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Human-AI Collaborative Adaptive Typeface Generation: Eye-Tracking Fixation Metrics in Instagram Branding

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Abstract. *Integrating artificial intelligence into typographic design opens new opportunities for social media branding, especially on visually intensive platforms like Instagram. This study investigates how typefaces developed in collaboration with AI may influence visual engagement metrics. We designed an assessment framework that couples collaborative typeface generation with simulated eye-tracking analysis. Three adaptation scenarios were evaluated: static, semi-adaptive, and fully adaptive typefaces, based on fixation duration, fixation count, and heatmap visualization. Interestingly, when analyzing the simulation results, a pattern emerged: the typefaces generated through iterative human-AI processes tended to attract longer, more frequent visual fixations. These preliminary results thus point to the potential value of collaborative approaches to typographic design in social media contexts. The present study provides a methodological framework to assess AI-assisted visual assets using human attention metrics.*

Keywords *Human-AI Collaboration, Adaptive Typeface, Eye-Tracking Metrics, Visual Engagement, Instagram Branding*

INTRODUCTION

Recent developments in artificial intelligence have repositioned computational systems in graphic design from passive tools to active collaborative agents within the creative process (Fragiadakis et al., 2025). This shift is particularly relevant for visually saturated social media platforms such as Instagram, where intensified competition for user attention necessitates continuous refinement of visual communication strategies (Colombo et al., 2023). As AI-assisted design tools become increasingly integrated into professional practice, their influence on visual identity formation and branding workflows has become more pronounced (Indrawati et al., 2025). Accordingly, systematic evaluation of how these tools perform in capturing visual attention is essential to ensure that human creativity remains meaningfully embedded within AI-supported design processes (Tan & Menon, 2025).

Typography occupies a central role in contemporary visual communication, evolving from a primarily functional element into a key driver of brand identity and visual differentiation (Chu et al., 2023). While AI-driven systems can rapidly generate extensive typographic variations, it remains unclear whether such outputs effectively attract and sustain viewer attention. This disconnect between generative capacity and evaluative validation represents a critical challenge for both design research and social media branding strategy. Bridging this gap requires empirical or modeled approaches that can assess engagement potential beyond aesthetic novelty alone.

This study is motivated by the question of whether human–AI collaborative processes can produce adaptive typefaces that exhibit higher modeled visual engagement than conventional or

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static typographic designs. Existing literature has predominantly examined either the technical dimensions of AI-assisted design or user experience metrics in isolation (Jiang et al., 2021; Sarkar, 2023) Relatively few studies have investigated their intersection, particularly in the context of dynamically generated typography for social media environments. Addressing this gap, the present research adopts an integrative perspective that combines collaborative design processes with attention-based evaluative modeling.

Accordingly, this study proposes a framework that integrates structured human–AI typeface generation with simulation-based eye-tracking assessment. The aim is not to predict real-world branding success, but to explore indicative attention patterns under controlled, platform-specific conditions (Jin et al., 2025). By providing a systematic, repeatable evaluation environment, the framework supports informed decision-making on AI-assisted typographic outputs prior to real-world deployment. Ultimately, this work contributes to the growing body of research on human–AI co-creativity by offering an exploratory methodological bridge between generative design and visual attention modeling.

The central research question guiding this study is: How does human–AI collaborative adaptive typeface generation influence modeled visual attention metrics in Instagram branding scenarios? It is hypothesized that increased AI adaptivity, when guided by human design input, will be associated with higher modeled fixation durations and engagement indices in simulated eye-tracking scenarios. These propositions are examined through comparative scenario-based analysis rather than empirical behavioral observation. As such, the findings are intended to provide exploratory insights into collaborative design dynamics rather than definitive claims about user behavior or market performance.

LITERATURE REVIEW

A. AI-Generated Typography

Research on AI-generated typography has evolved along several technical trajectories, including rule-based parametric systems, generative font frameworks, and machine learning–driven models trained on typographic datasets (Huang & Huang, 2021; Kadner et al., 2021). Parametric approaches typically allow designers to manipulate predefined variables such as stroke width, contrast, and spacing, offering transparency and controllability but limited adaptivity. In contrast, machine learning–based systems emphasize variation and novelty, often at the expense of interpretability and designer control (Choi & Hyun, 2024). Despite these advances, existing studies predominantly assess typographic quality in terms of legibility and aesthetic variation, with limited attention to how such outputs perform in attention-driven digital environments.

The potential of adaptive typography has been frequently discussed in relation to personalization and contextual responsiveness (Zhang et al., 2020). Rather than emphasizing speculative visions of transformation, recent scholarship has begun to recognize the practical challenges associated with maintaining brand coherence and design integrity within adaptive systems (Zhu et al., 2024). Notably, few studies have systematically evaluated AI-generated typefaces using attention-based metrics, particularly within social media contexts characterized by rapid visual consumption. This absence of evaluative linkage between typographic generation mechanisms and viewer attention measurement constitutes a critical gap addressed by the present study.

B. Human–AI Collaboration in Design

Contemporary design research increasingly conceptualizes AI not as a fully autonomous agent, but as a collaborative partner operating within human-guided workflows (Lai et al., 2021). Interpretability and designer oversight have been identified as central conditions for productive creative interaction, enabling designers to meaningfully guide, constrain, and refine computational outputs (Cabrera et al., 2023). Studies suggest that the most effective design outcomes emerge from hybrid interaction models in which human judgment and machine-generated variation are iteratively aligned (Song et al., 2024). These findings indicate a shift away from automation-centric narratives toward adaptive, dialogic modes of design practice.

At the same time, critical perspectives caution against unexamined use of collaboration terminology, emphasizing the need for clearly defined interaction frameworks that specify the distribution of agency between human designers and AI systems (Sarkar, 2023). Empirical work demonstrates that the degree of human involvement varies depending on task complexity, domain constraints, and evaluative criteria (Rastogi et al., 2023). Positioned within this discourse, the present study adopts a human-in-the-loop adaptive iteration model, where AI-generated typographic variations are continuously guided and validated by human designers rather than operating autonomously. This positioning aligns the study with emerging best practices in collaborative computational creativity.

C. Eye-Tracking and Visual Engagement Metrics

Eye-tracking has become a widely adopted method for examining visual attention, offering quantitative indicators such as fixation duration and fixation count that reflect cognitive processing and attentional allocation (Azer et al., 2024). These metrics have been extensively applied in interface evaluation, advertising research, and social media content analysis, where rapid visual engagement is critical (Cheng et al., 2023; Joseph & Murugesh, 2020). Compared to subjective self-report measures, fixation-based indicators provide more objective insight into how visual stimuli are processed under time-constrained viewing conditions. As such, they are particularly relevant for evaluating design elements embedded within scrolling-based platforms.

However, while eye-tracking methods are well established in human–computer interaction and usability research, their application to the evaluation of AI-generated design artifacts remains limited (Jones et al., 2023; Wu et al., 2020). Recent reviews indicate growing interest in attention-based assessment for user experience evaluation, yet direct connections between eye-tracking metrics and AI-assisted creative outputs are still underexplored (Falkowska et al., 2025). This methodological separation suggests an opportunity to integrate computational design research with attention modeling approaches, particularly through simulation-based eye-tracking when empirical data collection is constrained.

D. Digital and Social Media Branding in the Instagram Context

Instagram's visually oriented interface imposes distinct constraints on branding strategies, requiring design elements to capture attention within seconds amid dense streams of competing content (Doyle et al., 2022). Empirical studies have shown that visual consistency and aesthetic coherence significantly influence brand perception on the platform, yet typographic design remains comparatively underexamined (Anialasalam et al., 2025). This gap is notable given typography's established role in shaping brand identity and guiding visual hierarchy in digital communication. Consequently, the effectiveness of typographic choices on Instagram is often assumed rather than systematically validated.

Although brands increasingly invest in data-informed visual storytelling, typography selection in social media contexts continues to rely largely on convention and designer intuition rather than evidence-based evaluation (Chelsea Sutanto et al., 2024). Prior research highlights the relevance of platform algorithms that prioritize user engagement, suggesting that attention-sensitive typographic strategies could offer practical value for personal and commercial branding (Pertiwi & Irwansyah, 2020). Nonetheless, few studies have combined adaptive typography with quantitative attention modeling to inform branding decisions on Instagram. This limitation further underscores the need for integrative evaluative frameworks.

E. Research Gap Synthesis

Taken collectively, existing research on AI-assisted design, adaptive typography, eye-tracking metrics, and Instagram branding has developed largely in parallel rather than in convergence. While each domain contributes valuable theoretical and methodological insights, their intersections particularly the evaluation of human-guided AI-generated typography using attention-based metrics in social media environments remain insufficiently explored. Table 1 summarizes these disciplinary disconnections and positions the present study as an integrative response. By linking collaborative design processes with simulation-based visual attention assessment, this research addresses a gap at the intersection of computational creativity and digital branding evaluation.

Table 1. Research Domain Connections and Disconnections

Research Domain	Current Emphasis	Underexplored Connections	Our Approach
AI-assisted Design	Technical capabilities and workflow efficiency (Indrawati et al., 2025)	User-centered evaluation of visual outputs	Applying engagement metrics to collaborative outputs
Adaptive Typefaces	Legibility and aesthetic variation (Sawyer et al., 2020)	Social media branding applications	Testing adaptation specifically for Instagram contexts
Eye-tracking Research	Cognitive load and attention patterns (Chen et al., 2022)	Assessment of generatively designed elements	Using metrics to evaluate human-AI collaborative outputs
Instagram Branding	Visual consistency and content strategy (Colombo et al., 2023)	Typography as an engagement factor	Examining typeface performance in feed environments

The conceptual relationships among these domains are further articulated through an iterative framework illustrated in Figure 1. The model depicts a cyclical process in which human-guided AI generation produces adaptive typographic outputs, which are evaluated using modeled visual attention metrics in an Instagram context. Feedback derived from these evaluations informs subsequent design iterations, reinforcing a continuous refinement loop. This integrative structure highlights the exploratory yet systematic nature of the proposed approach and clarifies its contribution to research on human–AI co-creative systems.

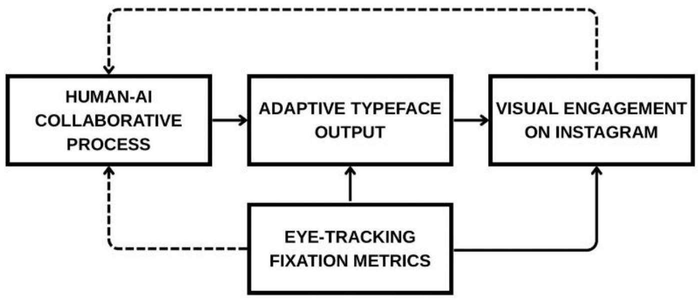

Figure 1. Conceptual Relationships between Collaboration, Adaptation, and Measurement

Figure 1 visualizes the proposed integrative framework, illustrating how human-guided AI processes, adaptive typographic outputs, and attention-based evaluation interact within a cyclical design system. The Human–AI Collaborative Process initiates typographic generation, which is then contextualized within Instagram's visual environment. Modeled eye-tracking fixation metrics serve as evaluative mechanisms, providing quantitative feedback on visual attention patterns. This feedback is subsequently incorporated into iterative design refinement, emphasizing the role of structured human oversight in adaptive AI-assisted typography.

METHODS

A. Research Design

This study adopts a simulation-based research design to examine the relationship between adaptive typographic variation and modeled visual attention outcomes. This approach was selected due to the practical constraints associated with large-scale biological eye-tracking studies in social media environments, where multiple uncontrolled variables simultaneously influence viewer behavior. While acknowledging reduced ecological validity compared to in vivo eye-tracking, the simulation-based design provides controlled experimental conditions that enable systematic comparison across typographic scenarios (Falkowska et al., 2025). By isolating typographic variables while holding layout and contextual elements constant, the approach minimizes confounding effects that are common in naturalistic Instagram feeds.

The use of simulation allows for focused investigation of typographic influence on attention without compromising methodological rigor. In real-world social media contexts, isolating typography effects is particularly challenging due to algorithmic content ordering, heterogeneous user behavior, and concurrent visual stimuli (Mohapatra & Zayapragassarazan, 2021). Accordingly, the simulated environment replicates key characteristics of Instagram viewing conditions while maintaining alignment with established eye-tracking research practices (Joseph & Murugesh, 2020). This design ensures replicability and flexibility, allowing future studies to extend or refine the simulation parameters for related design-performance investigations.

B. AI-Assisted Typeface Generation Framework

As illustrated in Figure 2, the adaptive typeface generation process employs a parametric generative typeface system assisted by AI-based optimization within a human-in-the-loop workflow. Rather than functioning as an autonomous creative agent, the AI component operates as a computational exploration mechanism constrained and guided by human-defined design parameters. These parameters include stroke weight, contrast, letter spacing, and structural proportions, as well as qualitative brand attributes specified by human designers. The system outputs multiple adaptive typeface variants per iteration, reflecting controlled variation rather than unconstrained novelty.

Human designers retain decision-making authority throughout the generation pipeline. Their role encompasses defining initial constraints, iteratively adjusting parameters, selecting candidate outputs, and final aesthetic approval. This collaborative structure aligns with established principles of interpretable and controllable human–AI interaction in creative contexts (Cabrera et al., 2023). By combining computational variability with human contextual judgment, the framework emphasizes complementarity between machine efficiency and human expertise rather than automation-driven substitution (Song et al., 2024).

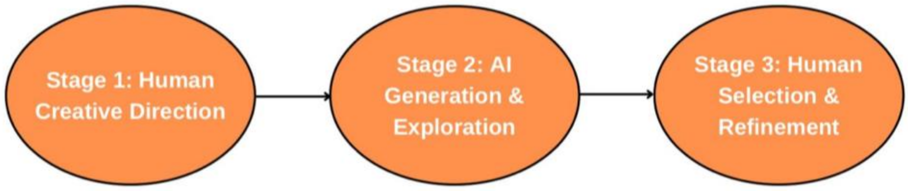

Figure 2. Human-AI Collaborative Typeface Generation Pipeline

C. Eye-Tracking Simulation Setup

Visual attention was evaluated using a saliency-based eye-tracking simulation model designed to approximate fixation behavior within Instagram feed environments. The simulation generates predicted fixation maps based on visual salience, typographic prominence, and spatial layout cues derived from prior eye-tracking research (Cheng et al., 2023; Wu et al., 2020). For each typographic scenario, the simulation was executed across multiple iterations (ranging from 100 to 500 runs per condition) to capture variability in modeled attention patterns. This iterative approach enables aggregation of descriptive statistics rather than reliance on single-run outputs.

The primary metrics extracted from the simulation include fixation duration, fixation count, and attention heat distribution across predefined areas of interest (AOIs). Fixation duration reflects modeled processing depth, fixation count indicates attention recurrence, and heat distribution represents spatial concentration of visual attention (Azer et al., 2024). These metrics represent modeled attention patterns rather than direct measurements of human gaze behavior and should therefore be interpreted as indicative rather than empirical. The simulation outputs are subsequently normalized to support comparative analysis across typographic conditions.

D. Eye-Tracking Metrics Configuration

Table 2 summarizes the fixation-based metrics used to quantify modeled visual engagement across typographic scenarios. These metrics were selected due to their established reliability in evaluating visual attention across digital interfaces and social media contexts (Cheng et al., 2023; Wu et al., 2020). Fixation duration is interpreted as an indicator of cognitive processing depth, while fixation count reflects sustained or repeated attention allocation. A composite engagement index was computed by integrating normalized fixation duration and fixation count values to provide a holistic indicator of attention potential (Azer et al., 2024).

Although these metrics do not capture subjective interpretation or emotional response, they provide objective and comparable indicators of visual attention performance. Their combined use enables triangulation across different dimensions of attention allocation, thereby strengthening the robustness of the evaluative framework. Accordingly, the metrics are applied consistently across all simulation scenarios to ensure methodological comparability. This configuration supports descriptive rather than inferential interpretation of engagement differences.

Table 2. Metric Definitions and Applications

Metric	Measurement Focus	Scale	Example Value
Fixation Duration	Processing engagement	Milliseconds	280 ms
Fixation Count	Attention recurrence	Count	15
AOI Focus	Element centrality	Screen Region	Primary_Headline
Engagement Index	Combined appeal measure	0-1 Scale	0.81

E. Simulation Workflow

The simulation workflow, illustrated in Figure 3, translates adaptive typographic outputs into quantifiable attention metrics through a structured, multi-stage process. Generated typeface variants serve as inputs to the simulation engine, which models Instagram-specific viewing behavior, including rapid initial exposure and scrolling-based attention allocation (Colombo et al., 2023). Particular emphasis is placed on early fixation behavior, reflecting the short decision window during which users determine whether to engage with or bypass content (Azer et al., 2024). This modeling choice aligns with established findings on attention dynamics in feed-based platforms.

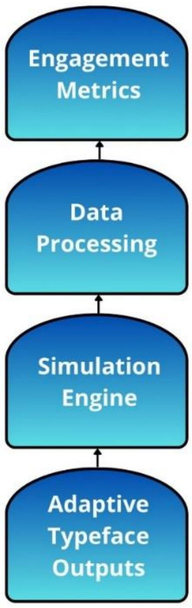

Figure 3. Eye-Tracking Simulation Workflow

Following simulation execution, raw fixation outputs are processed to extract descriptive metrics and aggregate attention patterns. The standardized workflow ensures consistent measurement across all experimental conditions while maintaining contextual relevance to social media environments. Although simulated, the workflow is designed to approximate key perceptual constraints of Instagram usage, thereby balancing control with contextual fidelity. This structured process facilitates reproducibility and systematic comparison across typographic configurations.

F. Expert Evaluation Procedure

To complement the quantitative simulation results, an expert validation procedure was conducted to incorporate professional design judgment. A panel of three to five experts with backgrounds in typography, visual communication, and branding evaluated the generated typeface outputs. Experts assessed each typeface based on predefined criteria, including legibility, stylistic coherence, and alignment with brand identity goals. Evaluations were conducted using a Likert-scale and comparative ranking approach, enabling structured qualitative comparison across scenarios.

The expert review serves as a contextual validation layer rather than an independent outcome measure. Its purpose is to examine whether modeled attention trends correspond with professional aesthetic and functional assessments (Mohapatra & Zayapragassarazan, 2021). By integrating expert judgment with simulation-based metrics, the evaluation framework captures both quantitative attention indicators and qualitative design considerations. This mixed validation approach strengthens the interpretive credibility of the findings while remaining consistent with the exploratory scope of the study.

RESULTS

A. Scenario Overview

The three experimental scenarios summarized in Table 3 represent progressively increasing levels of human–AI collaboration, ranging from conventional static typography to fully adaptive, collaborative typeface generation. This structured progression enables descriptive comparison of modeled visual attention outcomes under controlled typographic conditions rather than causal inference. Each scenario was designed using an identical layout and contextual parameters to ensure that observed differences could be attributed primarily to typographic adaptation mechanisms. Accordingly, comparisons across scenarios are descriptive rather than inferential and should be interpreted as indicative trends within simulated environments.

Table 3. Scenario Characteristics and Expectations

Scenario	Process Description	Design Complexity	Expected Engagement
S1	Conventional static approach	Minimal	Baseline
S2	Limited AI assistance	Moderate	Incremental
S3	Integrated collaboration	High	Enhanced

The stepwise increase in design complexity and AI involvement provides a systematic framework for observing how different collaboration intensities correspond with modeled engagement patterns. Rather than asserting performance superiority, the scenarios establish a comparative baseline for examining relative differences in simulated attention metrics. This design allows consistent observation of engagement tendencies while maintaining methodological transparency. Such an approach aligns with best practices for exploratory simulation-based design research.

B. Visualization Output

The fully adaptive typeface condition (S3) exhibited more concentrated modeled fixation regions than the static (S1) and semi-adaptive (S2) scenarios, suggesting a higher average visual focus within specific typographic areas. These patterns are consistent with prior findings that adaptive visual elements may influence attention allocation in feed-based environments (Azer et al., 2024). However, the observed differences in the heatmap reflect modeled attention tendencies rather than direct measurements of human gaze behavior. The visualization supports the quantitative findings by illustrating relative differences in attention concentration. Rather than serving as confirmatory evidence, the heatmaps function as complementary descriptive representations of simulated engagement patterns. This visual correspondence enhances interpretability without overstating causal claims. The consistency between visual and numerical outputs reinforces the internal coherence of the simulation framework.

C. Descriptive Metrics Comparison

Figure 5 summarizes the descriptive statistics for fixation duration, fixation count, and the composite Engagement Index across all scenarios. As shown in Table 4, the fully adaptive scenario (S3) demonstrated higher mean modeled fixation duration and fixation count compared to S1 and S2, with corresponding differences in the Engagement Index. The Engagement Index was computed through normalized aggregation of fixation duration and fixation count values, resulting in a bounded scale between 0 and 1 to facilitate cross-scenario comparison (Azer et al., 2024). All values are reported as means with standard deviations, and no inferential statistical testing was conducted.

Table 4. Descriptive Statistics of Modeled Engagement Metrics

Scenario	Fixation Duration (ms) Mean ± SD	Fixation Count Mean ± SD	Engagement Index Mean ± SD
S1	210 ± 32	11.4 ± 2.1	0.62 ± 0.08
S2	245 ± 28	13.2 ± 1.9	0.71 ± 0.07
S3	278 ± 30	15.6 ± 2.3	0.82 ± 0.06

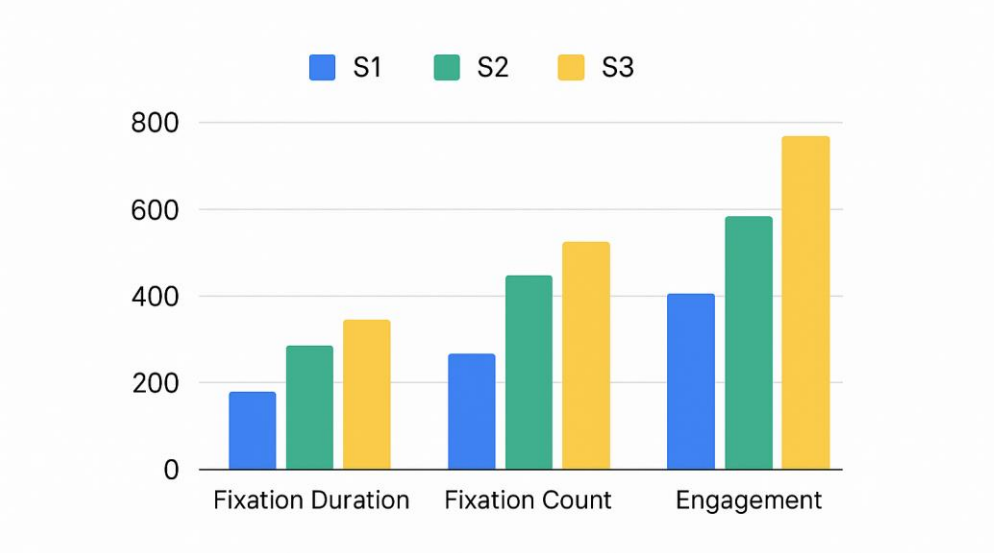

Figure 5. Metric Comparisons Across Collaboration Levels

The observed progression from S1 to S3 indicates higher average modeled fixation values associated with increased levels of human–AI collaboration. These results do not constitute statistical significance; rather, they reveal indicative patterns within simulated scenarios. The consistency of trends across multiple engagement metrics suggests potential benefits of adaptive typography in social media contexts, warranting further empirical validation using biological eye-tracking methods (Chelsea Sutanto et al., 2024). Thus, the findings are interpreted as exploratory rather than conclusive evidence.

DISCUSSION

The results of this study provide exploratory insights into the dynamics of human–AI collaboration in adaptive typographic design, rather than definitive claims about technological superiority. The observed differences across typographic scenarios suggest that collaborative interaction between human designers and AI systems may shape modeled visual attention patterns in ways that align with recent theoretical discussions on co-creativity and distributed cognition (Nguyen et al., 2024). Importantly, these findings do not imply that AI-driven design is inherently superior, but instead indicate that complementary competencies emerge through structured collaboration, echoing broader human–AI partnership research in other applied domains (Lai et al., 2021). From a design cognition perspective, this supports the view that creative outcomes often result from a negotiated agency between human judgment and computational exploration.

Across the simulated scenarios, the fully adaptive collaborative condition exhibited higher average modeled fixation duration, which may reflect a balance between typographic novelty and structural coherence. This balance is theoretically relevant, as research on visual cognition suggests that attention is more likely to be sustained when stimuli are neither overly predictable nor excessively unfamiliar (Mohapatra & Zayapragassarazan, 2021). Rather than interpreting this outcome as evidence of effectiveness in applied branding contexts, it should be understood as an indication of how adaptive variation can influence perceptual processing within controlled visual systems. Such findings contribute to an understanding of how design variables interact with attention mechanisms, without extending claims to user preference or behavioral intention.

From the standpoint of adaptive visual systems, the results reinforce the idea that iterative human–AI interaction can function as a regulation mechanism, moderating the extent of variation introduced by computational generation. In this configuration, AI contributes exploratory diversity, while human designers act as perceptual and contextual filters, selecting outputs that remain legible and coherent (Joseph & Murugesh, 2020). This interaction aligns with theories of human-in-the-loop systems, where creative control is distributed rather than delegated entirely to automation. Consequently, the observed attention patterns should be interpreted as emergent properties of collaborative system design, not as isolated effects of algorithmic generation.

The implications of these findings are therefore primarily theoretical rather than commercial. They suggest a reframing of AI in design practice from a productivity-oriented tool toward a cognitive partner within adaptive creative systems (Indrawati et al., 2025). The iterative cycles observed in this study illustrate how designers may increasingly engage in roles of constraint-setting, evaluation, and curation, complementing computational processes rather than replacing them. This perspective contributes to ongoing discourse on co-creativity, particularly within domains that rely on perceptual sensitivity and contextual judgment.

Although the study is situated within an Instagram-like visual environment, the discussion intentionally avoids claims about the effectiveness of branding or market performance. The simulated attention patterns should not be interpreted as predictors of audience response, commercial success, or return on investment. These findings should be interpreted as exploratory insights into collaborative design dynamics rather than predictive indicators of market performance. Instead, the contribution lies in demonstrating how attention-based evaluation frameworks can be integrated into adaptive design research, offering a controlled means of examining human–AI interaction in visual systems (Anialasalam et al., 2025; Jin et al., 2025).

Finally, the discussion highlights the importance of maintaining conceptual boundaries between modeled perceptual indicators and real-world outcomes. While adaptive typography has been theorized as a mechanism for responsiveness in digital environments, this study positions it as an object of investigation within human–AI co-creative theory rather than a guaranteed solution to engagement challenges. By emphasizing cognition, collaboration, and system adaptivity, the discussion remains aligned with the exploratory scope of the research and avoids advocacy-driven conclusions.

Several limitations must be acknowledged when interpreting the findings of this study. Although the simulation-based approach enabled controlled comparisons of typographic variations, it necessarily reduced real Instagram viewing behavior to abstract visual attention patterns. As a result, the ecological validity of the findings remains limited when compared to biological eye-tracking studies involving real participants (Jones et al., 2023). Individual differences, spontaneous gaze behavior, and unconscious visual responses often critical in service and branding research could only be approximated within the current modeling framework rather than directly observed (Azer et al., 2024).

The use of synthetic testing conditions further constrains the generalizability of the results. In real social media environments, user engagement is shaped by complex personal, social, and contextual factors that could not be fully incorporated into the simulation model (Chen et al., 2022). Moreover, by isolating typography as the primary design variable, the study did not account for interactions between typography, imagery, color, and layout that commonly characterize Instagram content and influence visual engagement patterns (Colombo et al., 2023). This analytical focus was intentionally adopted to maintain experimental control, but it inevitably limits the representational richness of real-world visual communication settings.

While eye-tracking-inspired metrics were employed to approximate visual attention (Wu et al., 2020), they could not fully capture the biological and cognitive subtleties of human perception that may influence branding outcomes. Physiological responses, emotional salience, and attentional fatigue remain outside the scope of the current simulation-based indicators. Nonetheless, the observed consistency across simulated metrics suggests that the identified patterns warrant further investigation using more sophisticated empirical techniques (Chelsea Sutanto et al., 2024; Doyle et al., 2022). These findings should therefore be viewed as indicative rather than confirmatory evidence of visual engagement dynamics.

Finally, the sample characteristics and cultural assumptions embedded in the model represent additional constraints. Visual preferences and engagement behaviors may vary significantly across demographic groups and cultural contexts, limiting the applicability of the findings beyond the modeled scenarios. Furthermore, the rapid evolution of AI technologies and social media platforms means that the present study captures only a temporal snapshot of a dynamic landscape. These limitations highlight the need for longitudinal, cross-cultural, and platform-diverse research to further validate and refine AI-assisted design evaluation frameworks.

CONCLUSION

This study explores human–AI collaboration in the context of Instagram branding through a simulation-based framework focusing on collaborative design processes, adaptive typography, and modeled visual engagement metrics. Rather than making predictive or performance-oriented claims, the proposed framework offers an exploratory methodological approach for assessing AI-assisted design outputs in relation to indicative human attention patterns. The primary contribution of this study is methodological, as it addresses common limitations in evaluating human–AI creative collaboration under controlled conditions (Fragiadakis et al., 2025). Conceptually, the framework positions artificial intelligence as an assistive component embedded within a human-in-the-loop design workflow, supporting a balanced understanding of creative agency in visual communication research (Song et al., 2024).

The findings suggest that AI-assisted typography may be meaningfully evaluated through simulation-based methods when direct empirical measurement is not feasible; however, these insights should be interpreted with caution given their modeled nature. Future research is required to validate the proposed framework using biological eye-tracking methods with real users to improve ecological validity (Falkowska et al., 2025). Additional studies may also extend the framework across different cultural contexts, platforms, and design domains to examine the generalizability of human–AI collaboration patterns. Overall, this study represents an initial step toward developing responsible and human-centered evaluation frameworks for AI-assisted visual communication, emphasizing the complementary roles of human judgment and computational support in design practice (Colombo et al., 2023).

AI Use and Ethics Disclosure

AI tools were used as assistive components within a human-guided design and simulation framework for generative assistance and computational modeling purposes. All conceptual decisions, experimental design, analytical procedures, interpretations of results, and conclusions remain the full responsibility of the authors, and the use of artificial intelligence did not replace human judgment. However, it supported exploratory design evaluation under controlled conditions. Potential sources of bias may arise from the datasets, modeling assumptions, and parameter settings employed in the simulation process, which were acknowledged and addressed through cautious interpretation of findings and explicit framing of results as exploratory rather than predictive. Ethical considerations related to AI-generated design outputs were taken into account, emphasizing transparency, accountability, and the responsible use of computational tools in accordance with current ethical standards for AI-assisted research in graphic design and visual communication.

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