Guided Creativity: AI Intermediation for Enhancing Originality and Quality in Visual Design

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Designers often improve the quality of their work by learning from others' successful designs. Yet this process can also trigger creative fixation, where exposure to exemplars constrains originality in subsequent work. This paper introduces AI intermediation, a novel approach that leverages generative models to overcome this challenge. Our approach generates variations of leading designs that preserve core semantic concepts while differing visually, and provides these variations to designers instead of the original exemplars. This allows communicating valuable insights and inspiring novel interpretations without inducing fixation. We empirically validate the proposed approach using field experiments involving professional designers in logo design contests. The results show that designers with AI intermediation produce (1) higher-quality work than those with no exposure to exemplars, and (2) more-original work than those directly exposed to exemplars. We further decompose the sources of creativity and demonstrate that, while the generative model yields distinct variations, human creativity remains pivotal in enhancing both originality and quality. Consequently, AI intermediation presents an efficient facilitator to human-driven creative process.

Keywords: Generative AI, Creativity, Ideation, Crowdsourcing, Aesthetic Design.

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1 Introduction

Good Artists Borrow, Great Artists Steal

Pablo Picasso

Learning from successful precedents is a fundamental approach to quality improvement and innovation across creative domains (Lidwell et al., 2010; Norman, 2013). Exposure to high-performing exemplars enables designers and organizations to discern effective strategies, align with evolving audience expectations, accelerate development by building on proven concepts, and raise baseline standards (Carpenter and Nakamoto, 1989; Cooper and Kleinschmidt, 1995; Von Hippel, 1986; Zhang et al., 2022). Many impactful innovations are not entirely novel, but rather creative reinterpretations or combinations of existing successful ideas. For organizations, Aerie built on the key message of Dove's Real Beauty campaign, yet forged a distinct brand identity that resonated well with its target audience (Maheshwari, 2016). Similarly, for individuals such as influencers, Ryan Trahan achieved massive success by studying MrBeast's viral content formats and adapting them with unique personal elements (Larner, 2022). These examples illustrate how inspiration drawn from success can be productively channeled into novel and successful creative outcomes.

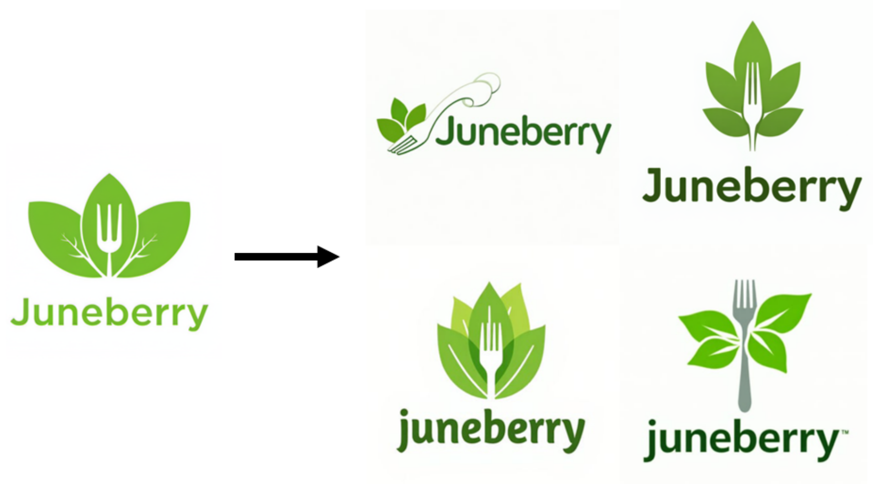
However, learning from successful examples carries an inherent risk: creative fixation, where exposure to specific solutions causes creators to inadvertently anchor on the superficial features of observed exemplars, diminishing the novelty and diversity of subsequent outputs (Berger and Heath, 2007; White and Argo, 2011). When creative fixation becomes widespread, the resulting homogenization can inflict significant damage. In the marketplace, this leads to visual saturation and audience fatigue, as initially distinctive concepts, such as Facebook's Corporate Memphis illustration style, become ubiquitous and lose their appeal (Huang, 2022). Strategically, visual convergence erodes the competitive advantage conferred by original designs, as pioneering brands see their unique identities diluted by look-alikes. This can lead to defensive legal measures, such as Oatly's lawsuits over packaging aesthetics and Apple's disputes with Samsung regarding "slavish copying" of design (BBC News, 2021; Reuters, 2011). Beyond these competitive concerns, creative fixation anchors designers to premature solutions instead of pursuing potentially superior alternatives in the broader design space, which limits brands' access to diverse stylistic options required for differentiation and customer appeal.

The challenge of balancing learning from successful exemplars against the risk of design fixation often occurs in internal design processes within organizations, but it is particularly acute in crowdsourcing contests (Burnap et al., 2023; Terwiesch and Xu, 2008; Jiang et al., 2022; Mihm and Schlapp, 2019). Open contests, which allow participants to view leading submissions, typically yield higher average submission quality (Wooten and Ulrich, 2017b; Zhang et al., 2019). However, this transparency leads to significant imitation and a loss of originality due to fixation on early successful entries (Erat and Krishnan, 2012; Kornish and Ulrich, 2011; Hofstetter et al., 2021; Koh and Cheung, 2022). In contrast, blind contests, which withhold peer submissions, tend to foster greater originality and broader exploration but may result in submissions of lower average quality as learning opportunities are eliminated. This poses an important question: Can mechanisms be developed to facilitate learning from successful designs while simultaneously mitigating the detrimental effects of fixation to preserve creative exploration?

We propose AI intermediation, an approach that disseminates high-quality design ideas by sharing design variations rather than the original exemplars. We use a generative model to create variations that preserve the core concepts from the original designs while making them visually distinct, thereby mitigating fixation when observed by other designers. The shared core concepts in these variations allow designers to learn from the best designs; the visual distinctions prevent direct replication and encourage creative adaptation. This approach contributes to research on human-AI collaboration by viewing the role of the generative model as facilitating information transmission between humans (designers in our context), rather than serving solely as a tool for individual augmentation.

We illustrate the design variations in Figure 1. The image on the left is the high-quality logo created by a professional designer ("original logo"), and we show four variations of this logo on the right side. All variations retain core elements (brand name, leaf and fork motifs) while differing in typography and specific rendering, providing visual distinctness. Designers can refine these variations or draw inspiration from them, though we show in our empirical application that they primarily serve as a source of inspiration, emphasizing the complementarity between designers' creativity and the generative model.

Figure 1: Illustrative Example of AI Variations



Notes: The original logo (left) for "Juneberry", featuring leaves and a fork, is transformed by our generative model into four distinct variations (right). These variations maintain core thematic elements (leaves, fork, natural and fresh aesthetic) while differing in specific arrangements.

Practical implementation of AI intermediation requires developing a specialized pipeline capable of generating high-quality variations. For our proof-of-concept application, we develop an approach that combines image-to-text models to textually describe the core elements of original designs and text-to-image models to create variations. We fine-tune the text-to-image model using a two-stage approach. First, the model learns foundational logo design principles through reconstructive training. The training involves a curated set of professionally designed logos from a leading design platform, so that the generated images resemble professional designs. In the second fine-tuning step, we guide the generative model toward well-performing logos and away from poorly performing ones. We calibrate the design quality using our survey-based measures of quality collected for about 100 logos.

The proposed generative model creates visually coherent logo variations that are semantically similar to the original logos but visually distinct. We achieve these goals by translating original logos into structured textual descriptions and then using the extracted descriptions to guide image generation. Intuitively, our approach recognizes that language is an imperfect medium for communicating visual designs. Textual descriptions are sufficiently precise to capture the core ideas from the original logo (alignment), but cannot fully articulate all visual details (distinctiveness).

To empirically evaluate the AI intermediation approach, we conduct a field experiment within a real-world logo design contest. The experiment involves over 200 professional designers recruited on a leading crowdsourcing platform. We randomize designers' access to logo exemplars in a creative brief across three treatment arms: Open, where designers view high-quality logos previously created for the focal brand; Blind, where designers view no logo exemplars; and Variation, where designers view AI variations of original logos, such as shown in Figure 1.

We characterize the impact of the different contest types on the quality and originality of submissions. Quality is the primary objective of business creative processes. In the logo contest setting, the quality of the logos is often judged by the client who sponsors the contest, and for many brands, the primary purpose of the logo is to attract consumers via online ads. As such, we evaluate quality using survey-based ratings on how well logos attract clicks in online ads. Our second metric, originality, indicates whether designers are exploring novel ideas rather than converging on the provided exemplars. To evaluate originality, we calculate perceptual and embedding-based distance measures between submitted logos and exemplars from the brief. Our originality scores focus on high-quality designs, to separate originality from the quality dimension, and to mimic the practical setting where clients choose aesthetics after the initial quality screening.

Our findings confirm that AI intermediation successfully transmits valuable information, leading to quality improvements over the blind condition, while spurring greater creative exploration resulting in higher originality for high-quality submissions compared to the open condition. The overall quality of designs from the variation condition is on par with the open condition, and both are about 10% higher than the blind condition. The originality of logo designs from the variation condition is on the same level as the blind condition and substantially higher than the open condition. For brands, this translates into access to a richer pool of high-quality, diverse solutions, increasing the likelihood of identifying designs that not only meet objective quality criteria but also satisfy subjective aesthetic preferences.

Do quality and originality improve because of the visual variations introduced by the model, or because the model's outputs inspire designers? Understanding which of these mechanisms is the driving force is important. If it is the former, brands could directly rely on the model outputs instead of the designers. If it is the latter, the observed improvements would highlight the continued importance of human designers and the power of human-AI collaboration. To address this question, we collected professional refinements for the AI variations. The refinements were conducted by the human designers and focused on removing artifacts of the generative model, with minimal changes to the semantic and stylistic elements.[1] We demonstrate that designers' best submissions from the variation condition were substantially more original and of higher quality than tightly refined AI variations. Thus, we conclude that human designers in the AI intermediation approach do not merely refine the variations. Instead, they leverage machine-generated concepts as springboards for significant creative leaps to achieve novel and distinct designs.

While our proof-of-concept focuses on logo design, the conceptual idea of AI intermediation applies more broadly to visual design settings where creativity is shaped by social learning. First, creative fixation is a pervasive challenge whenever people build on each

[1]We rely on refinements, as opposed to the direct model outputs themselves, since the variations can contain graphic imperfections. In order to ensure that these imperfections do not influence the results in the quality survey, we obtain the click rating for the refinements.

other's work. By deliberately introducing algorithmic variation, AI intermediation counters this tendency and helps sustain diversity in the design space. Second, concerns about AI-driven homogenization of creative outputs are increasingly prominent (Kleinberg and Raghavan, 2021; Castro et al., 2023; Anderson et al., 2024). Purely automated systems risk converging on stylistically similar solutions, undermining originality. In contrast, our framework preserves human agency: the generative model facilitates exchange of ideas, rather than replaces human creativity. Human judgment remains central in curating, refining, and building upon AI variations, and our findings show that this interplay is crucial to performance. More generally, AI intermediation offers a way to scale creative exploration in domains such as product aesthetics and packaging, advertising imagery, or web interface design, where human creativity and social learning are critical but could benefit from structured injections of variety.

The remainder of the paper proceeds as follows. Section 2 reviews relevant literature and positions our contribution. Section 3 introduces the generative pipeline, including the model overview and the fine-tuning procedures. Section 4 describes the experimental design and empirical findings from the field experiment. Section 5 replicates our main experiment with a brand from a different industry. This additional study demonstrates the robustness of our primary findings and evaluates performance gain with multiple, rather than single, AI variations per original exemplar. Finally, Section 6 summarizes the key insights from our study, explores broader managerial implications beyond logo design contexts, discusses limitations, and identifies avenues for future research.

2 Related Literature

The advancing capabilities of generative models have attracted growing research into their potential to augment human creativity. Studies have explored various modes of human-AI interaction, including generative models as an ideation partner, co-creator, or evaluation tool in settings such as story composition, advertisement creation, and artwork creation (De Freitas et al., 2025; Doshi and Hauser, 2024; Chen and Chan, 2024; Zhou and Lee, 2024). Findings show that iterative human-AI processes can often combine the strengths of humans and AI to outperform purely human or purely AI outcomes (Boussioux et al., 2024). These approaches generally focus on enhancing the creative output of an individual or a small, directly collaborating team.

These machine augmentation paradigms are being applied to solve business challenges. Scholars have used machine learning models to map brand attributes to visual logo characteristics for data-driven 'moodboarding', trained models for generating and screening automotive aesthetic designs, and demonstrated how machine-driven shape morphing can yield more market-attractive forms (Dew et al., 2022; Burnap et al., 2023; Chen et al., 2023). Similar to the broader machine-augmented creativity literature, these applications typically involve machines directly assisting a human designer or marketer in their creative tasks or decision-making processes, or using models to generate content that is then screened by humans (Heitmann et al., 2024). A complementary stream of findings suggests caution: prompting individuals with machine-generated exemplars can improve the creativity of individual outputs, but may lead to homogeneity at the group level (Ashkinaze et al., 2025; Holzner et al., 2025; Meincke et al., 2025).

Our work introduces a novel paradigm using generative models not merely for individual augmentation or direct co-creation, but as an intermediary to foster collective creativity. Our proposed AI intermediation operates by abstracting and diffusing the core conceptual elements of human submissions to other humans, transforming the original ideas into visually distinct variations. This mechanism aims to facilitate indirect social learning by communicating successful concepts across participants without triggering direct fixation, which is often caused by exposure to peer work. Therefore, our proposed approach addresses a different set of challenges related to the collaborative creative processes.

The theoretical foundation for AI intermediation stems from research on social learning, suggesting that abstracted exposure can mitigate the negative effects of direct observation. Research in psychology, design, and education has shown that direct exposure to existing solutions can lead to unconscious fixation, hindering the generation of diverse and novel ideas (Kohn and Smith, 2011). However, modifying the nature of exposure, such as through structured comparisons, curated examples, or partial copying, can preserve learning benefits while enhancing creative performance (Hofstetter et al., 2021). This principle resonates with concepts from optimization models that highlight the need to balance exploitation of known successes with exploration in the co-search process (Kennedy and Eberhart, 1995; Bratton and Kennedy, 2007). Our approach operationalizes this guided variation by automatically generating variants that share the same core concepts as the original design, encouraging generalization from core patterns rather than mimicry of specifics, and offering a scalable alternative to previous methods that require human supervision.

This learning-creativity tension that motivates our specific empirical setting is well-documented within crowdsourcing contests. Open contests, where participants view competitors' submissions and feedback, facilitate observational learning, leading to higher average quality but also causing imitation and reduced originality (Wooten and Ulrich, 2017a; Hofstetter et al., 2021; Koh and Cheung, 2022). Conversely, blind contests isolate designers, fostering broader exploration and novelty but potentially limiting quality improvement due to the absence of learning signals (Erat and Krishnan, 2012; Kornish and Ulrich, 2011). These findings suggest the difficulty of simultaneously improving submission quality via learning and improving submission originality via designer creativity within the traditional crowdsourcing approaches.

3 Generative Model for AI Variations

Before empirically testing the AI intermediation approach, we need a generative model to create variations. While powerful, current off-the-shelf solutions often struggle with following established stylistic principles and precise visual interpretation of design requirements. The introduced visual artifacts can confuse designers rather than effectively transmit successful design exemplars. We illustrate the challenges with current off-the-shelf models in Appendix B. In this section, we provide details about the construction and validation of our custom generative pipeline.

Recall that AI intermediation aims to enhance creative outcomes by facilitating learning from successful precedents while simultaneously mitigating fixation and fostering broader exploration. To achieve this, we focus on three properties for the generated variations: (i) semantic alignment with the original design, (ii) visual distinctiveness, and (iii) visual reasonableness. Semantic alignment ensures that the core, valuable ideas from successful submissions are effectively communicated to other designers, enabling learning and quality improvement. Visual distinctiveness introduces variation in the stylistic elements to prevent direct imitation of the original exemplar. Both criteria stack on top of visual reasonableness: the variations must look like reasonable logos, follow professional graphic design principles, and contain limited artifacts. This is essential for adoption; our focus groups with logo designers indicated a strong aversion to low-quality or overtly artificial outputs, which they deemed unlikely to provide meaningful inspiration.

Achieving these properties requires an automatic generation process capable of both nuanced understanding and controlled synthesis. To this end, we developed an integrated custom pipeline. The pipeline first focuses on extracting design concepts by translating original logos into structured textual descriptions. This step helps to isolate the semantic essence of a design from its specific visual rendering. Subsequently, these textual descriptions serve as prompts for a fine-tuned text-to-image (T2I) model that generates logo variations. We next detail the methodologies employed in each stage of our pipeline, including the specific fine-tuning techniques that improve variations to effectively serve in the AI intermediation approach.

3.1 Textual Description

The primary objective of the textual description stage is to accurately capture the original logo's core conceptual elements and format these concepts into structured prompts for the text-to-image generation. We construct structured logo descriptions using two complementary pieces: a brief summary that summarizes information from the creative brief and an open-form detailed description of the original exemplar generated by image captioning models.

The brief summary explicitly represents key logo attributes and nonvisual meta-information derived directly from the creative brief. Specifically, this part of the prompt includes contextual details such as the brand name, industry, and high-level styles, combined with visually salient features such as colors, typography, and composition. To facilitate efficient model learning, we employ standardized 'trigger words' (e.g., 'logo_style', 'symbol_color', etc). These trigger words explicitly delineate distinct logo features, guiding the model to establish systematic associations between textual descriptions and their corresponding visual outputs. For example, we show a brief summary of a logo from Figure 1 below:

LogoAI, white background, brand_name "Juneberry", industry restaurant, logo_style minimalist, modern, symbol_color green, white, font_color green

The open-form description complements structured prompts by capturing intricate visual-semantic details. To generate the nuanced narratives, we employ an off-the-shelf image captioning model, JoyCaption, which provides rich and holistic descriptions of visual arrangements and subtle stylistic nuances embedded within the logo (fpgaminer, 2025). Continuing the previous example, the description expands:

logo_object A minimalist logo featuring a white fork centered between green leaves with a twig-like branch. Below, the text "Juneberry" is written in a clean, green sans-serif font.

The open-form textual descriptions control the information flow from original exemplars to variations: The more information descriptions contain, the more perceptually similar variations are to the original exemplar. The structured descriptions we use capture core ideas of exemplars, yet are insufficient to articulate all visual details. We demonstrate this relationship in Appendix D.

We combine the brief summary and the description into a standardized textual prompt. The downstream T2I model is fine-tuned to generate logos using this prompt structure.

3.2 Generate Logos

To generate logo variations from structured textual descriptions, we fine-tune a pre-trained T2I model, FLUX.1-schnell, using Low-Rank Adaptation (LoRA) (Black Forest Labs, 2024; Hu et al., 2022). This approach begins with a state-of-the-art base model and progressively adapts its capabilities to the specific context in two stages. The first stage focuses on instilling foundational design principles to generate visually reasonable logos. The second stage further improves the model's capabilities by optimizing for a specific dimension of output quality (click attractiveness) using contrastive learning techniques. Both stages contribute to improving the model's interpretation of textual prompts.[2]

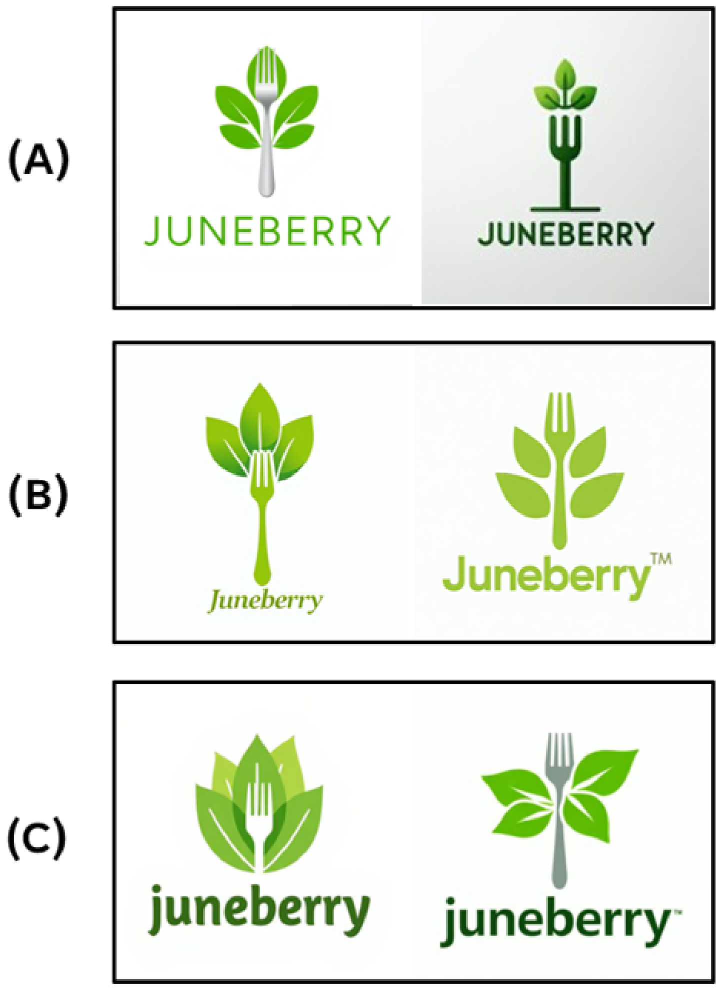
We conducted focus groups with professional logo designers to study their established design process and the value of machine-generated solutions. The interviews highlighted two issues: First, machine-generated logos often fail to follow graphic design conventions, sometimes rendering elements too realistically or with excessive complexity for logos. For example, in Figure 2(A) (left), the fork appears overly realistic for a logo design, and there is insufficient contrast between the color of the forks and the leaves. Second, these models can exhibit strong stylistic biases, such as the "clip art" tendency of DALL-E 3 shown in Figure 2(A) (right), which produces outputs that appear generic and unprofessional. We provide additional examples of critical stylistic artifacts in Appendix B. These stylistic artifacts lower the logo quality, and are so frequent in current off-the-shelf models that designers cannot efficiently learn and iterate on ideas from the produced variations.

The fine-tuning is designed to address these challenges. The initial Logo LoRA (Sec-

[2] In Appendix B we conduct a survey experiment showing that our proposed generative model pipeline outperforms FLUX.1-schnell image-to-image generation in producing more visually distinctive logos.

tion 3.2.1) directly addresses the challenge of instilling domain-specific knowledge and trains the model to generate visually reasonable logos that align with detailed textual prompts. The Logo LoRA helps ensure that the generated logos are not only relevant to the original concepts but also adhere to established design aesthetics. The subsequent Optimization LoRA (Section 3.2.2) further elevates the generative performance by learning from survey-based preference data on click attractiveness.

Figure 2: Logos Generated by Different Models



Notes: This figure shows AI variations generated by different models using the same prompt: (A)Left logo is generated by DALLE 3; Right logo is generated by FLUX.1-schnell; (B) outputs by pre-trained model + Logo LoRA; (C) outputs by pre-trained model + Logo LoRA + Optimization LoRA.

3.2.1 Logo LoRA

We first train the model to reproduce the graphic design conventions and various styles in logos. To do this, we curate a large dataset of professionally-designed logos and train the model to recreate these logos based on their textual descriptions.

Data. We acquired data from a crowdsourcing design platform to create a specialized training set for this fine-tuning stage. Focusing on the restaurant industry as a proof-of-concept, we curated this dataset from past contest data, implementing several screening criteria to enhance training feasibility and mitigate the impact of low-quality images. At the contest level, we excluded contests requiring taglines or non-English brand names, given the known challenges of training accurate text generation with diffusion models. At the logo level, we removed images with low resolution and noisy backgrounds (e.g., logos on business cards). This screening process produced approximately 1,000 contests, from which we allocated 90% for the training set and 10% for hold-out validation; the training set included about 25,000 logo images.

Fine-Tuning. We adopt a LoRA approach (Hu et al., 2022), a widely used technique for fine-tuning large models for specific applications. LoRA constrains the model training to a small subset of parameters, thereby retaining the original capabilities of the base model while adapting it to the specific task of logo generation. This approach is computationally efficient and ensures that the fine-tuned model can still remember concepts from the base model for logo generation. For example, if the fine-tuning logo dataset contains no examples with birds but the base model possesses prior knowledge of what a bird looks like, the fine-tuned model can still produce a visually coherent bird-themed logo.

During training, we finetune both the text encoder and the denoising network. The text encoder processes the structured textual prompt and converts it into an embedding that guides the image generation. We fine-tune the text encoder to help the model learn the trigger words introduced in Section 3.1. The denoising network is the primary image generator. It takes text embedding as a condition and learns to synthesize a logo that visually reflects the prompt.[3]

We illustrate the outputs from the Logo LoRA in Figure 2(B). Compared to the outputs of off-the-shelf models, the outputs are more aligned with professionally designed logos from the crowdsourcing platform: they follow design principles better.

3.2.2 Optimization LoRA

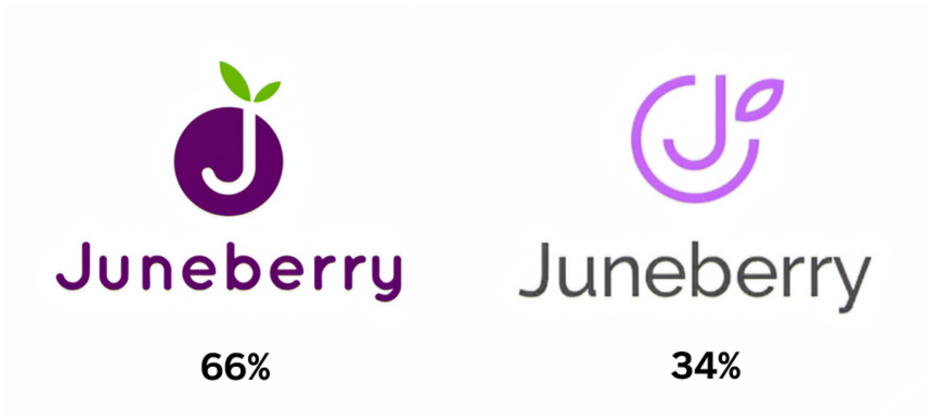
In the Logo LoRA, we train the model to reconstruct professionally-designed logos. One challenge is that even within the curated set, there still exists variation in quality, and the model could be further improved if we train the model to yield more high-quality examples and avoid low-quality examples. In our proof-of-concept, we define the logo quality by how well it can attract clicks in display ads. Online advertising is a common use case for brand logos among small businesses. Our findings can be extended to other quality dimensions, such as visual appeal, brand perceptions, or memorability.

Data. We measure click attractiveness using an online survey. We first select 50 pairs of logos from contests of restaurant brands in our training data. These 50 pairs are selected so that they feature similar semantic concepts (such as a fork and green leaves), but they are visually different designs. One illustrative example is shown in Figure 3. Each survey participant reviewed 25 logo pairs, and for each pair, indicated which logo they are more likely to click on in an online advertisement. We recruited 100 participants so that each pair receives 50 responses.

We assume that holding semantic logo attributes fixed, visual patterns not captured in the attributes can drive a logo to be more or less click-attractive. In Appendix E, we compare the visual characteristics of the high-quality and low-quality logos (Liu et al., 2020; Zhang et al., 2022). The color brightness and symmetry of the logos are significantly different between the groups. This observation aligns with previous research that symmetric logos are perceived to be more preferable and that brightness shapes perceived organizational orientation that

[3]Appendix C provides additional details about LoRA and latent diffusion models.

Figure 3: Illustrative Pairs for Optimization LoRA Training



Notes: This figure shows an example of the logo pairs used in the training of the Optimization LoRA. The two logos are similar in their composition and style. However, the left logo has substantially higher click attractiveness (66%) than the right logo (34%)

could interact with perception of restaurant brands, and this could contribute to higher click attractiveness (Luffarelli et al., 2019).

Fine-Tuning. To capture the visual patterns of logos with higher click attractiveness and further align the image generation with logo design conventions, we use a separate LoRA with a contrastive loss (see details in Appendix C). The fine-tuning is constructed in a manner that for each pair of logos, the model learns to generate logos similar to the logo that performs better (higher click attractiveness) and different from the logo that performs worse. We illustrate variations generated by adding the Optimization LoRA to the Logo LoRA in Figure 2(C).

3.3 Generative Pipeline Validation

We conducted extensive validation to demonstrate that the proposed generative pipeline yields reasonable logos that are semantically aligned with the original logo exemplars and visually distinct. First, we use a survey experiment to validate that logo variations are viewed as being more similar to the source exemplars compared to the most similar other logos in the design contest from which they were sourced. Second, we show that Optimization LoRA systematically increases the color brightness and symmetry in outputs. These characteristics are correlated with higher click attractiveness. Third, since the generative pipeline can produce logos that have some distortions (e.g., typos or minor graphic imperfections), we conduct a survey experiment where we induce artificial distortions to original logos. We show that, while the distortions have some negative impacts on perception, they are not dramatic, and even logos with minor distortions still convey meaningful information. We provide the full details on these studies in Appendix E.

4 Field Experiment

To empirically test whether AI intermediation can effectively facilitate learning across designers while avoiding creating fixation, we conduct a field experiment. The field experiment is implemented within a logo design contest, where we hired professional designers from freelancer.com. Specifically, we compare the performance of designers under AI intermediation to that of designers in two traditional types of contests: the open condition with full exposure to exemplars and the blind condition with no provided exemplars.

The open and blind benchmarks represent the two poles of the learning-creativity tradeoff: the open condition often yields higher logo quality at the expense of lower originality, due to creative fixation. In contrast, the blind condition can lead to higher originality but lower quality, as designers are not learning from each other. The proposed variation condition is designed to strike a balance between these extremes. We hypothesize that AI intermediation can effectively 'perturb' signals of success; the variations are close enough to communicate valuable core concepts (improving quality over the blind condition), yet visually distinct enough to mitigate the strong convergent pull that causes fixation (boosting originality over the open condition).

4.1 Study Design

The core of our experiment involves manipulating designers' access to a curated set of 60 logo exemplars for a small business restaurant. These logo exemplars were collected by the focal restaurant four years prior to our research, and received varying click attractiveness scores in our online survey, and thus spanning the quality spectrum. We manipulated whether these exemplars are provided to professional designers as an inspiration to create a *new* logo for the same restaurant in a crowdsourcing design contest. The crowdsourcing design contest had a typical contest prize of $250 to incentivize participation by experienced designers.[4]

Participants were randomly assigned to one of three experimental conditions:

- Open condition: Designers viewed the contest brief alongside a gallery displaying the 60 pre-seeded exemplars and their click-attractiveness rating.
- Variation condition: Designers viewed the brief and a gallery presenting four AI variations (created by our model) for each of the 60 pre-seeded exemplars, alongside the original exemplars' ratings.
- Blind condition: Designers received only the contest brief, with no access to pre-seeded exemplars or their variations.

For open and variation conditions, the exemplars (or their variations) are ranked by their click attractiveness and presented on 5 pages, with 12 exemplars (or 48 variations for 12 exemplars) presented on each page.[5]

We illustrate the experimental conditions in Figure 4. All participants can view the creative brief, which includes information about the restaurant brand and a textual description of client preferences. Additionally, in the open condition, the participants could view the

[4] The focal restaurant obtained the initial logos in a private crowdsourcing design contest in 2021. These logos are not public to web search, thus designers in our study have no external access to logo exemplars unless provided by us. The focal brand was also not included in the training of the generative pipeline in Section 3.

[5] In Section 5, we conduct a follow-up study that highlights that the results do not qualitatively change if we use a single variation instead of four per exemplar.

60 logo exemplars, and in the variation condition, we displayed 4 variations for each of the exemplars (without showing the original logos). The logo exemplars were organized across five gallery pages according to their click attractiveness. Access to the galleries is restricted to assigned designers based on their designer IDs. Designers in the variation and blind conditions have no access to these original logos. Designers were informed that the goal was to create logos effective at attracting clicks in online display ads, and for the open and variation conditions, that the gallery ratings reflected the click-attractiveness.

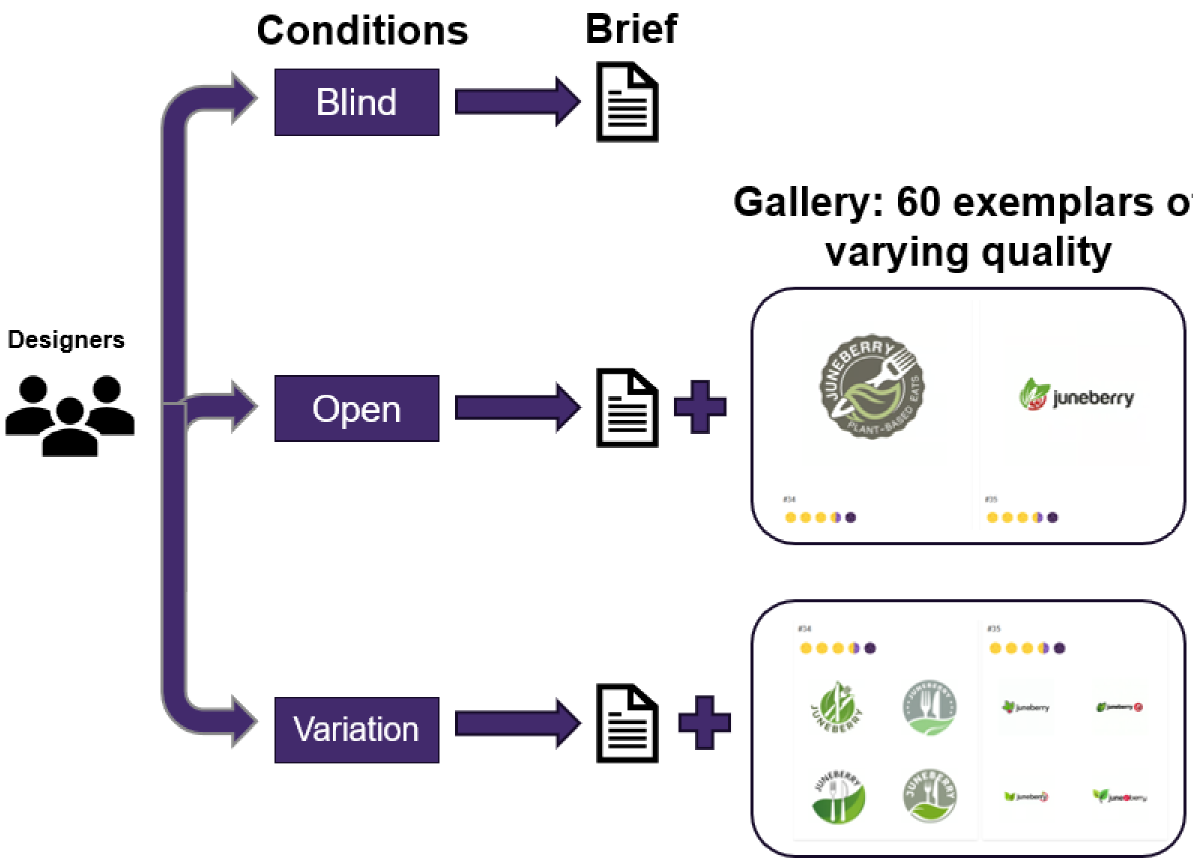
The use of a gallery of logos within a brief balances the realism and methodological rigor. First, our study design follows the standard industry practice of including inspirational examples within a creative brief. Clients often provide examples of their favorite logos to indicate stylistic preferences. These examples can include internationally recognized brands such as BMW or Lacoste. Our study extends this idea by leveraging high-quality exemplars for the client's brand. Second, by providing a fixed set of exemplars from the outset, we ensure that every designer, regardless of when they join, operates within a consistent and controlled informational environment. This contrasts with traditional open contests, where designs are typically shown as they are submitted to the platform.

The contest ran for seven days and followed typical specifications on the platform. To simulate realistic client feedback (ratings) during the contest, we randomly sampled 10 new submissions daily from each condition and provided ratings to designers. These ratings were sent through the platform in private messages, so that each designer could only see the rating for their own work if it was among the sampled submissions.[6] We ensured that designers remained unable to observe any information about other designers' submissions during the contest.

A total of 485 designers registered for the experiment, with 208 designers submitting at least one logo (Table 1). These participants were roughly equally distributed across the three

[6]To collect these ratings, we measured click attractiveness using online survey, similar to Study 2 in Appendix E. To ensure comparability, we benchmark the designers' submission to the original exemplars from the brief.

Figure 4: Experiment Design



Notes: This figure illustrates the three treatment arms that correspond to the three types of design contests in the experiment. Upon registration, designers are randomized into three conditions: designers in the blind condition observe the textual creative brief; designers in the open condition observe the textual brief and a gallery that presents 60 exemplars with corresponding quality measures; designers in the variation condition observe the textual brief and AI variations generated by our pipeline using the same 60 exemplars as in the open condition. For each exemplar, designers observe 4 variations and the quality rating of the original exemplar.

conditions. While the blind condition showed a slightly higher participation ratio among registered designers, this difference was not substantial compared to the variation condition, suggesting that any unfamiliarity with the variation condition did not significantly deter participation.

Table 1: Participants across Different Conditions

Condition	**Registered designers**	**Participating designers**	**Submissions**
Open	155	65 (41.9% of registered)	319
Variation	161	64 (39.8% of registered)	367
Blind	169	79 (46.7% of registered)	341

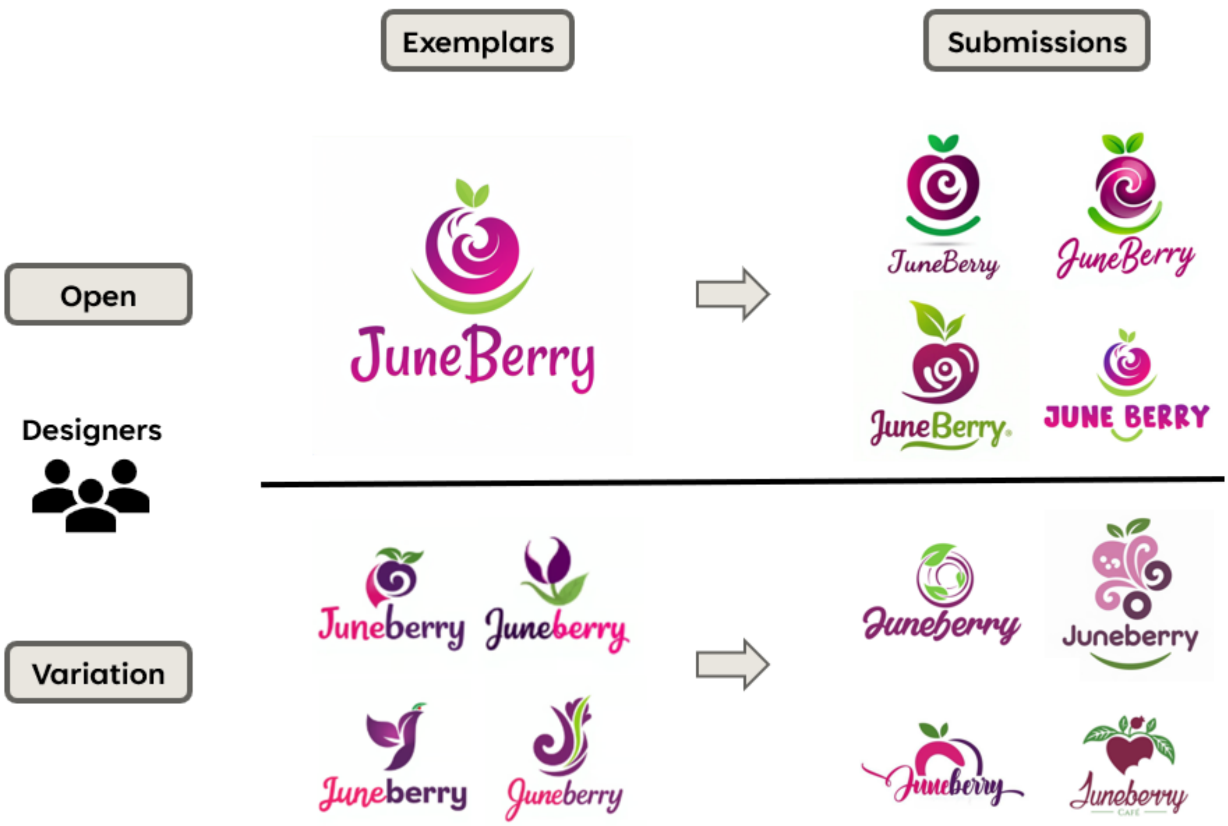
Notes: This table reports the sample sizes in different experimental conditions. Registered designers refer to those having viewed the contest information and creative brief. Registered designers are not required to participate in the contest. We define "participating designers" as designers submitting at least one design.

To characterize the participating designers and validate the randomization, we collected designer-level variables representing their experience and expertise from platform data. In Appendix F, we provide the variable definitions and descriptive statistics. Participating designers had high client ratings and substantial experience, with an average of over 20 completed projects. Balance checks on the designer attributes across the three conditions reveal no notable differences. Similarly, checks on participation patterns, including submission depth, entry timing, and continuous engagement, showed no substantial differences across conditions. This suggests the experiment was conducted with experienced designers under comparable conditions, allowing for a robust test of AI intermediation.

4.2 Originality

Recall that one primary objective of AI intermediation is to mitigate creative fixation and foster greater originality compared to direct exposure. Figure 5 provides an illustrative example of creative fixation. In the open condition, designers submit multiple adaptations of a leading design: the submissions closely resemble the original exemplar with minimal changes to the semantic elements and typography. In contrast, presented with AI variations that are visually different from the original exemplar, designers in the variation condition create more varied design explorations, suggesting a broader diffusion of the core idea.

Figure 5: Diffusion of Leading Ideas in Open and Variation Conditions



Notes: This figure shows an example of creative fixation in the open condition, and how leading designs get "diffused" to more original designs in the variation condition. The upper panel shows one leading exemplar designers of the open condition observe and subsequent submissions sharing close similarity to the exemplar. The lower panel shows AI variations of the same leading exemplar designers of the variation condition observe and the subsequent submissions sharing close similarity to the exemplar.

We investigate the "incremental originality" of submissions, defined as their distinctness from their most similar leading exemplars. We measure incremental originality using two complementary approaches: a scalable, embedding-based metric and a perception-based metric derived from human evaluations (Liu et al., 2020; Burnap et al., 2023; Compiani et al., 2025).

Embedding-Based Originality. We use a pre-trained CLIP model to extract embeddings for all submissions and the 12 leading exemplars displayed on the first page of the gallery(LAION, 2022).[7] CLIP captures both visual and conceptual information (Radford et al., 2021). The embedding-based originality of each submitted logo i is calculated as its minimum cosine distance to the 12 leading exemplars:

$$\text{Originality Emb}_i = \min_{i' \in \text{Leading Exemplars}} \frac{e_i \cdot e_{i'}}{|e_i| * |e_{i'}|}$$

Perception-Based Originality. We collected perceived similarity ratings between the submitted logos and leading exemplars on three dimensions: color palette, composition, and style. These dimensions are salient logo characteristics that appear in creative briefs and are important in logo evaluation (Dew et al., 2022; Henderson and Cote, 1998). For each pair of logos and each dimension, 15 survey participants evaluated similarity using a 7-point Likert scale. The three dimensions are highly correlated ($\rho_{color,composition} = 0.826$; $\rho_{color,style} = 0.855$; $\rho_{composition,style} = 0.944$), and Principal Component Analysis suggests a common factor explaining 90.8% of variation. We thus use the mean over these three dimensions to define the perception-based originality score for each submitted logo i:

$$\text{Perceived Originality}_i = \min_{i' \in \text{Leading Exemplars}} AVG(\Delta\text{Color}_{i,i'}, \Delta\text{Style}_{i,i'}, \Delta\text{Composition}_{i,i'})$$

We then conducted a regression analysis at the submission level, clustering standard errors at the designer level to account for multiple submissions from the same participant:

$$\text{Originality}_i = \sum_{c=1,2,3}^{C} \beta_c \mathbf{1}[\text{Cond}_{d(i)} = c] + \gamma \text{Day}_i + \delta^T X_{d(i)} + \epsilon_i \quad (1)$$

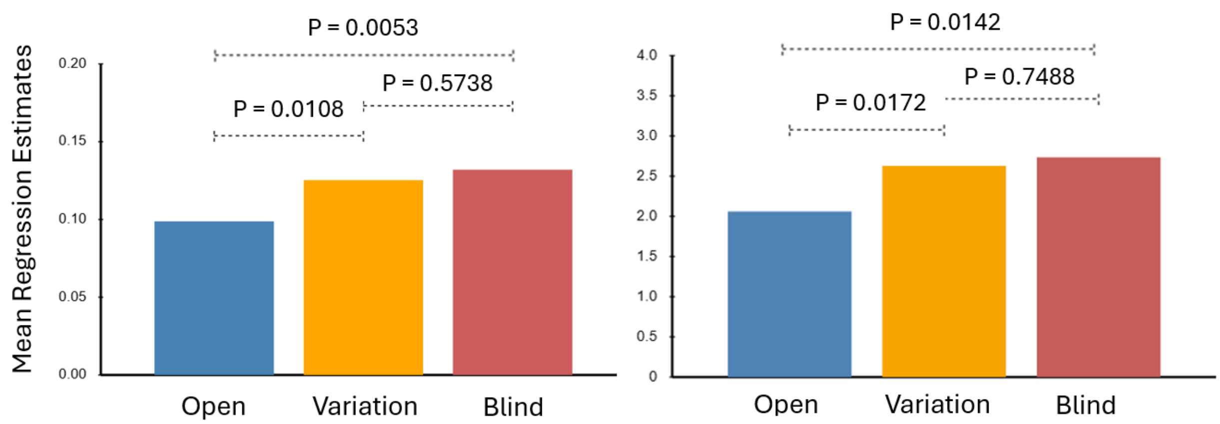
$$\epsilon_i = \eta_{d(i)} + \omega_i \quad (2)$$

[7] We focus on the first page because designers typically refer to top-rated logos to understand client preferences, and our gallery data shows most visits occur on the first page.

where $Originality_i$ represents the embedding or perception-based originality of submission; β_c corresponds to the 3 factors for Open, Blind, and Variation conditions; Day_i is the date on which i is submitted; $d(i)$ is the designer creating i; and $X_{d(i)}$ represents the designer $d(i)$'s performance characteristics from the randomization checks.

Figure 6 summarizes differences in the embeddings-based and perception-based originality measures across the experimental conditions. We provide the estimated coefficients in Appendix F. In Figure 6, we focus on on the top-50 submissions with the highest quality ratings in each group. We consider these submissions to align with the business objective, as brands typically select aesthetically appealing designs from a pool of high-quality options. [8] For both originality measures, the variation condition substantially outperforms the open condition, reaching levels similar to the blind condition($\Delta^{emb}_{open,variation} = -0.027, p = 0.011$; $\Delta^{emb}_{variation,blind} = -0.008, p = 0.574$; $\Delta^{perceived}_{open,variation} = -0.569, p = 0.016$; $\Delta^{perceived}_{variation,blind} = -0.106, p = 0.749$).

Figure 6: Mean Regression Estimates on Submission Originality across Conditions



Notes: This figure shows the condition estimates from specification 1. The left panel shows the estimates for embedding-based originality, and the right panel shows the estimates for perception-based originality. P-values are for the contrasts between condition estimates.

These results confirm that AI intermediation successfully mitigates creative fixation, enabling designers to produce more original high-quality submissions compared to direct

[8] In Appendix F, we replicate the analysis of the originality scores and demonstrate that our main findings are robust to different definitions of high-quality designs.

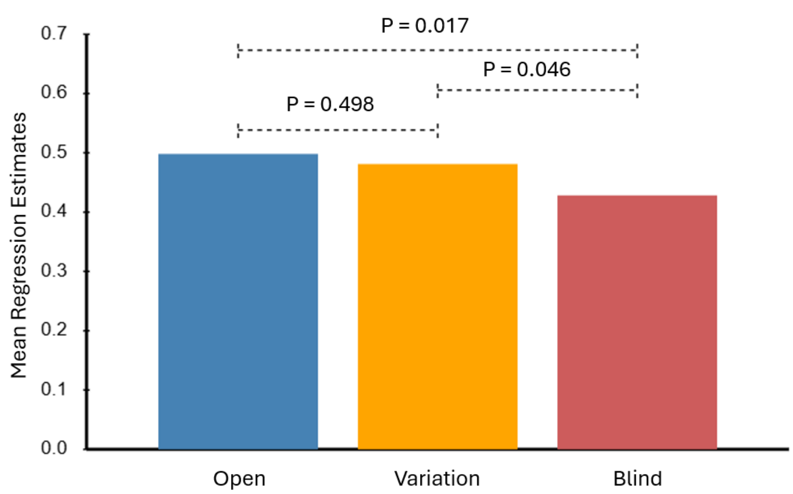
exposure to leading exemplars. The similar level of originality between submissions from variation and blind conditions suggests that the mitigation is as effective as not showing any exemplar information to designers.

4.3 Quality

Having established that AI intermediation enhances originality compared to directly sharing the examplars among designers, we next examine whether this increased creativity comes at the cost of submission quality.

To assess the impact on average submission quality, we conducted a similar regression as in the originality analysis. We provide the estimated coefficients in Appendix F. Pairwise contrasts in estimated coefficients in Figure 7 reveal that the AI Intermediation (Variation) condition significantly outperformed the blind condition, yielding a 5.5% average increase in click attractiveness ($\Delta^{click}_{variation,blind} = 0.053, p = 0.046$). The performance of the variation condition was comparable to that of the open condition ($\Delta^{click}_{open,variation} = 0.017, p = 0.498$). These results suggest that variations effectively transmit valuable information from leading designs, facilitating a level of learning and quality improvement similar to direct exposure.

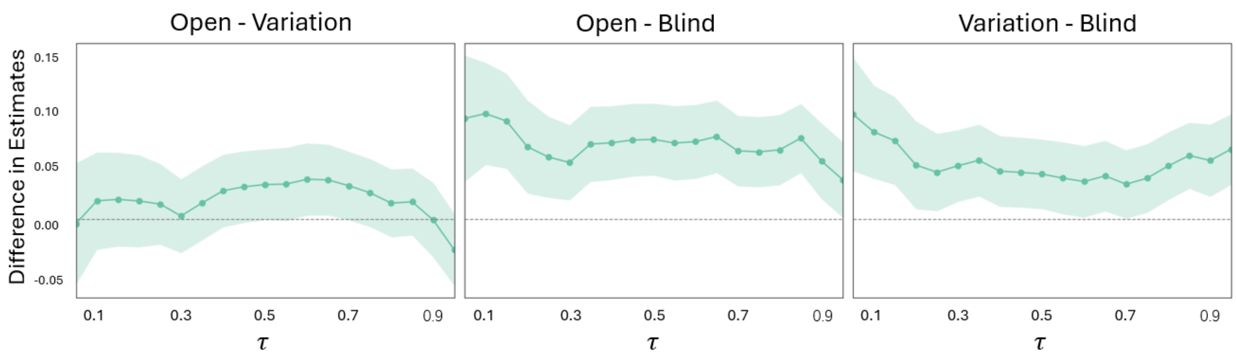
Figure 7: Mean Regression Estimates of Click Attractiveness



Notes: This figure shows the condition estimates from specification 1, with click attractiveness being the dependent variable. P-values are for the contrasts between condition estimates.

In Appendix F, we investigate whether AI intermediation improves the quality of top designs using a quantile regression. Figure 8 presents the contrasts between condition factors. On the x-axis, we report the submission quality quantile τ. On the y-axis, we show the difference in estimated coefficients for different experimental conditions. The variation condition consistently outperforms the blind condition by 5% to 7.5%. Comparing the open condition and the variation condition, the open condition has a thin performance edge for medium τ. Otherwise, these experimental conditions yield similar performance.

Figure 8: Quantile Regression Estimates of Click Attractiveness across Conditions



Notes: This figure shows contrasts of condition estimates with 95% CI. The panels, from the left to the right, show: the difference in quality estimates between the open and the variation conditions; the difference in quality estimates between the open and the blind conditions; the difference in quality estimates between the variation and the blind conditions. The estimates are from quantile regression under specification 1, with click attractiveness being the dependent variable. On each panel, the y-axis shows the difference in estimates, and the x-axis shows the quantile level(τ).

In summary, AI intermediation not only enhances originality but also maintains high submission quality, achieving performance levels on par with full exposure while significantly outperforming the blind condition. This indicates that the learning benefits derived from observing leading exemplars are largely preserved in AI variations, demonstrating that increased creativity does not come at the expense of quality.

4.4 Relative Contribution in Human-AI Co-Creation

Recall that under the AI intermediation approach, the generative model produces visually distinct design variations, which human designers use as an inspiration in their creative process. We next investigate the relative contribution of AI variations versus the subsequent human effort to the performance gains.

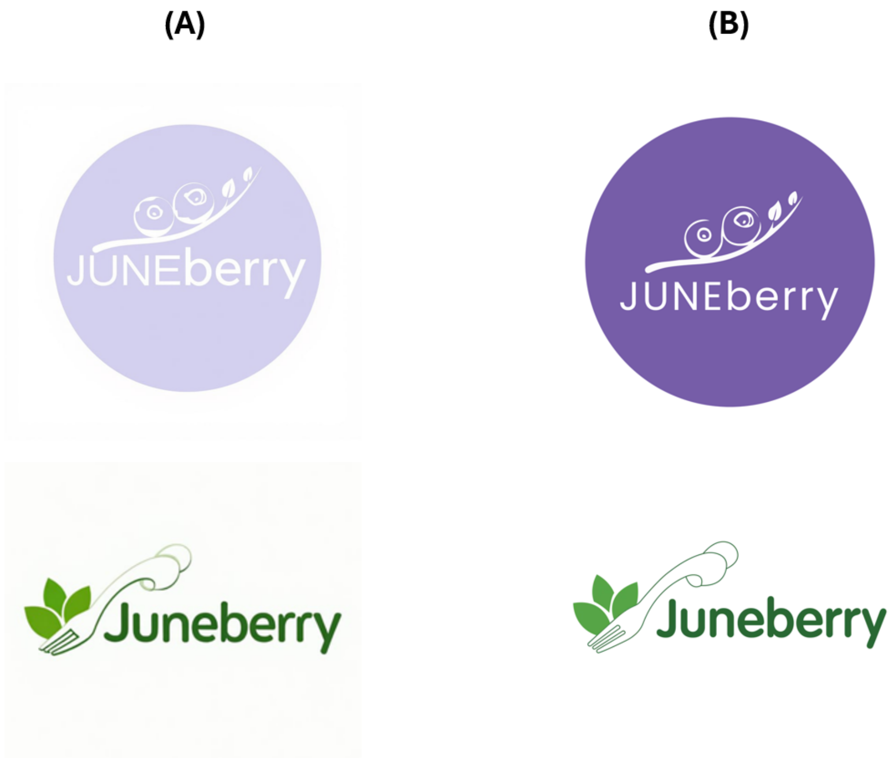
To understand how much value human creativity adds beyond machine-generated designs, we need a baseline that represents what AI variations could achieve with minimal human intervention. We thus recruited professional designers to create refined variations: AI variations that are polished by human designers to a ready-to-use state with minimal modifications to the stylistic and semantic elements. The refined variations also serve as a proxy for outputs by highly capable future generative models.

We collected refined variations of all 48 AI variations that appeared on the front page of the brief in the variation condition (Section 4.1). We provide two examples of the refined variations in Figure 9: Refined logos (Column B) tightly follow their corresponding AI variations (Column A). Designers implement minor changes to align logos more closely with graphic design principles, such as improving the color contrast, cleaning the lines, and using standardized fonts.

We validated that the refined images closely follow the initial AI variations using CLIP-based embeddings. The embedding-based originality scores for the refined images have 0.992 correlation with the originality scores of the variations (Figure F.7). This confirms minimal conceptual deviation during refinement. On the other hand, human refinement leads to an improvement in design quality (click attractiveness; mean difference = 0.05, SE = 0.009, t = -5.535, $p < 0.001$). This suggests that there is still potential to further improve the generative capacity of the model proposed in Section 3.

Quality. Figure 10(A) compares the click attractiveness of the refined variations to high-quality submissions from the variation condition (top 50 in quality ratings). We focus on high-quality submissions because refined variations are based on leading exemplars and a fair comparison will be against leading human designs. High-quality submissions from the variation condition demonstrate substantially higher quality than refined variations ($\Delta^{click} = 0.200$, $SE = 0.018$, $t = 10.891$, $p < 0.001$). This suggests that professional designers can

Figure 9: Examples of Refined Variations



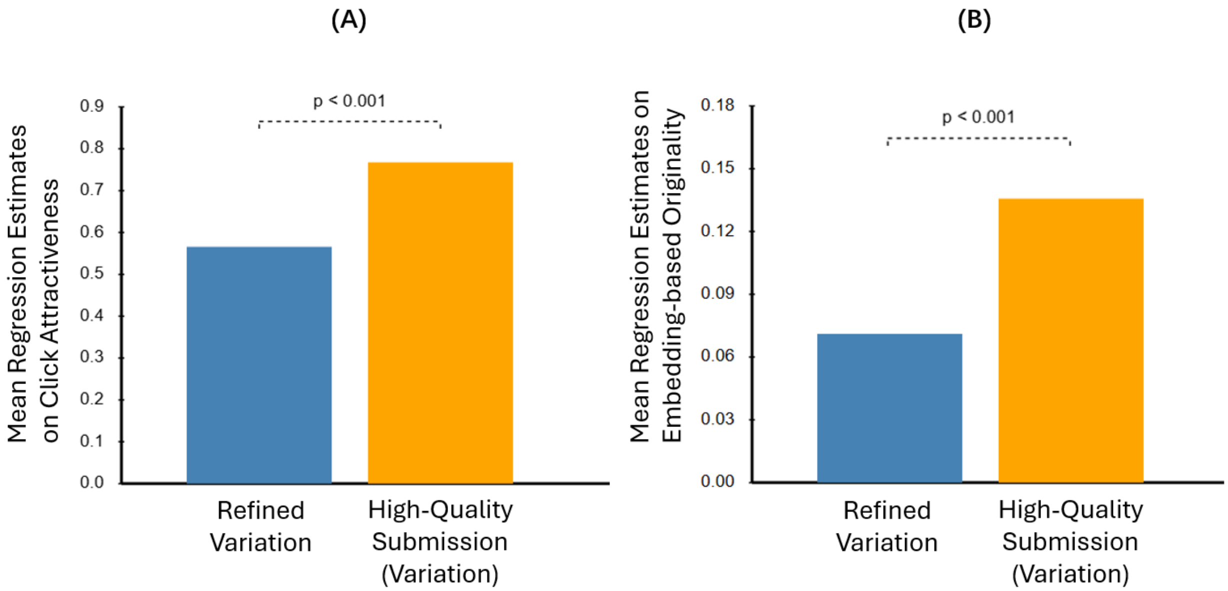
Notes: This figure shows two examples of refined variations. Column (A) shows two machine-generated logos; Column (B) shows the corresponding human-refined versions.

introduce substantial improvements in quality beyond a pure refinement of the AI designs.

Originality. Figure 10(B) conducts the same comparison on embedding-based originality. High-quality submissions from the variation condition demonstrate substantially higher originality than refined variations ($\Delta^{originality} = 0.063,\ SE = 0.011,\ t = 5.796,\ p < 0.001$), indicating that designers use AI variations as creative springboards to explore broader design spaces rather than simply refining AI output.

Our findings highlight the synergistic contributions of the AI variations and human designers. While advancements in generative modeling can provide increasingly polished design concepts potentially reaching the quality of refined variations, as of today, human creative intervention remains crucial for exceeding baseline machine capabilities and achieving truly novel outcomes. Human designers do not merely polish designs, but introduce creative ideas

Figure 10: Mean Regression Estimates of Click Attractiveness and Originality of Refined Variations and High-Quality Submissions of Variation Condition



Notes: This figure compares refined variations to the high-quality submissions in the variation condition. The left panel shows regression estimates for click attractiveness; The right panel shows estimates for embedding-based originality. P-values are for the contrasts between condition estimates.

to improve both originality and quality in the visual design process.

5 Additional Application: Healthcare Logos

In this section, we conduct a replication study for our main experiment using a brand from a different industry. This additional study helps us evaluate robustness of our main findings by focusing on the healthcare industry, which has more standardized logo design conventions than restaurants. The second purpose for this study is to investigate whether the number of exemplars in the variation condition matters to performance. Recall that in Section 4, designers in the variation condition observed four variations for each exemplar to help designers learn the most successful design decisions by comparing variations. This experimental design leaves the question of whether the difference in originality between the variation and open conditions is driven by the creative differences introduced by the generative model, or merely by designers observing four times more logo examples in the variation condition. To study this question and better understand the application scope of AI intermediation, the experiment in this section includes an experimental condition with a single variation per original exemplar in the AI intermediation condition.

Study Design. In the additional application, we closely follow the experimental design from Section 4. We conduct a logo design contest for a healthcare brand with four conditions: *Open* (full exposure to 60 rated exemplars of varying quality), *Blind* (no exemplar exposure), *Variation(4)* (exposure to four variations per exemplar), and *Variation(1)* (exposure to a single variation per exemplar). The one variation presented in the *Variation(1)* condition is randomly sampled from the four variations presented in the *Variation(4)* condition.

We follow the same designer recruitment process and contest settings as in the main experiment. The only difference is that we extend the contest to two weeks for this experiment to gather more samples due to the additional treatment arm.

We report the participation statistics in Table 2. A total of 440 designers registered for the design contest, with 292 designers submitting at least one logo. These participants were roughly equally distributed across the four conditions. Together, we gather 2199 submissions. For the randomization check, again, we collect designer demographics and present the results in Appendix 5. There are no significant differences in participation or demographics between conditions.

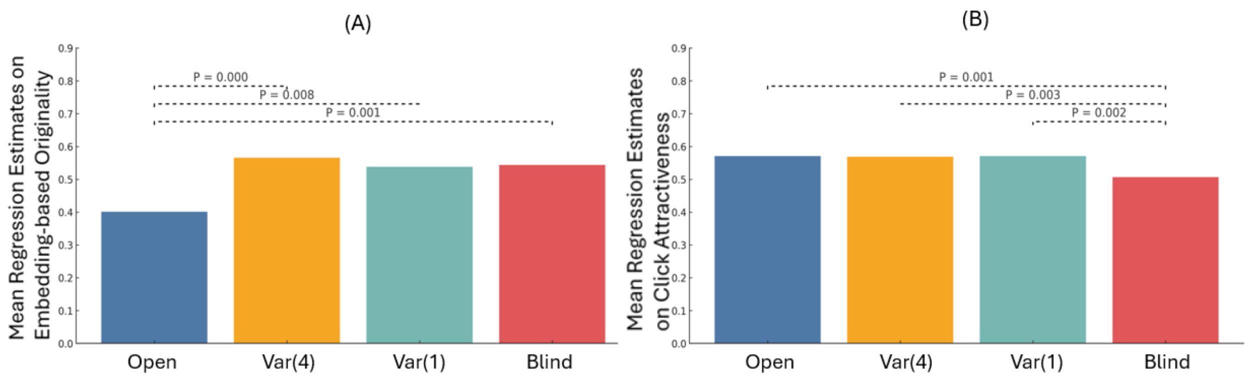
Table 2: Participants across Different Conditions

Condition	**Registered designers**	**Participating designers**	**Submissions**
Open	105	70 (66.7% of registered)	499
Variation(4)	120	76 (63.3% of registered)	550
Variation(1)	105	71 (67.6% of registered)	575
Blind	110	75 (68.2% of registered)	575

Notes: This table reports the sample sizes across experimental conditions. Registered designers refer to those having viewed the contest information and creative brief. Registered designers are not required to participate in the contest. We define "participating designers" as designers submitting at least one design.

Results: Originality. We use the same embedding-based method to measure originality. Figure 11 (A) shows the regression estimates on high-quality submission originality (Top 50 submissions in quality per condition) across conditions.[9] The results are consistent with our findings in the previous experiment: the variation(4) and blind conditions have higher originality than the open condition. Moreover, the variation(1) condition also demonstrates higher originality than the open condition. Although the variation(4) condition achieves slightly higher originality than the variation(1) condition, the difference is not statistically significant. This shows that AI intermediation can alleviate creative fixation on exemplars, largely independent of the number of variations designers observe.

Figure 11: Additional Application: Mean Regression Estimates of Submission Originality and Quality



Notes: This figure shows the condition estimates under specification 1. The left panel shows estimates for click attractiveness; The right panel shows estimates for embedding-based originality. P-values are for the contrasts between condition estimates.

Results: Quality. Similar to our primary study, we use click attractiveness as the quality measure. Figure 11 (B) shows the regression estimates on quality across conditions. The quality results resemble our findings in the previous experiment with all three conditions with exemplar information (open, variation(4), and variation(1)) significantly outperforming the blind condition, while showing no meaningful differences among themselves. The quantile regression confirms this pattern held across the entire quality distribution.

[9]Detailed results and results under other definitions for high-quality submissions are in Appendix G.2.

Discussion. These results show the robustness of AI intermediation's effectiveness across different contexts and design parameters. The findings that multiple variations provide only marginal benefits suggest that the core value of AI intermediation lies in alleviating the direct visual fixation on exemplars rather than providing extensive diversity in variations.

Our findings have practical implications for implementation, as generating fewer variations per exemplar reduces computational costs while maintaining effectiveness. The success across both restaurant and healthcare contexts, despite the latter's more constrained design conventions, indicates that AI intermediation can facilitate creative learning even in settings with well-established visual norms.

6 Conclusion

This paper proposes using generative AI as intermediation between designers to facilitate creative learning: communicating the key ideas of successful concepts across designers without inducing creative fixation. We demonstrate the effectiveness of AI intermediation in a real-world logo design contest involving professional designers. Our proof-of-concept study highlights two primary effects. First, AI intermediation provides quality guidance: after observing variations of the high-quality exemplars, professional designers produce higher-quality logos than those with no exemplar information. Second, AI intermediation helps to mitigate fixation: high-quality submissions from the variation condition exhibit higher incremental originality than those from the open condition. Through a follow-up study, we show that these effects are not primarily driven by designers directly using the model outputs in their submissions, but rather as sources of inspiration that lead to quality and originality improvements relative to the variation exemplar.

These findings present important implications for visual design. By facilitating a portfolio of diverse high-quality concepts, AI intermediation can provide brands with more viable options that cater to different stylistic preferences and design objectives. We demonstrate this mechanism in a competitive design context, but the potential applications extend to collaborative environments. AI intermediation can act as a bridge for sharing creative information between design teams: When promising concepts are identified from market research or managerial guidance, AI variations can diffuse these concepts without causing creative fixation.

Limitations and Future Research

Additional applications could explore more dimensions of 'variation'. In our proof-of-concept, we focus on brand logos and demonstrate that the length of structured descriptions from our pipeline can provide limited controllability over the perceptual similarity of variations with original exemplars. In more complex creative domains such as advertisements, product aesthetics, or architecture, variation can occur along multiple and orthogonal dimensions, such as shape, color, function, narrative tone, and cultural references. An important line of inquiry concerns whether generative models are capable of producing dimensionally controlled variations, and how those dimensions interact with design goals.

A second avenue for future work lies in expanding the AI intermediation paradigm to domains beyond visual design. Language-based creativity, such as product naming and slogan writing, multimedia campaigns, and cross-modal design, such as packaging or branding experiences, all involve complex mappings between ideas and representations. Investigating whether similar AI-intermediated abstraction techniques can foster creative learning in these domains could significantly broaden the scope and utility of the intermediation approach. Additionally, deployment of such systems would benefit from an understanding of human trust, interpretability, and cognitive reception of machine-generated content, especially when it is positioned not as a co-creator but as a facilitator of communication.

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Appendix

Table of Content

A Logo Design Contests

In logo design contests, clients post their brief publicly. The brief usually includes the basic brand information and expected logo attributes. Some clients will attach a few logo designs to provide "style inspiration". During the contest, designers can submit multiple designs, and clients can provide ratings or feedback to the submissions. After the contest ends, the client selects a winner and the winning designer is awarded the prize. Figure A.1 provides two example briefs and sampled submissions.

We begin by descriptively documenting evidence for the learning-creativity tradeoff in pre-existing logo design contests by sampling 2000 logo contests in the past 5 years. We aim to characterize whether blind contests produce more original logos and open contests produce logos that are higher quality.

For our measure of originality, we use the same embedding-based method as we do in the experimental analysis in Section F.3. In particular, we extract the CLIP embeddings of logo images and then calculate, for each logo, the average embedding distance between its embedding and embeddings of other logos of the same contest. To be able to compare across contest types, we take the average submission (of the contest) originality to measure the contest-level originality. Figure A.2 shows the distributions of contest originality across the two types of contests, which shows that blind contests produce more original submissions.

For our measure of quality, it is infeasible to collect the click-rating measure that we use in our experiment. Thus, we resort to using the client ratings for a selected subset of submissions, but it is unclear what criteria clients use for these ratings and which submissions they decide to rate. Nonetheless, in Figure A.3 we can still compare these ratings across contest types as a noisy measure of quality and find suggestive evidence that the open contests produce higher quality than the blind contests, but it is hard to reach definitive conclusions without a clearer understanding of the data generating process for these ratings.

Figure A.1: Illustrative Brief and Submissions

Brand name: Group 1 High performance home builders

Describe who/what this design is about:
High Performance home

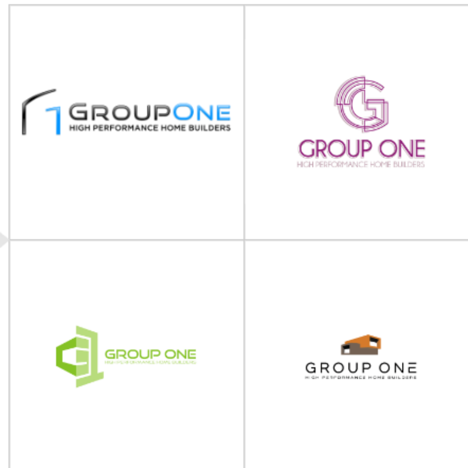
Industry type: Construction

What kind of design are you looking for? Symbolic; Initials; Illustrative

How would you describe the style in your logo? Masculine; Modern; Cutting-edge; Sophisticated; Professional; High Tech

what colors would you like? No Yellow Light blue, dark blue, black, white

Do you have any additional suggestions or ideas? Very sleek!!! Very expensive company



Brand name: HealthChart

Describe who/what this design is about:

HealthChart (capitalized "C" intentional) is a software application that guides people to optimal health and wellness based on their personal health profile and advanced algorithms (including AI) that predict disease risks based on the most current medical science. It shows an individual the ways to reduce these risks and improve longevity. The term "Chart" in the name is to convey the idea of navigation, as in a ship using a chart to reach a destination.

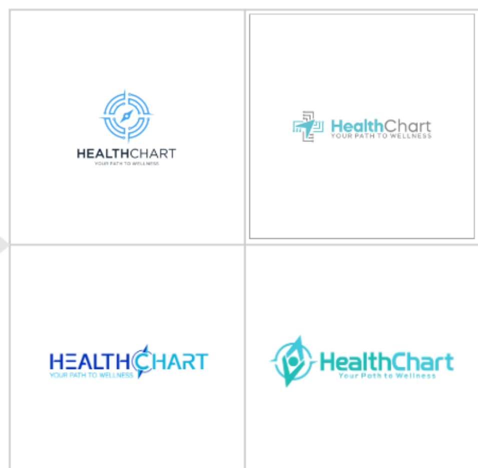
Industry type: Health

What kind of design are you looking for? Symbolic

How would you describe the style in your logo? Cutting-edge; Professional; High Tech

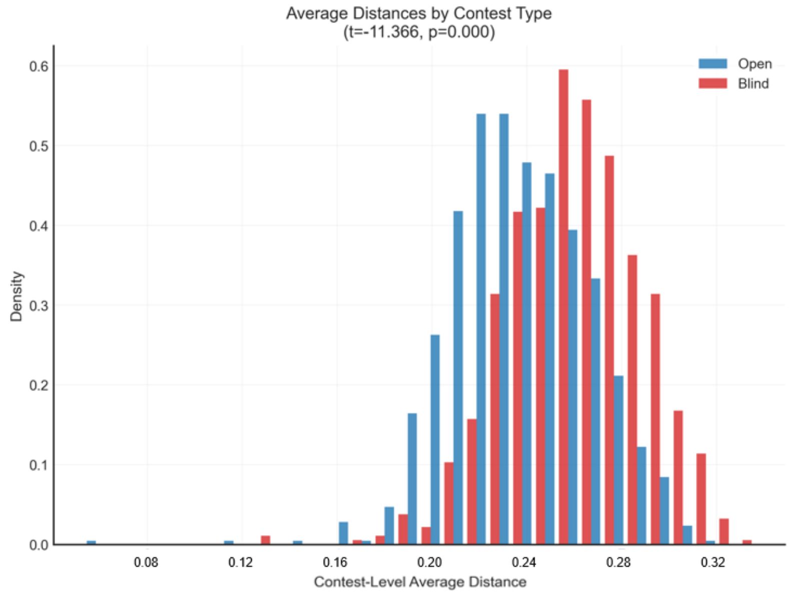
what colors would you like? Light Blue

Do you have any additional suggestions or ideas? A stylized compass with compass "needle" may be a strong concept. The logo should include this graphic plus the name HealthChart.



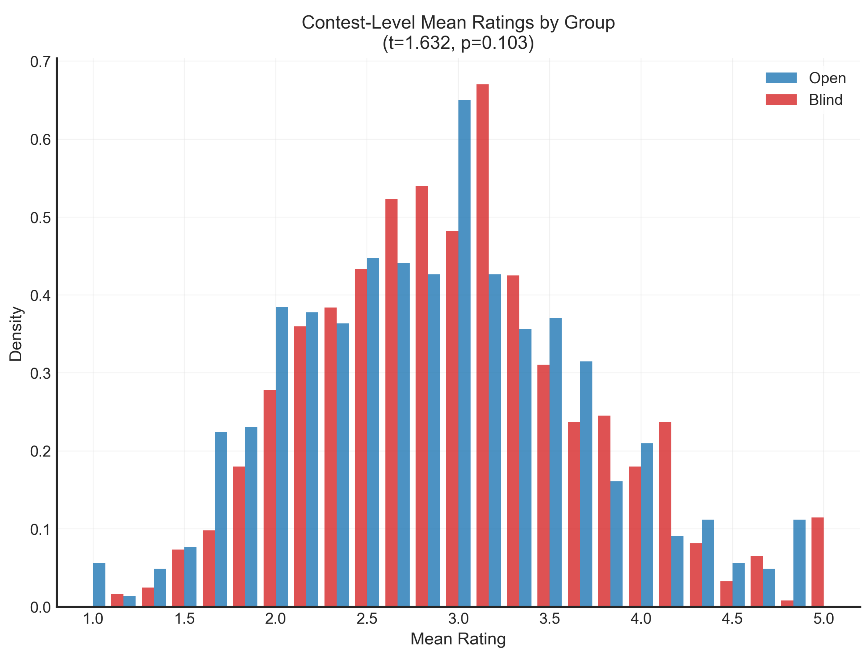
Notes: This figure provides two logo design contest examples. On the left of the upper and lower panels are the brief that clients provide. This sets up the design context. On the right of the panels are submissions from designers. Notice how very different designs can fit well with the design context and thus preference signals from clients are important for designers to navigate the design space.

Figure A.2: Submission Originality of Open and Blind Contests



Notes: This figure reports the distribution of contest-level embedding-based originality of the two types of contests. Treating contest as the unit of analysis, a t-test shows that the blind contest are of higher originality levels.

Figure A.3: Submission Quality of Open and Blind Contests



Notes: This figure reports the distribution of contest-level quality ratings of the two types of contests. Treating contest as the unit of analysis, a t-test shows that the open contests receive higher quality ratings marginally.

B Logos Generated by Off-the-Shelf Models

In this section, we provide additional justification for using our custom generative model over existing off-the-shelf models.

We begin by providing examples of the logo variations produced by FLUX.1-schnell (Black Forest Labs, 2024) in Figure B.1. FLUX.1-schnell is the natural benchmark as one of the most advanced open-source commercial image-to-image model which serves as the base for the model we developed. While this is only one sample, it is clear that the four variations are very similar in the form, which invalidates our requirement that the variations should look visually distinctive from the original logo. We view this as being important for the implementation of AI intermediation and something we explicitly built into the model, which is not present in the base model.

To assess whether our model is able to better capture visual distinctiveness relative to image-to-image generation, we run a validation study using 60 randomly sampled logos from different brands. We use both our model and FLUX.1-schnell to generate 4 AI variations for each logo.[10] To measure the visual distinctiveness of a set of variations to the original logo, we use the average CLIP embedding distance between variations and their original logo. This gives us 60 average distances of AI variations and image-to-image variations. Paired t-test shows that AI variations are substantially more distinctive from the original logos (mean difference = 0.0414, SE = 0.0008, t = 51.102, $p < 0.001$). This shows that our model generates variations that are more visually distinctive relative to image-to-image generation.

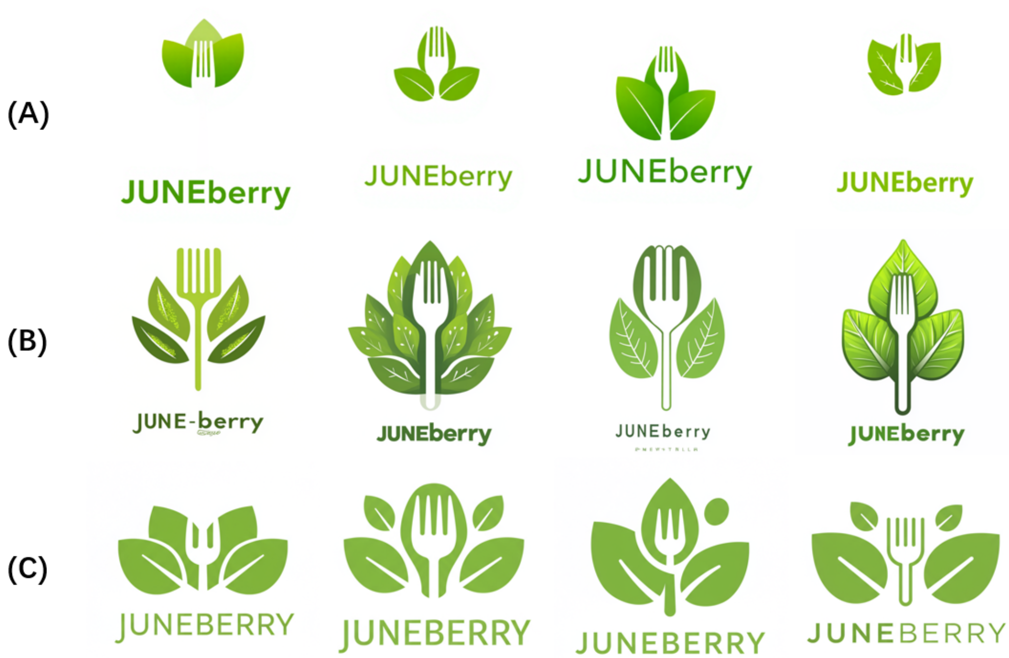
Apart from visual distinctiveness, we also show the issues with using off-the-shelf text-to-image models when using the structured textual description as the prompt. We present sample generated logos in Figure B.2. Figure B.2(A) again presents the outputs from FLUX.1-schnell which, apart from visual distinctiveness, violate basic design principles: the fork is white, following the original design idea, but there is no color contrast to the background color and the distance between graphic elements and typography is too large. Figure B.2(B) presents the outputs from Midjourney – a leading commercial model – which results in designs that are too detailed and complex to be used as logos. Figure B.2(C) presents the outputs from Imagen – Google's most advanced image generative model – which follow a completely different style from the original logo. We provide more examples for the Imagen model in Figure B.3 which again highlight uniformity in output style that is also misaligned with the original design.

[10]For FLUX.1-schnell, the method takes the original logo and structured textual description of the original logo as input.

Figure B.1: Variations Generated by Image-to-Image Model

Notes: This figure shows the variations generated by the image-to-image approach. The original logo is on the left, and the four images on the right are variations generated using FLUX.1-schnell.

Figure B.2: Variations Generated by Off-the-Shelf Text-to-Image Model



Notes: This figure shows variations generated by different text-to-image models. The variations are all generated using the structured description of the original logo in Figure B.1. (A) shows the outputs of FLUX.1-schnell. (B) shows the outputs of Midjourney. (C) shows the outputs of Imagen.

Figure B.3: Additional Variations Generated by Imagen

Notes: This figure shows one additional example of variations generated using Imagen. The original logo is on the left, and the four images on the right are variations generated by Imagen.

C Technical Details in Model Training

The pre-trained model that we use is a diffusion model. Diffusion models work by reversing a diffusion process to synthesize data. The model training process is shown in Figure C.1.

Initially, the image is encoded to image latent. Then a forward diffusion process gradually adds noise to the latent, transforming it from the initial state z_0 to a Gaussian noise z_T. At time step t, the noised latent is:

$$z_t = \sqrt{1-\alpha_t} z_0 + \sqrt{\alpha_t} \epsilon$$

Where ϵ is a Gaussian noise. The goal of Diffusion models is to learn to denoise the added noises so that a noisy state z_T can be reversed back to an image latent z_0. Therefore, at t, the loss is

$$||\epsilon - \epsilon_\theta(z_t, c, t)||^2$$

Here, θ is the model, c is the condition (i.e., embedding of the prompt). The denoised initial state z_0 is then decoded to obtain the final image. The loss is, in essence, a reconstruction loss of the original image. While minimizing the loss in the training, the model is learning to reconstruct the original logo as closely as possible given the logo description (prompt), thus implicitly forcing the model to learn graphic design principles and to align with the prompt.

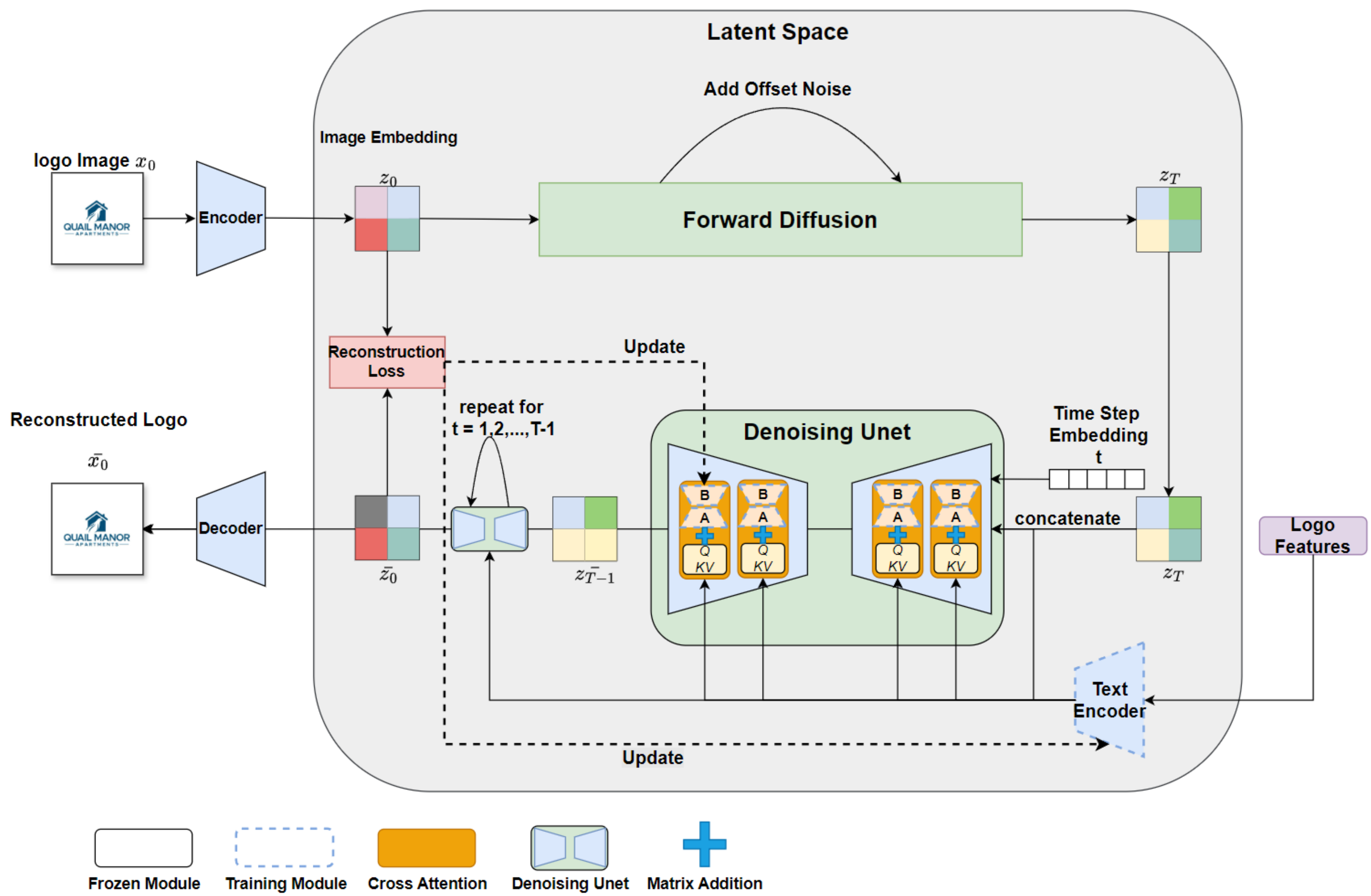
For fine-tuning, we use LoRA, a method that allows efficient adaptation of pre-trained models for downstream tasks (Hu et al., 2022). Suppose the cross-attention layer of the pre-trained model is $W_0 \in \mathbb{R}^{d\times k}$, where d, k are the original and output dimensions respectively. LoRA trains ΔW to minimize the denoising loss. It is efficient for it decomposes ΔW as $\Delta W = BA$, where $B \in \mathbb{R}^{d\times r}$ and $A \in \mathbb{R}^{r\times k}$, with r being way smaller than both d and k. Intuitively, LoRA is compressing the updated information to low-rank matrices. During inference, the weights of the new model $\theta + \theta_{lora}$ are $W_0 + \Delta W$.

In training of Logo LoRA as described in Section 3.2.1, we set the learning rate of the denoising network to be 6×10^{-6} and text encoder network to be 3×10^{-6}; r to be 128; batch size to be 10; and a cosine learning rate scheduler. The training converges at around 12 epochs, and takes less than 2 days on an A100 GPU.

For Optimization LoRA, instead of reconstruction loss, we propose a contrastive denoising loss:

$$\gamma||\epsilon_p - \epsilon_{\theta+\theta_{click}}(x_t, c, t)||^2 + ||\epsilon_n - \epsilon_{\theta-\theta_{click}}(x_t, c, t)||^2$$

Figure C.1: Illustration of A Latent Diffusion Model



Notes: This figure shows the training process of a canonical latent diffusion model.

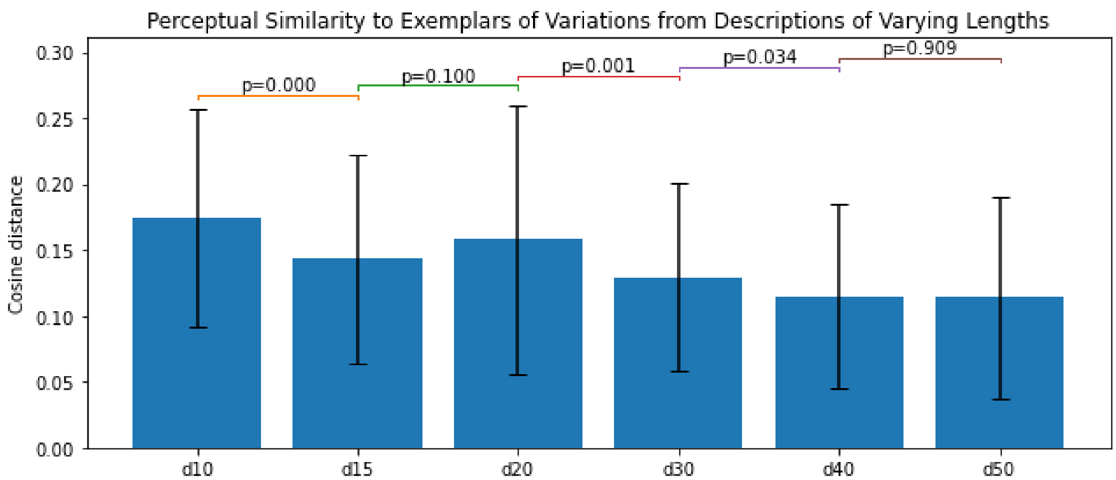
Here, each loss is calculated as the sum of the loss for the noise added to the positive sample ϵ_p and the noise added to the negative sample ϵ_n. γ represents the level of click rate differences between the two logos and is calculated as $ln(\frac{a}{b})$, where a is the larger click rate in a pair, and b is the smaller rate. c represents the common prompts of the two logos. The gradients of θ_{click} with respect to the contrastive loss are weighted by γ's of the pairs, meaning that the model learns more information from the pairs with larger click rate differences.

In training of Optimization LoRA as described in Section 3.2.2, we only update the denoising network, and the learning rate is 1×10^{-5}. The dimension of the Optimization LoRA is set to be 16. We use a cosine learning rate scheduler and batch size of 1. We train the model for 20 epochs. During inference, we set the weight of Optimization LoRA to be 1.

D Description Length to Control Variations

In this section, we demonstrate how the length of descriptions influences the perceptual similarity of variations to original exemplars. We inject system prompts to the image captioning model to limit the length of the descriptions. We test descriptions of varying lengths, from 10 words to 50 words, generate variations based on these descriptions, calculate the cosine distances between variations and original exemplars, and present the results in Figure D.1. As length increases, we observe an overall decreasing trend in cosine distances between variations and exemplars, meaning that as the descriptions become richer in information, the variations are more perceptually similar to the exemplars.

Figure D.1: Model Validation Results



Notes: This figure shows the perceptual distance of AI-generated variations to the original logos. The variations are generated from descriptions of different lengths: (from left to right) 10, 15, 20, 30, 40, and 50. The y-axis represents the average cosine distance between the variations and the original logos. The heights of bars represent group means and the bounds represent one standard deviation. The p values are from paired t-tests on variations generated by descriptions of consecutive lengths (e.g. 15 v.s 20; 20 v.s 30).

However, the level of controllability on variations using description length is not perfect. We observe that there is no difference between the distances to exemplars of variations generated based on descriptions of 40-words and 50-words. This is partly because logos are of relatively low complexity and the majority of its information can be described in short texts. The other reason is that the image captioning model is not trained to necessarily provide more information when length increases. We leave achieving controls on variation and testing its effectiveness on human designs through AI intermediation for future research.

E Generative Model Validation Details

In this section, we provide additional validation that our generative model yields reasonable logos for the professional application. Study 1 shows that the variations produced by our model are semantically aligned with the original logo. Study 2 compares the performance of two fine-tuning steps and demonstrates that the Optimization LoRA positively impacts the click-through rate of the generated variations. Lastly, Study 3 examines how the level of distortions seen in model outputs influences logo perceptions, which serves as a test on the reasonableness of model outputs.

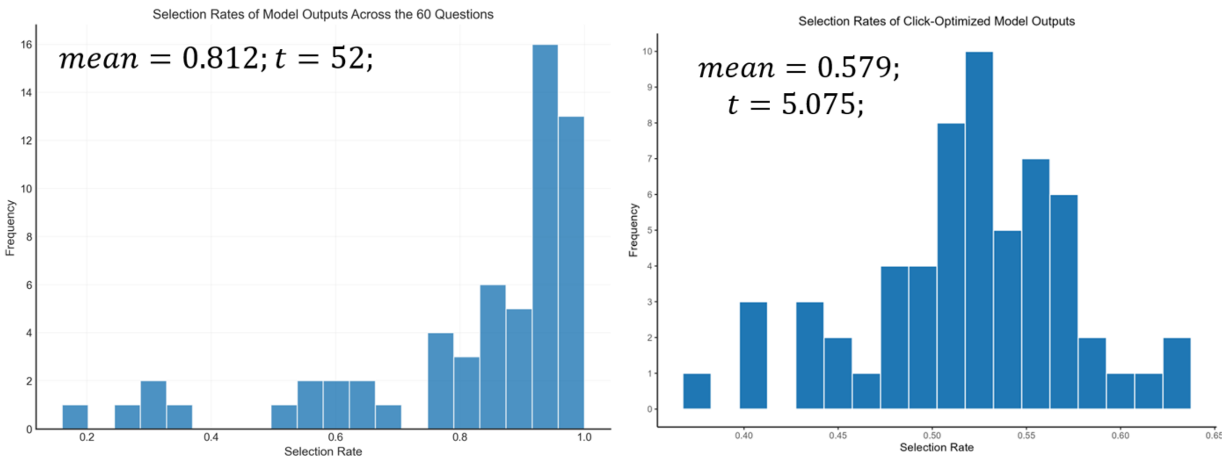
Study 1. To test whether our generated variations are semantically aligned with the original logos, we compared their perceived resemblance to the original logo against that of retrieval-based “most similar” logos from the same design contest. We first sampled 60 original logos from different brands. For each of these 60 logos, we used our full model pipeline (including both Logo LoRA and Optimization LoRA) to generate one variation. For each logo, we also identified a most similar logo from the same contest using an embedding-based retrieval approach. Specifically, for logos submitted by different designers of the source logo (we add this restriction for many times, a designer might submit one design multiple times), we find the one having the smallest cosine distance to the source logo. Human subjects were then presented with pairs consisting of our AI variation and the retrieval-based most similar logo, and asked to select which of the two better resembled the original logo. Each pair was evaluated approximately 100 times.

The results, illustrated on the left of Figure E.1, demonstrate strong semantic alignment. The mean selection rate for our AI variations was 0.812 (t=52, significantly different from 0.5), indicating that subjects perceived our variations as dominantly and substantially more resemblant to the original logo’s core ideas than the most visually similar alternative from the same contest. This supports the conclusion that our pipeline effectively captures and re-generates the semantic essence of the original designs.

Study 2. To assess the effectiveness of the Optimization LoRA fine-tuning stage in enhancing a specific dimension of logo quality, in this case, click attractiveness, we compared variations generated with and without this optimization. Using the same 60 original logos from Study 1, we generated two sets of variations: one set using the pipeline with only the Logo LoRA fine-tuning, and another set using the full pipeline including the Optimization LoRA. This resulted in 60 pairs of logos (one with Optimization LoRA, one without, both derived from the same input description).

We first noticed distributional shifts in model outputs. For the 60 pairs, logos generated with Optimization LoRA exhibit higher levels of brightness (mean difference = 5.61, SE =

Figure E.1: Model Validation Results



Notes: The left figure shows the selection rates in resemblance to the source logo of AI variation when presented against the most similar logo from the same contest; the right figure shows the selection rates in click attractiveness of variation generated with the Optimization LoRA when presented against the variation generated without the Optimization LoRA.

2.99, p = 0.065) and symmetry (mean difference = 0.0051, SE = 0.0024, p = 0.04). One illustrative example of the outputs without (on the left) and with Optimization LoRA (on the right) is in Figure E.2. We can see that Optimization LoRA does not significantly change the logo rendering, but does minor perturbations on features positively related to higher click attractiveness.

We then study whether such minor changes indeed lead to higher click attractiveness. Similar to the data collection for training the Optimization LoRA, human subjects in an online survey were shown these pairs and asked to select the logo they were more likely to click on. Each pair was evaluated approximately 100 times.

The findings, shown on the right of Figure E.1, indicate that the Optimization LoRA significantly improved the click-attractiveness of the generated logos. The mean selection rate for variations generated with the Optimization LoRA was 0.579 (t=5.075, significantly different from 0.5). This suggests that even with a relatively small labeled dataset (50 pairs for training), the contrastive fine-tuning process effectively guided the model towards producing outputs with enhanced performance on the targeted quality dimension. We conjecture that the incremental improvement in model performance increases with the size of the training data and the prevalence of common visual patterns in well-performing training examples.

Study 3. One important concern is that the generative model sometimes produces typos and graphic imperfections. We therefore study how these imperfections influence the perception of the logo and its usefulness to designers. This is important because in AI intermediation,

Table E.1: Visual Features

Feature	**What It Is About**	**Measure**
Chromatic contrast	Perceptual distance between two dominant spot colours	$\Delta E_{00}(\mathbf{c}_1, \mathbf{c}_2)$, the CIEDE2000 colour–difference between Lab centroids $\mathbf{c}_j = (L^*_j, a^*_j, b^*_j)$ of the two largest k-means clusters in Lab space.
Luminance contrast	Legibility of light vs. dark colours	$\dfrac{L_{\text{light}} + 0.05}{L_{\text{dark}} + 0.05}$, where $L = 0.2126\, R_{\text{lin}} + 0.7152\, G_{\text{lin}} + 0.0722\, B_{\text{lin}}$ and $R_{\text{lin}} = \begin{cases} R/12.92, & R \le 0.03928 \\ \left(\frac{R+0.055}{1.055}\right)^{2.4}, & \text{else} \end{cases}$ (similarly for G, B).
Colourfulness	Overall chromatic strength	$M = \sqrt{\sigma^2_{rg} + \sigma^2_{yb}} + 0.3\sqrt{\mu^2_{rg} + \mu^2_{yb}}$, with $rg = R - G$, $yb = \frac{1}{2}(R + G) - B$; μ, σ are the mean and SD of those channels.
Brightness	Typical lightness of coloured pixels	$\overline{L^*} = \dfrac{1}{N} \sum_{i=1}^{N} L^*_i$
Saturation (chroma)	Average colour strength	$\overline{C^*_{ab}} = \dfrac{1}{N} \sum_{i=1}^{N} \sqrt{a^{*2}_i + b^{*2}_i}$
Visual complexity	Density of lines	$\rho_E = \dfrac{\#(\text{Canny edges})}{\text{total pixels}}$
Horizontal symmetry	Bilateral balance of the mark	$S_H = 1 - \dfrac{1}{WH} \sum_{x=0}^{W-1} \sum_{y=0}^{H-1} \big[I(x, y) - I(W-1-x, y)\big]^2$, where $I(x, y)$ is greyscale intensity in $[0, 1]$ and the image is width W, height H.
Hue diversity	Breadth of the hue palette	$H = -\dfrac{1}{\log_2 K} \sum_{k=1}^{K} p_k \log_2 p_k$, with $K = 36$ equal-width hue bins and p_k their frequencies.
White background	Fraction of blank canvas	$R_W = \dfrac{\#\,\text{pixels s.t. } L^* > 95,\ \lvert a^*\rvert, \lvert b^*\rvert < 3}{\text{total pixels}}$.

Notes: Image-level logo dimensions used in the analysis. We provide the name, definition, and measures of these dimensions. All RGB values are first scaled to $[0, 1]$; Lab values follow the CIE 1976 standard.

Table E.2: Differences in Visual Features between Well-Performing and Ill-Performing Logos

Feature	**Mean difference (SE)**
Chromatic contrast	5.22 (5.80)
Luminance contrast	0.35 (1.24)
Colourfulness	0.03 (0.03)
Brightness	6.67** (3.45)
Saturation	4.45 (3.93)
Visual complexity	0.0008 (0.0014)
Horizontal symmetry	0.012* (0.0045)
Hue diversity	−0.52 (1.11)
White–background share	0.021 (0.027)

Notes: This table shows the differences in logo dimensions across the well-performing and ill-performing groups. Standard error in parentheses. $^*p < 0.05$, $^{**}p < 0.01$.

Figure E.2: Logos Generated Using the Same Prompt without (Left Logo) and with (Right Logo) Optimization LoRA

Notes: This figure shows variations generated by the model with and without the Optimization LoRA. The right logo exhibits higher level of symmetry and uses shades of green that are of higher brightness.

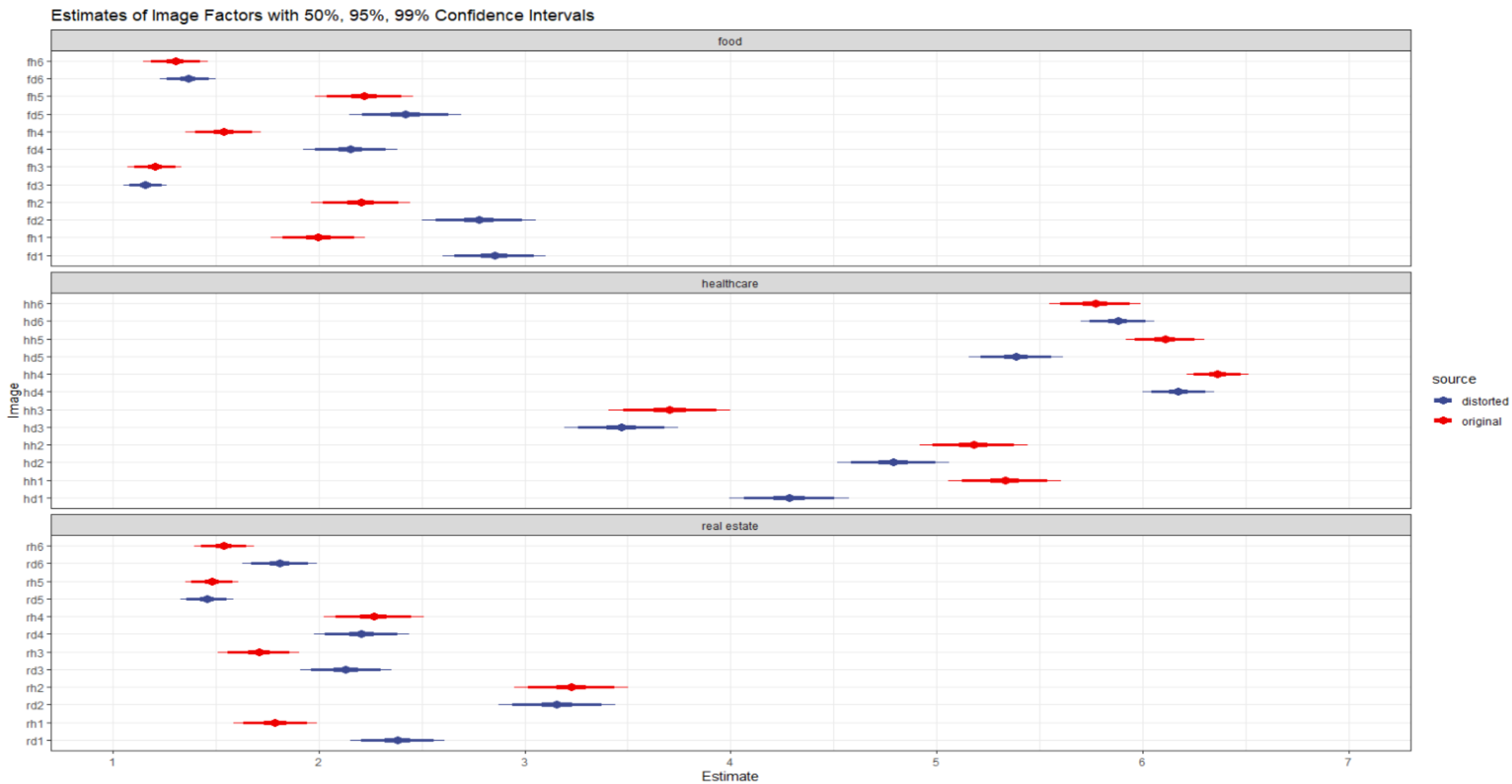
designers observe AI variations rather than the original submission, and AI variations tend to contain distortions. If such distortions significantly drive the perception of logos, the core idea of the logo that we want to convey in the variations might be compromised.

We select a perceptual dimension that is relatively straightforward for evaluation: the industry relevancy of the logo style. We select 6 logos from each of three industries: healthcare, restaurant, and real estate. For each logo, we use the image-to-image function of Stable Diffusion to manually add distortions similar to those we observe in model outputs. Thus, we have 18 original logos and 18 distorted logos. We then collect the perceived industry relevancy of these logos from an online survey. In the survey, subjects rate the perceived industry relevancy of the logo style to the healthcare industry on a scale of 1 to 7. The survey is 18 pages long, corresponding to the 18 original logos, and on each page, either the original version or the distorted version is presented. We recruited 400 subjects, and the rating distributions are shown in the Figure E.3. Here, the three rows show the ratings of restaurant, healthcare, and real estate logos respectively. Ideally, we should see a large density of ratings close to 1 for the restaurant and real estate logos, and a large density close to 7 for the healthcare logos. There are several takeaways from these figures. First, there is large heterogeneity across the perception of the industry relevancy of styles, especially for the healthcare logos. This coincides with previous findings. Second, the impact of distortions on perceptions also depends on specific logos. For example, in f3, we see essentially the same responses from the original and distorted logos. In f1 and f4, however, the original logos are perceived to be significantly less relevant to the healthcare industry than the distorted versions.

Figure E.3: Perceived Industry Relevancy

Notes: This figure shows the rating distributions in industry relevancy of the original and distorted logos. The three rows, from top to bottom, correspond to restaurant, healthcare, and real estate industries. Each grid of a row shows the rating distributions of the two versions of a logo.

Figure E.4: Estimates of Perceived Industry Relevancy



Notes: This figure shows the model estimates, under specification **??**, on industry relevancy of the original and distorted logos. The three rows, from top to bottom, correspond to restaurant, healthcare, and real estate industries. Two versions of the same logo are vertically positioned next to each other. Bars indicate the 50%, 95%, and 99% confidence intervals, respectively.

To control for subject-level effects, we run the following model to estimate the logo effects:

$$rating_{ij} = logo_i + u_j \ industry_i * version_i + \epsilon_{ij}$$

where $rating_{ij}$ is given by subject j on logo i, $industry_i$ and $version_i$ represents the industry and version (original or distorted) of logo i, and u_j here is the subject random effect. Since we have 3 industries and 2 versions, the random effects we model is a 6×6 structure. The estimates of the logo effects are shown in Figure E.4. The three panels show the estimates for restaurant, healthcare, and real estate logos from top to bottom. We position the two versions of the same logos next to each other on the y-axis. From the figure, it is clear that, although for some pairs there is minor discrepancy between the logo effects of the two versions, distortions do impact the perceived industry relevancy overall. The directions of the impact are as expected: for restaurant and real estate logos, distorted versions tend to be rated higher; for healthcare logos, distorted versions are rated lower. The distortions serve as additional noise to the original version, thus pulling the perception of the original logos towards the average. We then formally quantify the discrepancy brought in by distortions for healthcare logos. To do so, we apply a contrast between the effects of the two versions and get an estimate of -0.474 (SE = 0.103, 50% CI = [-0.543, -0.405], 95% CI = [-0.676, -0.272], 99% CI = [-0.739, -0.209]). To benchmark the discrepancy, we apply a contrast between the effects of original logos of the healthcare industry and the effects of original logos not of the industry. The estimate is 3.644 (SE = 0.118, 50% CI = [3.564, 3.724], 95% CI = [3.413, 3.875], 99% CI = [3.340, 3.948]). This shows that while distortion negatively impacts the perception, it does not make the original style completely indecipherable. Based on these findings, we conclude that, although distortions in machine-generated logos challenge their usefulness, some style information of the original logo can still be communicated through AI variations.

F Additional Results of Experiment

F.1 Supplemental Details in Experiment

Figure F.1: Brief

Brand name: Juneberry

Juneberry is an organic, fresh, and healthy vegan café. We have high-quality products and want to convey this quality in our logo.

Keywords: fresh, quality, vibrant, light, nutritious, nourishing, real food, premium, sustainable, fun

About the logo:
We want the logo to be modern and simple. We are open to ideas and any color scheme but envision more muted/lighter colors. Please include the text 'Juneberry' in the logo.
When submitting your designs, please use a white background and do not apply any special rendering effects.

IMPORTANT: We want to have a logo that can make our Facebook ads **more engaging and attract more clicks.**

We look forward to reviewing your creative submissions!

The brief of the blind condition is in Figure F.1.

The brief of the open condition contains the same initial text as the blind condition, but also has an additional paragraph at the end: *Suggestions: To inspire you and guide your designs, we provide ratings on logos that we previously collected in the gallery below. These ratings show how well logos attract clicks. The logos in the gallery are illustrative examples that do not participate in the current contest.*

Similarly, the brief of the variation condition contains the same initial text as the blind condition, but also has an additional paragraph at the end: *Suggestions: To inspire you and guide your designs, we provide ratings on logos that we previously collected in the gallery below. These ratings show how well logos attract clicks. We do not show original designs. Instead, we show variations that resemble them.*

F.2 Participation

Tables F.1 and F.2 present the summary statistics of designer-level variables of participating designers across the whole intervention and across the three conditions, respectively. We show participation patterns across the three conditions in Figures F.2 (number of submissions), F.3 (number of days with a submission), F.4 (entry time), and F.5 (entry dates). We conducted t-test across conditions and there is no statistically significant difference in any of these variables across conditions.

Table F.1: Designer Variables

Variable	**Description**	Mean	Median	Std
OverallReputation	Avg. system-generated past performance rating (0–5)	4.09	4.94	1.82
Professionalism	Avg. client rating of professional conduct (0–5)	4.07	4.94	1.83
HireAgain	Avg. client rating of rehire likelihood (0–5)	4.10	4.96	1.83
Quality	Avg. client rating of project quality (0–5)	4.07	4.95	1.83
NumJobs	Total number of completed projects	20.15	18.50	30.72
Reviews	Total number of client reviews received	19.50	18.00	29.86
HourlyRate	Designer-reported hourly rate	22.56	15.00	25.35

Notes: This table shows the designer-level demographics of participating designers. Note that the platform provides two design services. One is design contest, and the other is design projects, where clients approach individual designers for a task. Professionalism, HireAgain, and Quality are from client reviews when design projects are completed. OverallReputation is a weighted score calculated by the platform based on the three review dimensions. NumJobs refer to the number of completed design projects, and Reviews refer to the number of reviews received. HourlyRate is a designer self-reported hourly rate for design projects and it does not necessarily reflect the compensation designers receive.

Table F.2: Designer-Level Summary Statistics across Conditions

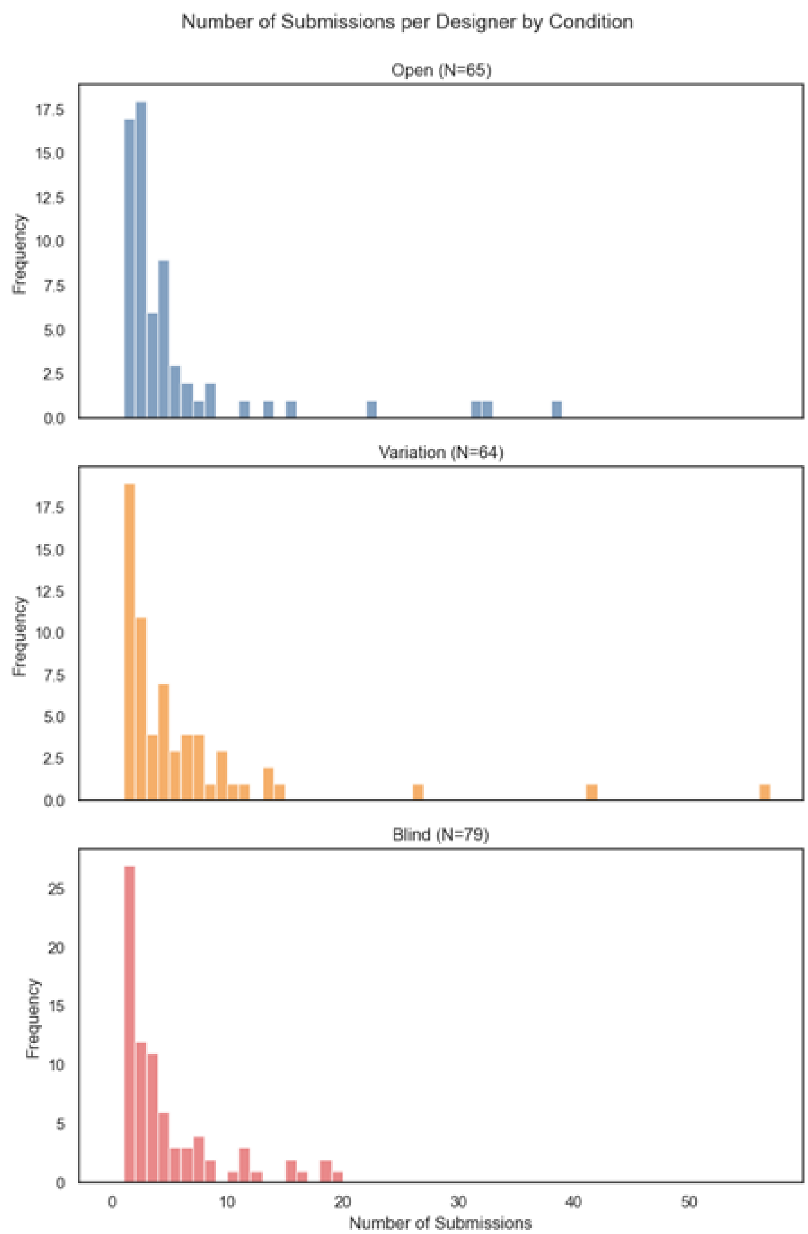
	Open	**Variation**	**Blind**
OverallReputation	4.12 (1.77)	4.09 (1.86)	4.05 (1.82)
Quality	4.13 (1.77)	4.10 (1.87)	4.04 (1.83)
Professionalism	4.13 (1.77)	4.09 (1.86)	4.07 (1.83)
HireAgain	4.11 (1.76)	4.10 (1.87)	4.03 (1.83)
NumJobs	22.05 (34.92)	20.16 (32.06)	18.58 (25.12)
Reviews	21.45 (34.16)	19.53 (31.23)	17.86 (24.07)
HourlyRate	21.02 (22.10)	24.31 (33.00)	22.43 (19.92)

Notes: This table shows the designer-level demographics across the three conditions. All differences are not significant. Standard deviations are in parentheses.

F.3 Analysis on Quality and Originality

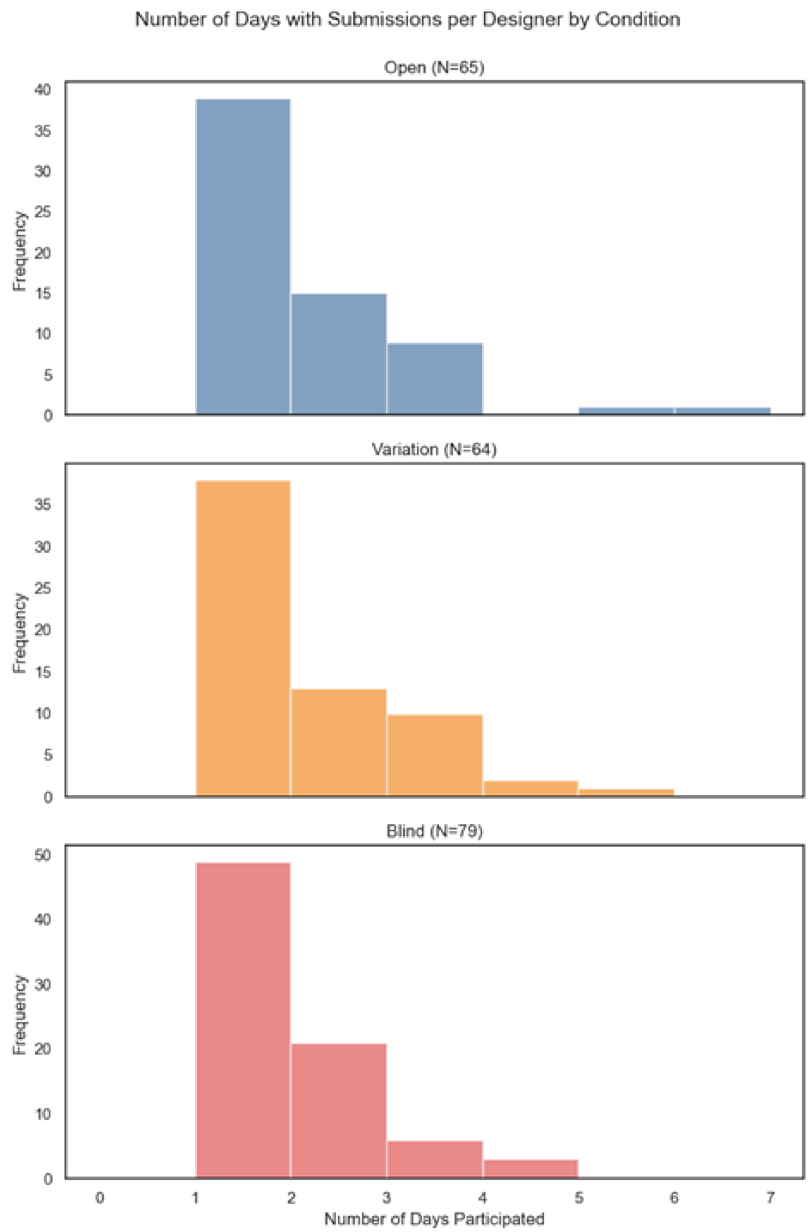
From the designer-level, AI intermediation boosts performances compared to the blind condition. The left plot of the Figure F.6 shows the distribution of designer-level average click attractiveness of their submissions. From the comparisons between the variation and blind conditions, we can see a clear shift to the right of the distributions. We then conduct t-test to confirm our observation ($\mu_{variation} = 0.51, SD_{variation} = 0.12, \mu_{blind} = 0.44, SD_{blind} = 0.14, t_{variation,blind} = 3.155, p_{variation,blind} = 0.002$). We also compare the click attractiveness

Figure F.2: Number of Submissions



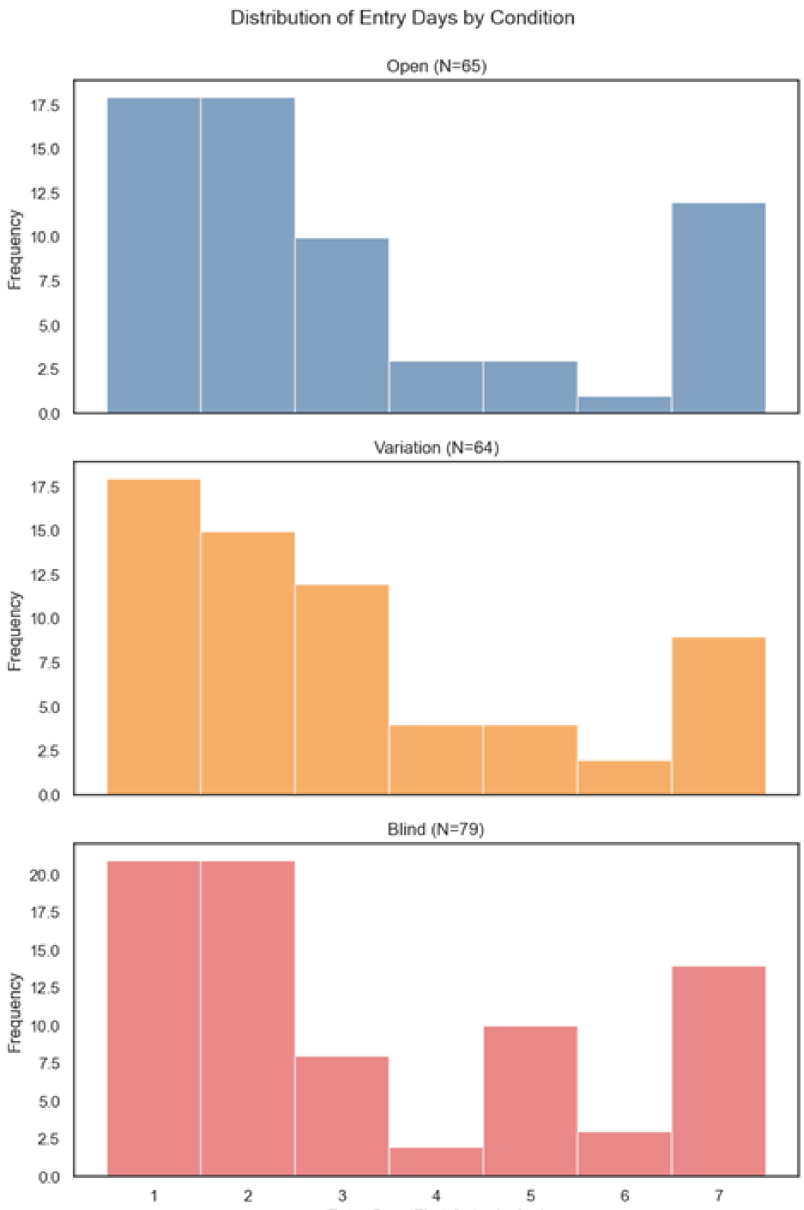
Notes: This figure shows the distribution of number of submissions per designer across the three conditions. In all three conditions, there are a few outlier designers that submit more than 15 designs. The mean submission is around 4 submissions per designer.

Figure F.3: Continuous Participation



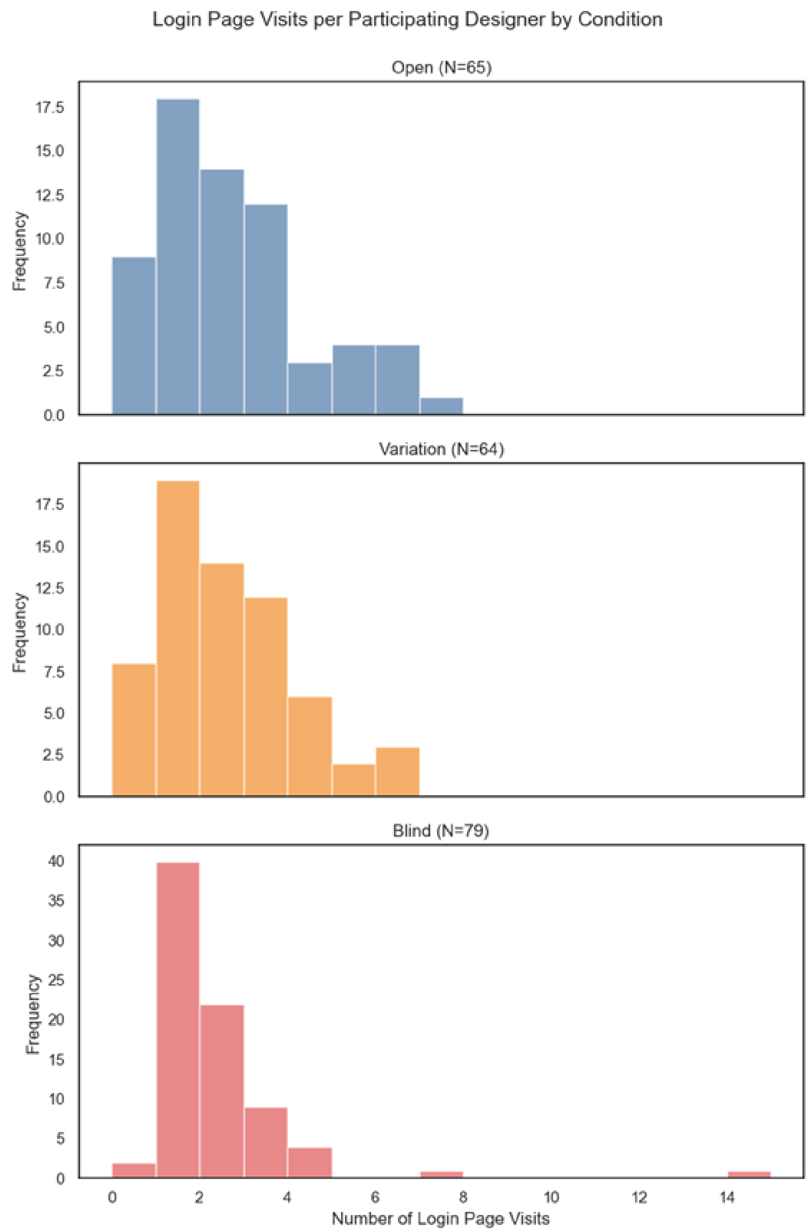
Notes: This figure shows the distributions on participating days across the three conditions. The participating days measure the level of continuous participation and represent the number of days a designer submits designs.

Figure F.4: Entry Time



Notes: This figure shows the entry dates of designers across the three conditions. The entry date is defined by the day on which a designer's first submission is made. Overall, most entries happen on the first two and the last days.

Figure F.5: Number of Brief Visits

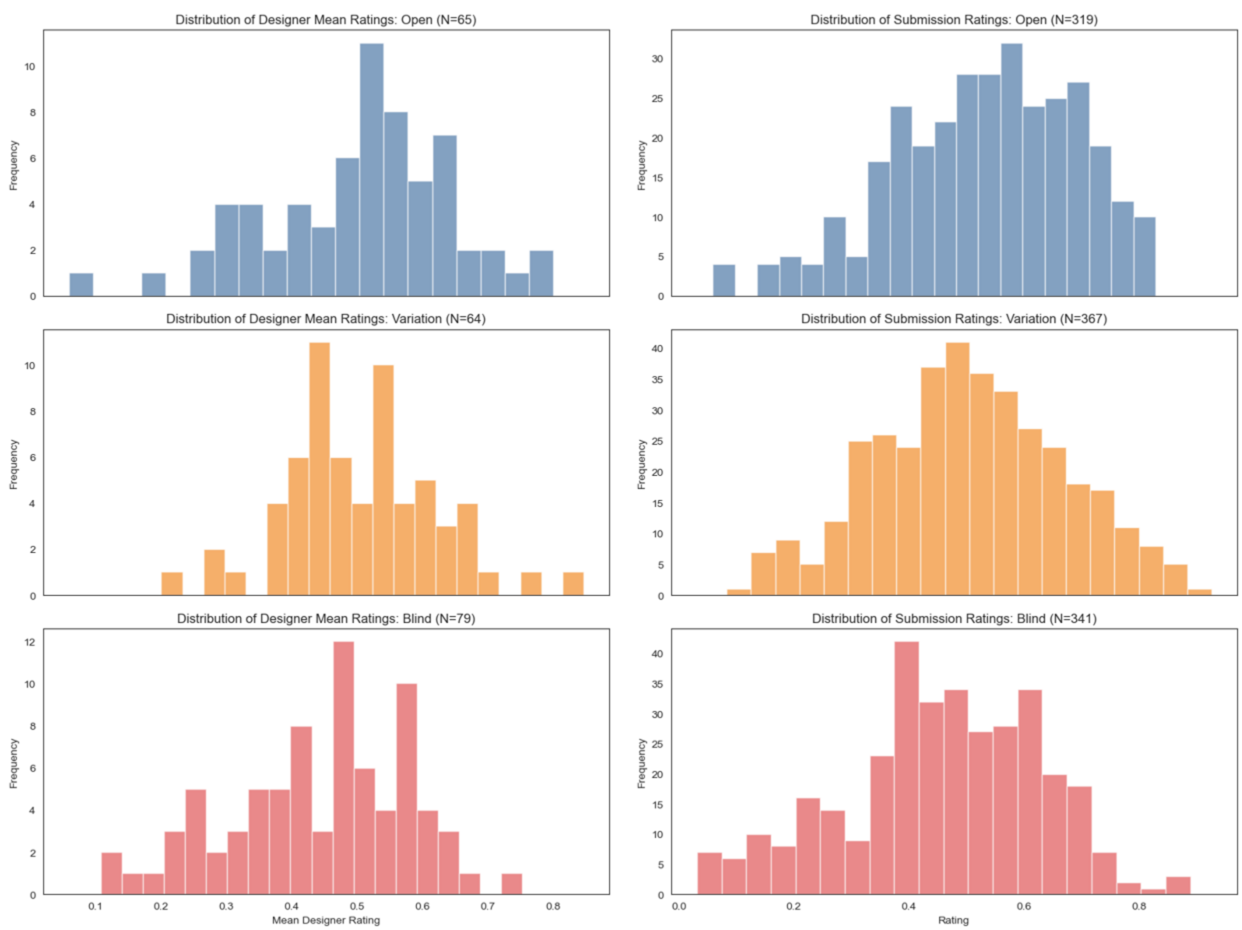


Notes: This figure shows the distribution of gallery visit times across the three conditions. Accessing the gallery to view exemplars requires login, and the login page visits measure the exposure frequency to exemplars. The open and variation condition have substantially more gallery visits than the blind condition. This makes sense for the brief of blind condition contains only brand information. To learn from exemplars, designers in the Open and variation conditions pay more visits.

between variation and open conditions ($\mu_{open} = 0.50, SD_{open} = 0.14, t_{open,variation} = -0.224$, $p_{open,variation} = 0.823$). This shows that the designer-level performances of variation condition is substantially better than blind condition, and is comparable to open condition. These results suggest that variations can communicate key ideas of leading logos, thus boosting the performance of subsequent submissions.

Table F.3 shows the average treatment effect on quality and Table F.6 shows that similar patterns hold for the contrasts across different quantiles. Table F.4 shows embedding-based results under different specification of 'high-quality' submissions and Table F.5 shows perceived originality of the three dimensions: color palette, style, and composition. Tables F.4 and F.8 show the corresponding contrasts for the originality measures between conditions.

Figure F.6: Distributions of Click Attractiveness across Groups



Notes: This figure shows the distributions of click attractiveness on the designer and submission-level across the three conditions. The left panel shows the mean click attractiveness of designers' submissions. The right panel shows the click attractiveness of submissions.

Table F.3: Mean and Quantile Regression Results for Click Attractiveness

	Mean	$\tau = 0.95$	$\tau = 0.90$	$\tau = 0.75$	$\tau = 0.50$
Open	0.4981***	0.7313***	0.7042***	0.6255***	0.5358***
	(0.046)	(0.034)	(0.031)	(0.030)	(0.030)
Variation	0.4811***	0.7597***	0.7049***	0.6010***	0.5036***
	(0.045)	(0.036)	(0.034)	(0.031)	(0.030)
Blind	0.4282***	0.6946***	0.6503***	0.5629***	0.4616***
	(0.041)	(0.036)	(0.033)	(0.030)	(0.030)
SubmissionTime	0.0061	0.0066	0.0075*	0.0078*	0.0060
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
OverallReputation	0.2297*	0.4289**	0.2941**	0.3540**	0.2633*
	(0.112)	(0.143)	(0.111)	(0.108)	(0.109)
Quality	-0.0023	-0.1085	-0.0780	-0.0517	0.0060
	(0.091)	(0.117)	(0.100)	(0.089)	(0.082)
HireAgain	-0.1772*	-0.1724	-0.1523	-0.1916*	-0.2151**
	(0.077)	(0.089)	(0.099)	(0.076)	(0.071)
Professionalism	0.0157	-0.1631*	-0.0507	-0.0467	0.0179
	(0.077)	(0.064)	(0.078)	(0.082)	(0.094)
NumJobs	-0.0024	-0.0123	-0.0122	-0.0078	-0.0054
	(0.005)	(0.007)	(0.007)	(0.005)	(0.005)
Reviews	0.0027	0.0125	0.0123	0.0078	0.0055
	(0.005)	(0.007)	(0.007)	(0.005)	(0.006)
HourlyRate	0.0005	0.0003	0.0004	0.0006	0.0009*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(Pseudo) R-squared	0.052	0.0465	0.0408	0.0344	0.0285
Observations	1027	1027	1027	1027	1027

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Notes: Results are based on all submissions in the experiment. The first column shows the mean click attractiveness, and the third to fifth columns show the click attractiveness of top 5%, 10%, 25%, and 50% submissions respectively. The rows show the estimates of three condition factors under specification 1 and designer-level demographics used as controls. standard error are clustered on the designer level.

Table F.4: Average Impact on Embedding-based Originality

	Top 50 Each Condition	Top 100 Each Condition	Top 150 in All Submissions	Top 300 in All Submissions
Open	0.0988***	0.0761***	0.0830***	0.0768***
	(0.027)	(0.017)	(0.025)	(0.017)
Variation	0.1253***	0.0985***	0.1181***	0.0984***
	(0.026)	(0.017)	(0.024)	(0.017)
Blind	0.1329***	0.0961***	0.1147***	0.0970***
	(0.030)	(0.019)	(0.029)	(0.020)
SubmissionTime	-0.0039	0.0000	-0.0029	-0.0003
	(0.002)	(0.002)	(0.002)	(0.002)
OverallReputation	0.0347	0.1177*	0.0410	0.0887
	(0.116)	(0.054)	(0.111)	(0.063)
Quality	0.0585	0.0721	0.1064**	0.0365
	(0.066)	(0.056)	(0.034)	(0.052)
Professionalism	0.0212	-0.0499	-0.0870	-0.0093
	(0.148)	(0.068)	(0.103)	(0.079)
HireAgain	-0.0927*	-0.1003***	-0.0874*	-0.1019***
	(0.039)	(0.030)	(0.042)	(0.027)
NumJobs	-0.0025	-0.0033	-0.0012	-0.0017
	(0.004)	(0.003)	(0.003)	(0.004)
Reviews	0.0024	0.0034	0.0014	0.0017
	(0.004)	(0.003)	(0.003)	(0.004)
HourlyRate	-0.0002*	0.0001	-0.0002	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.136	0.074	0.212	0.059
Observations	150	300	150	300

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Notes: Results are based on high-quality submissions in the experiment. The columns show the embedding-based originality of high-quality submissions under different definitions. The first column uses the Top 50 submissions of each condition ranked by their click attractiveness. The second column uses the Top 100 submissions of each condition. The third column uses the Top 150 submissions in all conditions. The fourth column uses the Top 300 submissions in all conditions. The rows show the estimates of three condition factors under specification 1 and designer-level demographics used as controls. standard error are clustered on the designer level.

Table F.5: Impact on Perception-based Originality

	Color	Composition	Style	Overall
Open	2.0294*	1.9944**	2.1511**	2.0583**
	(0.857)	(0.670)	(0.741)	(0.748)
Variation	2.4204**	2.6705***	2.7904***	2.6271**
	(0.841)	(0.662)	(0.734)	(0.737)
Blind	2.5554**	2.7288***	2.9162***	2.7335***
	(0.896)	(0.726)	(0.800)	(0.800)
SubmissionTime	-0.0474	-0.0837	-0.0909	-0.0740
	(0.045)	(0.062)	(0.063)	(0.055)
OverallReputation	0.1951	1.1890	0.0575	0.4805
	(1.850)	(2.437)	(2.221)	(2.044)
Quality	2.1976	1.2914	1.3324	1.6071
	(1.173)	(1.783)	(1.700)	(1.536)
Professionalism	-1.4203	-0.9169	0.3052	-0.6773
	(2.810)	(3.792)	(3.676)	(3..378)
HireAgain	-0.8663	-1.1480	-1.0558	-1.0234
	(0.714)	(0.902)	(0.842)	(0.758)
NumJobs	-0.0626	-0.1097	-0.0785	-0.0836
	(0.052)	(0.080)	(0.080)	(0.069)
Reviews	0.0632	0.1122	0.0788	0.0847
	(0.053)	(0.083)	(0.082)	(0.072)
HourlyRate	-0.0026	-0.0032	-0.0044	-0.0034
	(0.002)	(0.003)	(0.002)	(0.002)
R-squared	0.112	0.092	0.105	0.103
Observations	150	150	150	150

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Notes: Results are based on high-quality submissions (Top 50 in click attractiveness of each condition) in the experiment. The columns show the mean perceived color, composition, style, and overall originality of submissions, respectively. The rows show the estimates of three condition factors under specification 1 and designer-level demographics used as controls. standard error are clustered on the designer level.

Table F.6: Contrasts of Group Factors on Click Attractiveness Across Selected Quantiles

τ	$\boldsymbol{\beta}_{\text{open}} - \boldsymbol{\beta}_{\text{var}}$	$\boldsymbol{\beta}_{\text{var}} - \boldsymbol{\beta}_{\text{blind}}$	$\boldsymbol{\beta}_{\text{open}} - \boldsymbol{\beta}_{\text{blind}}$
0.95	-0.028 (0.018)	0.065*** (0.017)	0.037** (0.019)
0.90	-0.001 (0.018)	0.055*** (0.017)	0.054** (0.018)
0.75	0.025 (0.016)	0.038** (0.016)	0.063*** (0.017)
0.50	0.032 (0.017)	0.042** (0.017)	0.074*** (0.017)

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Notes: Results are based on estimates in Table F.3. From left to right, the columns show the difference between the open and the variation conditions; the variation and the blind conditions; the open and the blind conditions. From top to bottom, the rows show the estimated effects on click attractiveness for Top 5%, 10%, 25%, and 50% submissions, respectively.

Table F.7: Contrasts of Group Factors on Embedding-based Originality

	$\boldsymbol{\beta}_{\text{open}} - \boldsymbol{\beta}_{\text{var}}$	$\boldsymbol{\beta}_{\text{var}} - \boldsymbol{\beta}_{\text{blind}}$	$\boldsymbol{\beta}_{\text{open}} - \boldsymbol{\beta}_{\text{blind}}$
Top 50 Each Condition	-0.0265* (0.0104)	-0.0075 (0.0134)	-0.0341** (0.0122)
Top 100 Each Condition	-0.0225** (0.0085)	0.0024 (0.0103)	-0.0201* (0.0099)
Top 150 in All Submissions	-0.0351*** (0.0091)	0.0034 (0.0142)	-0.0317* (0.0129)
Top 300 in All Submissions	-0.0216* (0.0089)	0.0014 (0.0107)	-0.0202* (0.0103)

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Notes: Results are based on estimates in Table F.4. From left to right, the columns show the difference between the open and the variation conditions; the variation and the blind conditions; the open and the blind conditions. From top to bottom, the rows show the estimated effects on embedding-based originality for the four definitions of high-quality submissions, respectively.

Table F.8: Contrasts of Group Factors on Perception-based Originality

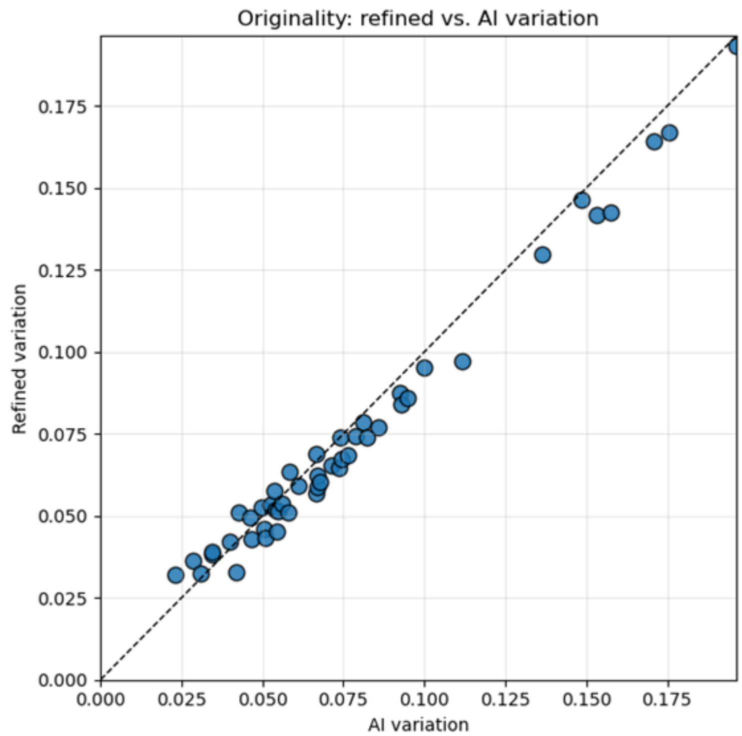
	$\boldsymbol{\beta}_{\text{open}} - \boldsymbol{\beta}_{\text{var}}$	$\boldsymbol{\beta}_{\text{var}} - \boldsymbol{\beta}_{\text{blind}}$	$\boldsymbol{\beta}_{\text{open}} - \boldsymbol{\beta}_{\text{blind}}$
Color	-0.3911 (0.2201)	-0.1349 (0.3012)	-0.5260* (0.2240)
Composition	-0.6761* (0.2652)	-0.0583 (0.3613)	-0.7344* (0.3139)
Style	-0.6393* (0.2558)	-0.1259 (0.3626)	-0.7651* (0.3080)
Overall	-0.5688* (0.2355)	-0.1064 (0.3322)	-0.6752* (0.2725)

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Notes: Results are based on estimates in Table F.5. From left to right, the columns show the difference between the open and the variation conditions; the variation and the blind conditions; the open and the blind conditions. From top to bottom, the rows show the estimated effects on perception-based color, composition, style, and overall originality, respectively.

F.4 Supplements to Contribution Study

Figure F.7: Embedding-based Originality of Refined Variation v.s. AI variation



Notes: This figure shows the relationship between the distance of AI variation to its source logo and the distance of the corresponding refined variation to its source logo. Each point represents a source logo. The x-axis shows the distance to its AI variation; the y-axis shows the distance to the refined version of its AI variation. A line of slope one fits these points well. This shows that the two distances of source logos are close, validating that these refined variations are similar to AI variations.

G Results of Additional Application

This section presents the analysis of the additional application described in Section 5.

The brief that designers observe – shown in Figure G.1 – is similar to the brief provided in the original study except for the change in the focal firm and requested logo. The brief for other conditions goes through the same modification process as in F.1. Designers in the variation(1) and variation(4) conditions observe the same brief.

G.1 Participation

Table G.1 shows the summary statistics of the designer-level variables of participating designers across the four conditions. We conduct a randomization check by doing t-tests for

Figure G.1: Brief for Study 2

Brand name: Armor Health

Armor Health is a healthcare company that provides comprehensive medical, dental, and mental health services around communities in the United States.

Keywords: Professional, Reliable

About the logo:
We are looking for a modern and sleek logo that is inviting yet eye-catching. We are open to ideas and any color scheme. Please include the text 'Armor Health' in the logo.
When submitting your designs, please **use a white background** and **do not use any mockup**.

IMPORTANT: We want to have a logo that can make our Facebook ads **more engaging and attract more clicks.**

To inspire you and help guide your designs, we provide ratings on logos that we previously collected in the gallery below. These ratings show how well logos attract clicks.

each variable separately and confirm that there are no statistically significant differences in any of these variables across conditions.

Table G.1: Designer-Level Summary Statistics

	Open	**Variation(4)**	**Variation(1)**	**Blind**
OverallReputation	4.13 (1.80)	4.07 (1.87)	4.26 (1.64)	4.36 (1.53)
Quality	4.15 (1.81)	4.08 (1.87)	4.27 (1.65)	4.36 (1.53)
Professionalism	4.16 (1.81)	4.08 (1.87)	4.27 (1.65)	4.36 (1.54)
HireAgain	4.14 (1.81)	4.06 (1.87)	4.26 (1.64)	4.35 (1.53)
NumJobs	29.34 (47.17)	26.39 (54.53)	25.06 (49.56)	26.51 (54.49)
Reviews	28.07 (44.95)	25.39 (52.77)	24.56 (48.89)	25.93 (53.74)
HourlyRate	21.93 (17.96)	23.76 (19.87)	24.37 (23.95)	25.24 (35.18)

Notes: This table shows the designer-level demographics across the four conditions. All differences are not significant. Standard deviations are in parentheses.

G.2 Analysis on Originality

Table G.2 shows the regression estimates on submission originality across conditions. For the additional application, we focus on the embedding-based originality and we use the same method as in the main study to calculate the originality scores. Table G.3 shows the contrasts between condition estimates on originality. For multiple definitions of high-quality submissions, we consistently see that variation(1), variation(4), and the blind conditions outperform the open condition, and that there is no substantial difference between the former three conditions.

One concern is that submissions now fixate on the single variation rather than the exemplar. We investigate this by comparing the distance between what designers observe and their submissions. Specifically, we compare the originality score of submissions from the open condition against the distance between submissions and the single variations of the variation(1) condition. For Top 50 submissions per condition, the variation(1) condition demonstrates substantially larger distance to 'exemplars' than the open condition ($\Delta^{originality}_{Var(1)-Open} = 0.035,\ SE = 0.005,\ t = 6.550,\ p < 0.001$).[11] This shows that AI intermediation alleviates fixation not by shifting designs toward the AI variations, but by inspiring submissions that are more original relative to what designers were shown.

G.3 Analysis on Quality

Table G.4 shows the average treatment effect estimates on submission quality. As in the main study, we use click attractiveness as the quality measure and collect it using the same method as in the main study. Table G.5 shows the contrasts between condition estimates for selected quantiles and Figure G.2 shows the differences on the full support of quantiles. The results consistently show that variation(1), variation(4), and the open condition outperform the blind condition in submission quality.

[11] Please see detailed results in Table G.6.

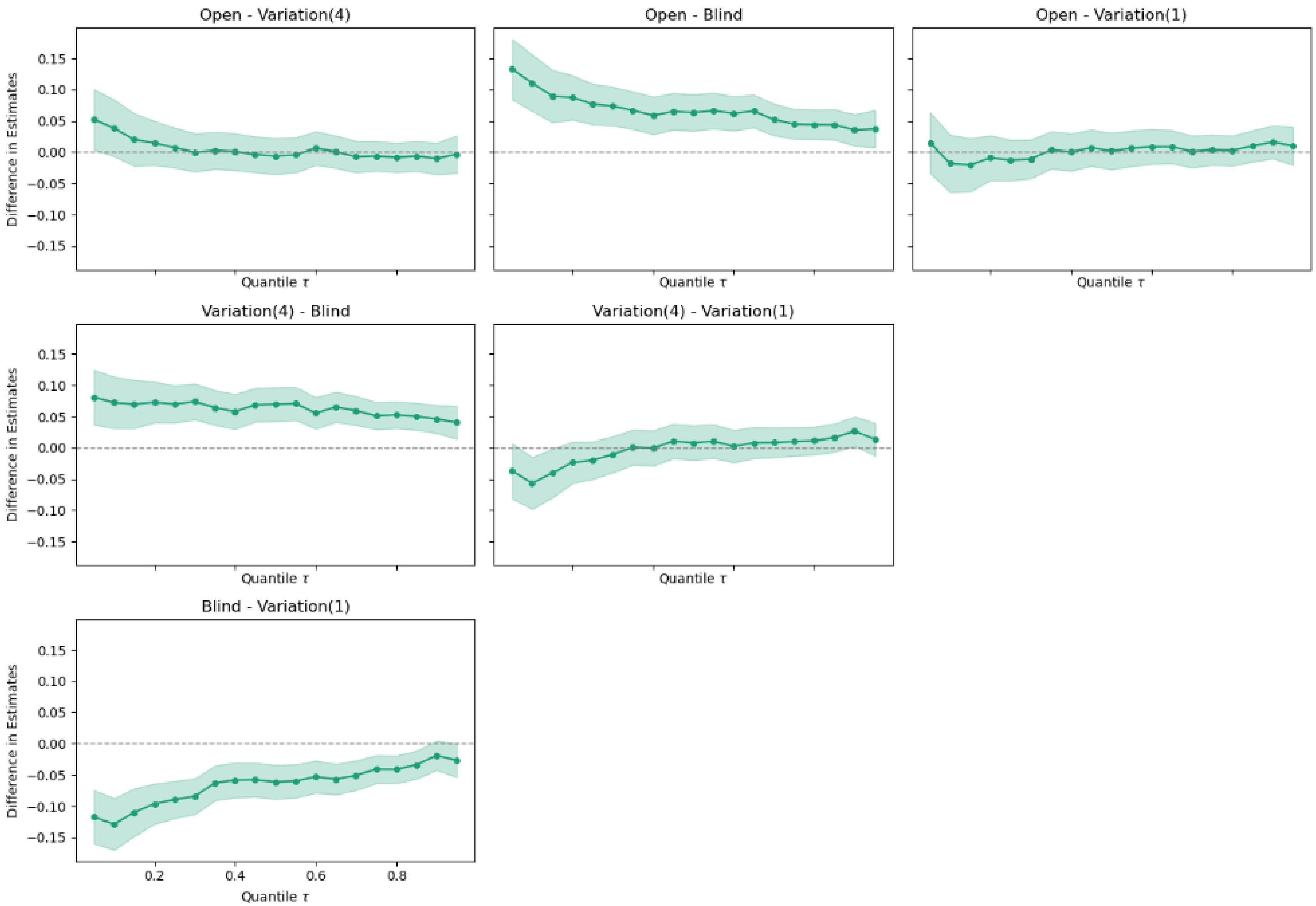
Table G.2: Impact on Embedding-based Originality

	Top 50 Each Condition	Top 100 Each Condition	Top 200 in All Submissions	Top 400 in All Submissions
Open	0.0373***	0.0468***	0.0390***	0.0445***
	(0.006)	(0.005)	(0.005)	(0.005)
Variation(4)	0.0541***	0.0606***	0.0547***	0.0575***
	(0.006)	(0.005)	(0.005)	(0.004)
Blind	0.0547***	0.0646***	0.0509***	0.0626***
	(0.007)	(0.005)	(0.006)	(0.005)
Variation(1)	0.0512***	0.0598***	0.0499***	0.0577***
	(0.008)	(0.005)	(0.007)	(0.005)
SubmissionTime	0.0002	-0.0001	-0.0000	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
OverallReputation	0.0176	0.0324	0.0073	0.0159
	(0.022)	(0.023)	(0.021)	(0.020)
Quality	-0.0165	-0.0247	-0.0161	-0.0243
	(0.014)	(0.013)	(0.013)	(0.014)
Professionalism	-0.0207	-0.0266	-0.0122	-0.0174
	(0.016)	(0.014)	(0.015)	(0.013)
HireAgain	0.0208	0.0189	0.0218	0.0261
	(0.019)	(0.016)	(0.014)	(0.015)
NumJobs	-0.0012	-0.0016**	-0.0010	-0.0007
	(0.001)	(0.000)	(0.001)	(0.001)
Reviews	0.0012	0.0016**	0.0010	0.0007
	(0.001)	(0.000)	(0.001)	(0.001)
HourlyRate	0.0002***	0.0002**	0.0002***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.225	0.180	0.248	0.174
Observations	200	400	200	400

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Notes: Results are based on high-quality submissions in the experiment. The columns show the embedding-based originality of high-quality submissions under different definitions. The first column uses the Top 50 submissions of each condition ranked by their click attractiveness. The second column uses the Top 100 submissions of each condition. The third column uses the Top 200 submissions in all conditions. The fourth column uses the Top 400 submissions in all conditions. The rows show the estimates of three condition factors under specification 1 and designer-level demographics used as controls. standard error are clustered on the designer level.

Figure G.2: Contrasts of Quality Estimates between Conditions



Notes: This figure shows contrasts of condition estimates with 95% CI. The panels show pairwise differences in click attractiveness estimates across quantiles: open vs. variation(4) (top left), open vs. blind (top center), open vs. variation(1) (top right), variation(4) vs. blind (bottom left), variation(4) vs. variation(1) (bottom center), and blind vs. variation(1) (bottom right). The estimates are from quantile regression under specification 1, with click attractiveness being the dependent variable. On each panel, the y-axis shows the difference in estimates, and the x-axis shows the quantile level(τ).

Table G.3: Contrasts of Group Factors on Embedding-based Originality

	$\boldsymbol{\beta}_{\text{Open}} - \boldsymbol{\beta}_{\text{Var(4)}}$	$\boldsymbol{\beta}_{\text{Open}} - \boldsymbol{\beta}_{\text{Var(1)}}$	$\boldsymbol{\beta}_{\text{Open}} - \boldsymbol{\beta}_{\text{Blind}}$	$\boldsymbol{\beta}_{\text{Var(4)}} - \boldsymbol{\beta}_{\text{Var(1)}}$	$\boldsymbol{\beta}_{\text{Var(4)}} - \boldsymbol{\beta}_{\text{Blind}}$	$\boldsymbol{\beta}_{\text{Var(1)}} - \boldsymbol{\beta}_{\text{Blind}}$
Top 50	-0.0169^{***}	-0.0139^{**}	-0.0174^{***}	0.0029	−0.0006	−0.0035
Each Condition	(0.0043)	(0.0053)	(0.0052)	(0.0048)	(0.0042)	(0.0054)
Top 100	-0.0138^{***}	-0.0130^{**}	-0.0178^{***}	0.0008	−0.0041	−0.0049
Each Condition	(0.0038)	(0.0040)	(0.0046)	(0.0039)	(0.0042)	(0.0045)
Top 200	-0.0157^{***}	-0.0110^{*}	-0.0119^{*}	0.0047	0.0038	−0.0009
in All Submissions	(0.0043)	(0.0051)	(0.0056)	(0.0043)	(0.0045)	(0.0054)
Top 400	-0.0131^{***}	-0.0133^{***}	-0.0181^{***}	−0.0002	−0.0050	−0.0048
in All Submissions	(0.0036)	(0.0038)	(0.0047)	(0.0032)	(0.0039)	(0.0042)

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Notes: Results are based on estimates in Table G.2. From left to right, the columns show the difference between the open and the variation(4) conditions; the open and the variation(1) conditions; the open and the blind conditions; the variation(4) and the variation(1) conditions; the variation(4) and the blind conditions; the variation(1) and the blind conditions. From top to bottom, the rows show the estimated effects on embedding-based originality for the four definitions of high-quality submissions, respectively.

Table G.4: Mean and Quantile Regression Results for Click Attractiveness

	Mean	$\tau = 0.95$	$\tau = 0.90$	$\tau = 0.75$	$\tau = 0.50$
Open	0.5735***	0.8193***	0.7727***	0.6989***	0.5908***
	(0.022)	(0.019)	(0.016)	(0.015)	(0.019)
Variation(4)	0.5699***	0.8228***	0.7833***	0.7053***	0.5973***
	(0.025)	(0.021)	(0.017)	(0.016)	(0.019)
Blind	0.5054***	0.7823***	0.7375***	0.6541***	0.5277***
	(0.024)	(0.019)	(0.016)	(0.016)	(0.019)
Variation(1)	0.5718***	0.8093***	0.7567***	0.6953***	0.5893***
	(0.024)	(0.022)	(0.019)	(0.017)	(0.020)
SubmissionTime	-0.0005	0.0010	0.0011	-0.0005	-0.0005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
OverallReputation	0.0845	-0.1471	-0.1195	-0.0251	0.0369
	(0.146)	(0.113)	(0.109)	(0.097)	(0.122)
Quality	-0.0132	0.0281	0.0471	0.0374	-0.0133
	(0.065)	(0.076)	(0.063)	(0.051)	(0.060)
HireAgain	-0.0431	0.0019	-0.0242	-0.0350	-0.0550
	(0.079)	(0.068)	(0.061)	(0.058)	(0.072)
Professionalism	-0.0255	0.1159	0.0953	0.0227	0.0322
	(0.075)	(0.060)	(0.060)	(0.054)	(0.067)
NumJobs	0.0012	0.0010	0.0025	0.0031	0.0044
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Reviews	-0.0011	-0.0010	-0.0026	-0.0030	-0.0043
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
HourlyRate	0.0001	0.0001	0.0002	0.0001	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(Pseudo) R-squared	0.0306	0.0153	0.0169	0.0148	0.0152
Observations	2199	2199	2199	2199	2199

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Notes: Results are based on all submissions in the experiment. The first column shows the mean click attractiveness, and the third to fifth columns show the click attractiveness of top 5%, 10%, 25%, and 50% submissions respectively. The rows show the estimates of three condition factors under specification 1 and designer-level demographics used as controls. standard error are clustered on the designer level.

Table G.5: Contrasts of Group Factors on Click Attractiveness

Model	$\boldsymbol{\beta}_{\text{Open}} - \boldsymbol{\beta}_{\text{Var}(4)}$	$\boldsymbol{\beta}_{\text{Open}} - \boldsymbol{\beta}_{\text{Var}(1)}$	$\boldsymbol{\beta}_{\text{Open}} - \boldsymbol{\beta}_{\text{Blind}}$	$\boldsymbol{\beta}_{\text{Var}(4)} - \boldsymbol{\beta}_{\text{Var}(1)}$	$\boldsymbol{\beta}_{\text{Var}(4)} - \boldsymbol{\beta}_{\text{Blind}}$	$\boldsymbol{\beta}_{\text{Var}(1)} - \boldsymbol{\beta}_{\text{Blind}}$
	0.0036	0.0017	0.0681**	−0.0019	0.0645**	0.0665***
Mean	(0.0206)	(0.0188)	(0.0213)	(0.0185)	(0.0215)	(0.0197)
	−0.0035	0.0100	0.0370*	0.0135	0.0405**	0.0270*
$\tau = 0.95$	(0.0152)	(0.0156)	(0.0154)	(0.0134)	(0.0135)	(0.0138)
	−0.0106	0.0160	0.0352**	0.0266*	0.0458***	0.0192
$\tau = 0.90$	(0.0128)	(0.0135)	(0.0129)	(0.0119)	(0.0115)	(0.0120)
	−0.0064	0.0036	0.0448***	0.0100	0.0513***	0.0412***
$\tau = 0.75$	(0.0121)	(0.0125)	(0.0122)	(0.0115)	(0.0112)	(0.0115)
	−0.0065	0.0015	0.0631***	0.0080	0.0696***	0.0616***
$\tau = 0.50$	(0.0146)	(0.0146)	(0.0149)	(0.0141)	(0.0138)	(0.0139)

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Notes: Results are based on estimates in Table G.4. From left to right, the columns show the difference between the open and the variation conditions; the variation and the blind conditions; the open and the blind conditions. From top to bottom, the rows show the estimated effects on click attractiveness for Top 5%, 10%, 25%, and 50% submissions, respectively.

Table G.6: Embedding Distance to Observed Exemplars

	Top 50 Each Condition	Top 100 Each Condition
Open	0.0413***	0.0466***
	(0.009)	(0.006)
Variation(1)	0.0762***	0.0842***
	(0.009)	(0.006)
SubmissionTime	0.0005	0.0003
	(0.001)	(0.000)
OverallReputation	0.0396	0.0361
	(0.030)	(0.027)
Quality	-0.0265	-0.0350
	(0.042)	(0.032)
Professionalism	-0.0252	-0.0327
	(0.016)	(0.019)
HireAgain	0.0134	0.0323
	(0.043)	(0.032)
NumJobs	-0.0017	-0.0005
	(0.003)	(0.002)
Reviews	0.0017	0.0004
	(0.003)	(0.002)
HourlyRate	-0.0001	0.0000
	(0.000)	(0.000)
R-squared	0.515	0.508
Observations	100	200

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$
Notes: Results are based on high-quality submissions from the open and variation (1) conditions of this experiment. The first column uses the Top 50 submissions of each condition ranked by their click attractiveness. The second column uses the Top 100 submissions of each condition. The rows show the estimates of the two condition factors under specification 1 and uses the smallest cosine distance between the submissions and the exemplars that designers observe (for the open condition, designers observe human logos as exemplars; for the variation(1) condition, designers observe AI variations as exemplars) as the dependent variable. The designer-level demographics are used as controls. standard error are clustered on the designer level.