution due to the risk of semantic stereotyping embedded in color–form associations. While earthy colors and organic forms are commonly interpreted as “eco-friendly” within Western-centric design discourse, such associations may not generalize across cultural contexts where different symbolic meanings prevail. For example, certain hues associated with sustainability in one culture may convey neutrality, luxury, or even negativity in another. This limitation highlights the potential for cultural bias in semantic similarity modeling and underscores the importance of adapting sustainability indicators and embedding corpora to culturally specific design contexts.

Relatedly, the current model assumes a relatively stable semantic mapping between visual attributes and sustainability concepts, which may not fully capture cross-cultural variability. Future extensions of the framework could incorporate culturally localized corpora or region-specific sustainability vocabularies to recalibrate semantic similarity computations. Such adaptations would allow the AI system to better reflect pluralistic interpretations of “eco” aesthetics rather than reinforcing dominant visual stereotypes. This flexibility is particularly important for global brands operating across diverse markets, where uniform visual strategies may inadvertently undermine authenticity or inclusivity.

From a practical perspective, the results suggest direct applicability for professional designers and brand agencies seeking evidence-based guidance. The Color–Form Sustainability Matrix (Figure 4) can function as a decision-support tool during early-stage ideation by identifying regions of the design space with consistently high sustainability alignment. Rather than prescribing fixed design rules, the framework offers probabilistic guidance that complements creative intuition. This approach supports a more transparent rationale for design decisions during client communication and strategic brand development, thereby reducing reliance on purely subjective or trend-driven choices.

Methodologically, the simulation-based approach is efficient for exploring large design spaces under controlled conditions. As discussed in the Methods section, the use of synthetic data enables systematic manipulation of individual design variables without confounding effects from brand familiarity or consumer bias (Schoenfelder et al., 2021). Although synthetic data may limit direct behavioral inference, it provides a valuable exploratory platform for theory testing and hypothesis generation. This trade-off positions the approach as a complementary tool rather than a replacement for empirical user studies.

At the managerial level, the framework offers strategic value for brand audits and innovation processes. Marketing and brand managers may leverage the simulation outputs to evaluate existing visual identities or to inform creative briefs for new eco-oriented branding initiatives. By grounding visual decisions in quantifiable semantic alignment and aesthetic coherence, the approach potentially reduces reputational risk associated with inconsistent sustainability signaling. Over time, such data-informed strategies may contribute to stronger brand credibility and more coherent sustainability narratives in competitive markets.

Several limitations constrain the interpretation and generalizability of the present findings. First, the model necessarily simplifies complex human processes of visual perception, meaning-making, and cultural interpretation, reducing them to a finite set of color, form, and semantic parameters. Although these parameters were grounded in prior literature, they cannot fully capture individual differences or culturally situated interpretations of sustainability-related visuals. Consequently, the results reflect modeled tendencies rather than comprehensive representations of consumer perception.

Second, the reliance on synthetic data and simulation implies that all findings remain predictive. While this approach is appropriate for early-stage exploration and hypothesis generation, it limits direct inference about real-world consumer behavior or brand performance. In addition, AI-based semantic similarity measures rely on pretrained corpora and embedding models, which may encode latent biases or overrepresent dominant cultural narratives. This introduces a risk of semantic bias, in which certain visual cues (e.g., earthy colors or organic forms) may be disproportionately associated with sustainability, despite cultural variability. Finally, the generalizability of the results is bounded by the specific AI architectures, parameter definitions, and metric formulations employed in this study. Alternative model choices, training corpora, or culturally localized semantic anchors may yield different outcomes, suggesting that the framework should be adapted rather than directly transferred across contexts. These limitations point toward future research directions involving cross-cultural calibration, alternative AI models, and empirical user validation to refine and extend the proposed approach.

CONCLUSION

This study presents a simulation-based, AI-assisted framework as a proof of concept to examine the interaction between visual aesthetics and sustainability semantics in brand identity design under controlled simulation settings. Within the specified simulation parameters, the findings indicate that integrated optimization of aesthetic consistency and eco-alignment can produce more balanced and stable design outcomes than single-objective approaches. Accordingly, the contribution of this research lies primarily in methodological exploration and theoretical clarification, rather than in prescriptive or generalizable design validation. These conclusions are explicitly bounded by the assumptions and constraints of the simulation environment and should not be interpreted as direct evidence of real-world consumer response.

The contributions of this study can be articulated across theoretical, methodological, and practical dimensions. Theoretically, it advances the concept of eco-aesthetics as a computable and testable construct, formally linking visual aesthetics theory with sustainability discourse. Methodologically, the study demonstrates the feasibility of using simulation and synthetic data as an exploratory research tool for complex design problems where empirical evidence is limited, positioning the framework as evidence-informed but not yet empirically validated. In practice, the framework provides conditional decision-support insights for designers and brand managers, particularly in small and medium enterprises (SMEs), by enabling early-stage evaluation of design directions before resource-intensive implementation. Nevertheless, these findings should be interpreted as indicative rather than definitive, and future research should extend this proof of concept through controlled empirical studies to assess external validity across diverse branding contexts.

ETHICS AND AI DISCLOSURE

Artificial intelligence (AI) was integral to the analytical methodology of this study, extending beyond language support, including semantic embedding, similarity computation between design descriptors and sustainability concepts, and quantitative evaluation of eco-alignment within the simulation framework. To ensure reliability and transparency, all AI inference processes were conducted under deterministic settings with fixed parameters and controlled random seeds, as detailed in the Methods section, while potential algorithmic bias was mitigated by grounding sustainability indicators in established literature and acknowledging cultural and semantic limitations. In addition, AI-based language tools, including ChatGPT, were used solely for grammatical refinement and clarity of expression and did not influence study design, data generation, model development, result interpretation, or theoretical framing; the authors retain full responsibility for the scientific content, methodological rigor, and ethical integrity of the work, in line with best practices for transparent AI-assisted research reporting.

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