

Louvain School of Management

Mathematical aesthetics in marketing design: revising the role of formulas in shaping visual harmony and consumer attraction

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Declaration on the use of generative AI

In accordance with university guidelines, I declare that generative AI tools (specifically OpenAI's ChatGPT/DALL-E 3 and Google's Gemini) were utilized during the development and drafting of this dissertation. The application of these tools was strictly limited to the following supportive tasks:

- **Language and stylistic enhancement:** As a non-native English speaker writing directly in English, AI was utilized strictly to refine academic phrasing, improve stylistic flow, and correct grammatical errors.
- **Coding and debugging:** AI was utilized to assist in writing, structuring, and debugging the Python scripts required to execute the Bradley-Terry logistic regression and Chi-Square statistical analyses.
- **Stimulus generation:** Generative AI was employed to develop the base visual stimuli (logos) used in the experiment. This was conducted via a strict Human-in-the-Loop (HITL) methodology to ensure the outputs adhered to precise mathematical parameters, as detailed in the Methodology chapter.

I affirm that the theoretical frameworks, experimental designs, analytical logic, and conclusions in this thesis are entirely my own original work. Additionally, I independently sourced, manually verified, and accurately cited all facts, models, and references without using AI for information retrieval.

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Chapter 1

Introduction

For centuries, finding a universal formula for beauty has been a primary goal in aesthetic research. In the sphere of marketing and corporate design, the use of objective mathematical rules, such as symmetry and the Golden Ratio, has become widespread among brands. The aim is to use these mathematical rules to create a reflection of premium quality for the brand. A pioneer of these mathematical criteria is George Birkhoff's aesthetic measure. He postulates that visual beauty can be calculated by maximizing structural order and minimizing cognitive complexity. Consequently, in digital design, mathematical order has become a foundational heuristic. The assumption is that geometric perfection directly translates into consumer attraction and brand trust.

However, human visual perception is not a purely mathematical mechanism. On one hand, strict geometric formulas allow rapid cognitive processing. On the other hand, modern psychobiological theories suggest that a moderate level of visual stimulation is needed to remain engaged. Designs created following absolute mathematical reduction often risk appearing sterile. Furthermore, a "universal consumer" is often assumed in contemporary marketing literature. This does not take into account human characteristics that alter the perception of structural order. The design sensitivity (Centrality of Visual Product Aesthetics), gender, and generational digital immersion of each individual act as very important perceptual filters. A significant gap remains in understanding if strict mathematical formulas act as universal indicators of quality, or if, for the modern consumer, cognitive load and demographic profiles highly influence the effectiveness of these mathematical formulas.

The primary objective of this research is to challenge the assumption that, for modern consumer preference in corporate design, the universal predictors are pure mathematical formulas. Derived from George Birkhoff's foundational theory, 14 specific mathematical criteria were used to evaluate aesthetic appeal. In this study, the aim is to quantify the responses of actual consumers when facing strict visual order. Furthermore, the purpose of this study is to in-

investigate how individual consumer profiles influence these aesthetic preferences. The use of psychographic and demographic filters allows this study to test five core hypotheses. These hypotheses determine how specific consumer traits alter the threshold of cognitive load and ultimately dictate visual preference. The psychographic and demographic filters used are: an individual's Centrality of Visual Product Aesthetics (CVPA), their generational cohort (specifically Generation Z versus older demographics), and their gender (viewed through the Selectivity Hypothesis).

The thesis is structured into four main chapters designed to achieve its research objectives. Chapter 1 presents the state of the art and formulates the research hypotheses by linking classical mathematical measures with insights from modern cognitive psychology. Chapter 2 details the quantitative methodology, including the development of 15 controlled visual stimuli used to generate 1,830 pairwise comparisons within a Targeted Incomplete Block Design. These comparisons are subsequently analyzed using a Bradley–Terry logistic regression model. In Chapter 3, the empirical results and hypothesis testing highlight the significant divergence between theoretical mathematical perfection and actual human visual processing. Finally, Chapter 4 synthesizes these findings into actionable managerial implications for brand strategy, discusses the limitations of the present study, and proposes directions for future research.

Chapter 2

State of the art: the intersection of mathematics, psychology, and design

2.1 The evolution of design comprehension

The pursuit of a universal "formula for beauty" has driven aesthetic research for over a century. Before the integration of advanced digital technology, the comprehension of design relied heavily on psychophysics and the search for objective mathematical rules. The foundation of empirical aesthetics was established by Gustav Fechner in 1876, who hypothesized that the relationship between the conscious and material aspects of reality could be expressed in exact mathematical terms (Fechner, 2014). Through empirical experiments, Fechner demonstrated a general human preference for rectangles with proportions approximating the Golden Section. This mathematical pursuit was formalized in 1933 when George Birkhoff introduced the concept of "Aesthetic Measure" ($M = O/C$), positing that orderly and simple objects are inherently perceived as more beautiful than complex or chaotic ones (Birkhoff, 1933). During this same era, researchers operating under the Gestalt approach, such as Arnheim (1965), studied the inherent tension and balance of forms, suggesting that specific compositional arrangements are preferred because they preserve meaning and ensure visual balance.

In the 1970s and 1980s, the paradigm shifted from purely objective stimulus properties to cognitive processing, heavily influenced by the rise of personal computing and digital media. D.E. Berlyne developed a psychobiological theory proposing that aesthetic appraisal is driven by an object's arousal potential and collative properties such as complexity and ambiguity (Berlyne, 1971). Building on this, Colin Martindale championed the cognitive approach, advancing the prototype theory of preference (Martindale & Moore, 1988). According to Martindale, an object's 'prototypicality' strongly influences consumer preference because it represents a clear mental category. This indicates that aesthetics are driven more by underlying

meaning than by strict formal features. Parallel to this psychological research, industrial design terminology shifted toward human-centered approaches and emotional aesthetics, recognizing product design as a vital marketing element freed from purely mechanical constraints.

As computing hardware rapidly advanced, the 2000s birthed "computational aesthetics" as an independent, interdisciplinary field bridging computer science, cognitive science, and art. Instead of relying solely on human surveys, researchers began utilizing computer algorithms to automatically extract and analyze low-level visual features like color, luminance, and edges to predict aesthetic ratings. This era marked a return to quantifying aesthetic judgments through mathematical methods, aiming to build systems capable of imitating human visual processing.

Today, in the modern era of deep learning and data-driven design, the study of aesthetics is largely dominated by artificial intelligence. The breakthrough of Convolutional Neural Networks (CNNs) has allowed models to automatically extract high-level semantic features from images, bypassing the limitations of classical theories that relied on rigid, single formal rules. However, this data-driven paradigm has introduced a significant "black box" challenge: while neural networks can accurately predict aesthetic scores, the models are often unexplainable. Because these computational models cannot clearly articulate *why* certain structural features correspond to subjective feelings of visual harmony, there remains a critical gap in integrating computational aesthetics with human psychology.

2.1.1 Theoretical framework: Gestalt psychology

To understand the cognitive mechanism behind these mathematical and computational aesthetics, it is essential to consider the foundations of Gestalt psychology (Wagemans et al., 2012). Developed over a century ago, Gestalt theory posits that visual perception is not merely the sum of individual sensory parts, but rather the result of the brain organizing stimuli into unified, global configurations.

The central tenet relevant to this research is the *Law of Pragnanz*, or the Law of Simplicity. This principle suggests that the human visual system naturally tends to perceive ambiguous or complex stimuli in their simplest, most stable, and most symmetrical forms. From a marketing perspective, this implies that symmetrical logos or those following the Golden Ratio are more easily processed because they align with the brain's innate preference for "good" Gestalt.

Furthermore, several *Laws of Perceptual Organization* explain how consumers integrate design elements:

- **Symmetry:** Regions that are symmetrical are more likely to be perceived as a distinct "figure" rather than a background, making the brand mark more memorable.
- **Similarity:** Elements sharing the same mathematical proportions or colors are grouped together by the observer, creating a sense of brand unity.

- **Proximity:** The spatial arrangement of elements influences whether a design is perceived as organized or chaotic, directly affecting the consumer's cognitive load.

By integrating Gestalt theory with processing fluency, this study argues that mathematical formulas in design act as "perceptual shortcuts", allowing for faster and more pleasant information processing, which ultimately leads to higher perceived product quality (Wagemans et al., 2012).

2.1.2 The processing fluency theory of aesthetic pleasure

While Gestalt psychology explains *how* the brain organizes visual information, it does not fully explain *why* humans experience a subjective feeling of pleasure when viewing mathematically ordered designs. To bridge the gap between objective structural parameters and subjective aesthetic appreciation, modern empirical aesthetics relies on the *Processing Fluency Theory* (Reber et al., 2004).

Processing fluency refers to the subjective ease and speed with which the human brain processes and integrates sensory information. According to the seminal work by Reber, Schwarz, and Winkielman Reber et al. (2004), aesthetic pleasure is not an inherent property of an object, but rather a function of the perceiver's processing experience. When a visual stimulus features high mathematical order (such as *Symmetry*, *Balance*, *Proportion*, and *Regularity*) it objectively reduces the cognitive load required to decode the image. In the context of Birkhoff's aesthetic formula ($M = O/C$), a design with high "Order" and low "Complexity" inherently facilitates high processing fluency (Reber et al., 2004; Winkielman et al., 2006).

From a neurobiological standpoint, when the brain processes a visual stimulus efficiently and without cognitive friction, it rewards the viewer with a brief, automatic flash of positive affect (a "good feeling"). However, human cognition is prone to metacognitive misattribution (Alter & Oppenheimer, 2009). Instead of recognizing this positive affect as a mere biological byproduct of easy cognitive processing, the consumer unconsciously misattributes this pleasant feeling to the inherent qualities of the object itself.

In a marketing and design context, this biological mechanism has profound implications. When a consumer views a highly cohesive and well-proportioned corporate logo, the rapid and effortless processing of these 14 mathematical criteria triggers immediate aesthetic pleasure. The consumer then misattributes this fluency-triggered pleasure into high-level brand appraisals, translating "this logo is easy to look at" into "this brand is of high quality, trustworthy, and stable" (Reber et al., 2004). Therefore, rather than merely dictating structural geometry, the 14 design criteria evaluated in this study actively drive processing fluency to shape consumer purchasing intent and brand perception.

2.2 The mathematical objectification of aesthetics

2.2.1 Birkhoff's aesthetic measure

Building upon the cognitive shortcuts identified by Gestalt psychology, Birkhoff postulated that aesthetic value is not purely subjective but can be calculated as a ratio of order to complexity (Birkhoff, 1933). The fundamental equation is expressed as:

$$M = \frac{O}{C} \quad (2.1)$$

where M represents the Aesthetic Measure, O represents Order (harmony, symmetry, and balance), and C represents Complexity (the cognitive effort required for perception). Birkhoff viewed the aesthetic experience as an economic exchange: the viewer pays a "cost" in cognitive effort (C) and receives a "reward" in the form of perceived order (O) (Douchová, 2016).

Birkhoff applied this formula to polygons using specific geometric parameters to objectify beauty. The refined formula for polygonal forms is:

$$M = \frac{V + E + R + HV - F}{C} \quad (2.2)$$

where V is vertical symmetry, E is equilibrium, R is rotational symmetry, HV is grid alignment, and F represents unsatisfactory form. Through this calculation, Birkhoff demonstrated that a square in an upright position ($M = 1.5$) is mathematically more pleasing than other basic shapes, such as the equilateral triangle ($M \approx 1.16$).

Later interpretations of Birkhoff's theory by information theorists linked "Order" to Redundancy (predictability) and "Complexity" to Entropy (unpredictability). Within digital and marketing design, several of these measures are particularly significant for consumer attraction, including *Balance*, *Equilibrium*, *Symmetry*, and *Unity* (Ali & Husni, 2021).

2.2.2 Critiques and limitations of Birkhoff's formula

While George Birkhoff's aesthetic measure ($M = O/C$) provided a groundbreaking mathematical framework for evaluating design, treating it as an absolute and universal truth overlooks critical psychological nuances. In the decades following its publication, the formula faced significant backlash from the scientific community for its structural rigidity, primarily regarding how it penalized visual complexity.

Prominent psychologists, most notably Hans Eysenck, heavily critiqued the fundamental mathematical logic of placing complexity solely in the denominator as a "cost". Eysenck (1941) pointed out a major theoretical flaw: if aesthetic beauty is achieved merely by maximizing order and minimizing complexity, then a completely blank white canvas or a perfectly uniform

square would theoretically be the most beautiful objects in existence. By treating complexity strictly as a negative attribute, Birkhoff's formula failed to account for the human need for visual stimulation.

This critique paved the way for D. E. Berlyne's psychobiological theory of aesthetics, which fundamentally shifted how complexity is understood in design. Berlyne demonstrated that human aesthetic preference does not follow a linear, inverse relationship with complexity. Instead, it follows an "Inverted-U" curve (Berlyne, 1971). At the extreme left of the curve, designs with near-zero complexity cause visual boredom and rapid disengagement. At the extreme right, designs with excessive complexity cause cognitive overload and visual confusion. Therefore, peak aesthetic attractiveness is consistently achieved at a *moderate* level of complexity (Berlyne, 1971; Pleyers, 2024). At this optimal midpoint, a design possesses enough structural order to facilitate fluent cognitive processing, yet retains enough visual variation to stimulate arousal and maintain the viewer's interest.

Consequently, in contemporary design evaluation, Birkhoff's parameters cannot be applied in a vacuum. The aesthetic criteria evaluated in this study (such as *Symmetry*, *Balance*, and *Proportion*) serve not to eliminate complexity, but rather to organize it. Effective corporate logos leverage mathematical order to anchor the viewer's attention, ensuring the design remains highly engaging without overwhelming the consumer's cognitive capacity.

2.2.3 Aesthetic design theory and measurement

In the modern field of aesthetic design, the visual form of a product is constructed from a specific "vocabulary" of design elements, most notably line, shape, color, and texture. Research suggests that an appealing form is one that achieves a calculated balance between structural order (concinnity) and the arousal created by complexity (Hu et al., 2022). To guide this process, designers utilize universal aesthetic principles as heuristic strategies to organize these visual elements effectively.

According to Hu et al. (2022), the academic measurement of product aesthetics can generally be divided into three distinct methodological groups: the analysis of form preferences, the quantification of emotional responses (such as Kansei Engineering), and the assessment of aesthetic design theory. The latter group, and the most relevant to this structural analysis, evaluates design based on classic aesthetic principles and compositional rules, evolving directly from Birkhoff's foundational $M = O/C$ formula. Later studies expanded on this by developing algorithms to quantify specific attributes such as *Symmetry* and *Balance*, particularly in the context of interface and 2D layout design.

2.2.4 Operationalizing mathematical concepts in digital design

Building upon Birkhoff's foundational theories and modern aesthetic principles, researchers have identified fourteen common aesthetic values within digital design (Ali & Husni, 2021). To provide a comprehensive evaluation of the experimental visual models, this study systematically examines these fourteen mathematical and structural concepts. These parameters are frequently utilized as primary measures to quantify and assess aesthetic appeal in digital environments:

- **Balance:** The distribution of optical weight in a picture. It can be formal (symmetrical), dynamic (asymmetrical), or radial balance.
- **Equilibrium:** Accomplished through centering the layout itself, where the center of the form coincides with the center of the frame.
- **Symmetry:** The extent to which elements mirror each other across predefined axes. It is typically evaluated in three directions (vertical, horizontal, and diagonal) to create a sense of formal stability.
- **Sequence:** The intentional arrangement of objects in a layout to facilitate the smooth and logical movement of the eye through the displayed information.
- **Cohesion:** The structural binding of the design, often promoted by consistent aspect ratios and aligned boundaries, ensuring the layout feels securely connected rather than fragmented.
- **Unity:** Grounded in Gestalt theory, this creates a connection between individual parts so they are perceived as a coherent whole. It is often achieved by using similar sizes, shapes, or colors for related information and utilizing strategic spacing.
- **Proportion:** The scale relationships between different elements or between an element and the whole body. Classic systems, such as the *Golden Ratio*, are frequently employed to achieve perceived harmony.
- **Simplicity:** The minimization of visual clutter through the careful combination of elements. It relies on reducing the number of distinct alignment points and layout structures to present a straightforward, comprehensible form.
- **Density:** The ratio of filled visual space (such as text characters or data elements) to the entire available frame. Optimal density ensures the design provides sufficient information without visually overwhelming the viewer.
- **Regularity:** The establishment of standard, predictable patterns through consistently spaced horizontal and vertical alignments, creating a structured and easily scannable grid.

- **Economy:** The careful and deliberate use of visual properties (such as styling, display techniques and colors) ensuring that only essential features are employed to convey the intended message.
- **Homogeneity:** An assessment of spatial balance that measures how evenly objects and visual weights are distributed among the four quadrants of the design frame.
- **Rhythm:** The creation of a visual tempo through regular, predictable patterns of change, repetition, or spacing among the design elements.
- **Complexity:** The overarching measure of aesthetic appeal in Birkhoff's theory, where the aesthetic measure (M) is defined as the ratio of Order (O) to Complexity (C). It balances structural organization against the cognitive load required to process the design.

2.3 Consumer perception and socio-demographic moderators

2.3.1 Mathematical heuristics: *Symmetry* and *Proportion*

Recent empirical research confirms that the mathematical concepts defined above, particularly *Symmetry* and *Proportion* in corporate logos, act as powerful visual heuristics for consumers. According to Wu (2025), symmetrical designs significantly enhance perceived product quality by signaling a sense of organizational and functional "stability". This association between *Symmetry* and quality is not direct but is mediated by the consumer's subconscious perception of balance and reliability in the brand's visual identity.

However, the effectiveness of this mathematical parameter is bounded by environmental factors. Wu (2025) demonstrated that the positive impact of *Symmetry* on quality appraisals is moderated by *cognitive load*. In situations where consumers are mentally taxed or distracted, the preference for symmetrical order diminishes, suggesting that the processing of mathematical aesthetics requires a threshold of available cognitive resources.

Similarly, the application of mathematical proportions, specifically the Golden Ratio, is highly sensitive to the dimensionality of the visual stimulus. Recent empirical experiments by Dumitrescu (2025) exploring the Golden Ratio across varying product types revealed that the classic 1.618 ratio maximizes perceived beauty almost exclusively in objects with negligible thickness, which are perceived essentially as flat, two-dimensional planes. In objects with pronounced three-dimensional depth, functional expectations and volume disrupt the pure aesthetic perception of the ratio.

This finding strongly validates the application of Birkhoff's formal proportion metrics to 2D corporate logos, where the absence of a third dimension allows the mathematical relationship between elements to be processed without structural interference. Furthermore, Dumitrescu

(2025) demonstrated that an individual's Centrality of Visual Product Aesthetics (CVPA) significantly moderates the perception of beauty regarding these ratios. This supports the central hypothesis that formal mathematical parameters (whether *Symmetry* or *Proportion*) are processed differently depending on a consumer's inherent design sensitivity and cognitive capacity.

2.3.2 Gender and age as perceptual filters

Building upon the constraints of cognitive load, demographic variables such as age and gender may further moderate a consumer's sensitivity to mathematical design. For instance, younger consumers, who frequently navigate high-distraction digital environments characterized by chronic high cognitive load, might exhibit a diminished reliance on formal *Symmetry* as a heuristic for quality. In contrast, older generations may be more attuned to these structural cues when evaluating brand stability.

Furthermore, gender presents another critical filter through which mathematical aesthetics are processed. The Selectivity Hypothesis proposed by Meyers-Levy and Sternthal (1991) posits that men and women employ divergent information processing strategies. Women typically engage in comprehensive processing, possessing a lower threshold for noticing and elaborating on subtle visual cues. Conversely, men tend to process information selectively, relying primarily on highly salient features. In the context of logo *Symmetry* and *Proportion*, this suggests that female consumers may continue to perceive the subtle "stability" of a mathematical design even under elevated cognitive load, whereas male consumers might overlook these parameters unless they are prominently presented (Wu, 2025).

Recent empirical research strongly supports the premise that visual aesthetics are processed differently across these exact demographic segments. In a comprehensive study of digital consumer behavior, Stefko et al. (2022) demonstrated highly significant differences in how visual appeal is perceived based on both generation and gender. Their findings reveal that younger consumers (Generation Y) place a significantly higher emphasis on visual appeal compared to older demographics (Generation X). Furthermore, the study confirmed that female consumers exhibit a higher sensitivity to visual aesthetics than male consumers. This contemporary data reinforces the Selectivity Hypothesis, suggesting that female and younger consumers are more likely to utilize visual heuristics, such as mathematical *Symmetry* or *Proportion*, as primary drivers for brand evaluation.

This behavioral divergence is further supported by structural equation models examining digital purchase intent. Shaouf, Lü, and Li Shaouf et al. (2016) investigated the effect of web advertising visual design, confirming that visual cues affect the genders differently. Their model revealed that visual design has a direct, significant impact on purchase intentions for male consumers, but lacks this direct effect for female consumers. Because males tend to act as selective processors, they are more easily influenced by highly salient peripheral visual cues (such as a

prominently displayed symmetrical logo or a layout utilizing the Golden Ratio). Conversely, because females engage in comprehensive processing, their purchase intentions are heavily mediated by deeper attitudinal evaluations rather than initial visual heuristics alone. Therefore, the strategic use of mathematical design concepts must account for these gendered pathways to maximize brand attitude and purchase intention.

Ultimately, this study utilizes Birkhoff's critical distinction between "formal" associations (objective mathematical structures) and "connotative" associations (subjective meaning and demographics). Birkhoff's original theory attempted to strip beauty of its subjective components. However, "Formal" mathematics only defines the theoretical potential for beauty. In reality, "Connotative" factors, specifically the age and gender of the consumer, act as perceptual filters that determine how much "Order" the viewer actually perceives. Consequently, this thesis aims to test whether these demographic factors moderate the perception of formal mathematical order, investigating the empirical gap between objective mathematical efficiency and subjective human preference.

2.3.3 Individual differences: Centrality of Visual Product Aesthetics (CVPA)

While demographic factors such as age and gender establish broad perceptual filters, aesthetic appreciation is fundamentally subjective and not uniformly distributed even within the same cohort. While mathematical parameters such as *Symmetry* and *Proportion* exert a measurable influence on visual appeal, their impact depends heavily on an individual's intrinsic psychological traits. To understand this deeper, individual-level variance, researchers rely on the concept of the Centrality of Visual Product Aesthetics (CVPA). Originally conceptualized by Bloch et al. (2003), CVPA is defined as the overall level of significance that visual aesthetics holds for a particular consumer in their relationship with products.

CVPA is a validated individual-difference construct comprising multiple facets, including the inherent value placed on design, aesthetic acumen, and emotional response intensity (Bloch et al., 2003). Recent literature has further extended this construct, demonstrating that high-CVPA consumers (often termed "design-sensitive" individuals) exhibit stronger emotional experiences and perceive higher value in aesthetically pleasing products (Dumitrescu, 2021). Furthermore, research indicates that a consumer's inherent sensitivity to design actively moderates how they process visual complexity and formal aesthetic features (Pleyers, 2024).

2.4 Research hypotheses

Based on the theoretical framework established in the preceding sections, the following hypotheses test how the 14 mathematical aesthetic parameters (Birkhoff's criteria) influence consumer preferences, and how this effect is moderated by individual differences.

2.4.1 Design sensitivity and behavioral influence

Drawing from the Centrality of Visual Product Aesthetics (CVPA) Bloch et al. (2003) and processing fluency theories Reber et al. (2004), the first set of hypotheses explores how a consumer's conscious aesthetic valuation and purchasing behaviors moderate their preference for mathematical order.

- **Hypothesis 1 (H1):** The preference for mathematically ordered designs (encompassing the 14 Birkhoff variations) compared to the base design will be significantly higher among respondents who report that a product's visual appearance is as important as its functionality (High CVPA proxy).
- **Hypothesis 2 (H2):** The positive effect of mathematical aesthetic parameters on visual preferences will be mitigated (or rendered non-significant) among consumers reporting a low sensitivity to design (Low CVPA proxy), indicating a cognitive disengagement from the aesthetic evaluation process.
- **Hypothesis 3 (H3):** Respondents who report that logo design strongly influences their daily purchasing decisions will exhibit a significantly higher preference for mathematically ordered designs, confirming that these formal criteria act as a visual heuristic for product quality and reliability.

2.4.2 Demographic filters: age and gender

The second set of hypotheses applies the Selectivity Hypothesis and theories of cognitive load to test how inherent demographic filters alter visual processing mechanisms.

- **Hypothesis 4 (H4) - Age:** Younger consumers (e.g., Generation Z), who typically process digital information in high-distraction, high-cognitive-load environments, will exhibit a lower systematic preference for strict mathematical order compared to older generations.
- **Hypothesis 5 (H5) - Gender:** Based on the Selectivity Hypothesis, female respondents will demonstrate a stronger preference for mathematically ordered logos than male respondents, as they possess a lower threshold for elaborating on comprehensive visual cues and structural stability.

2.4.3 Exploratory and control variables

To ensure the robustness of these hypotheses, two additional survey metrics are utilized. First, the respondent's highest level of education ("*Quel est votre niveau de diplôme le plus élevé ?*") is included as an exploratory demographic filter. This variable is tested strictly to verify whether general academic background acts as an unintended moderating filter on visual processing.

Second, professional or educational involvement in graphic design, marketing, or visual arts serves as a strict control variable to measure *design expertise*. In the field of empirical aesthetics, the "Expert versus Novice" paradigm dictates that individuals with formal training process visual stimuli differently than laypeople (Bloch et al., 2003). Design professionals tend to engage in top-down cognitive processing, explicitly analyzing structural elements such as *Proportion* and formal *Symmetry*. In contrast, the general consumer typically relies on bottom-up, affective processing, evaluating designs based on immediate emotional resonance.

Furthermore, formal training inherently inflates the "Acumen" dimension of the Centrality of Visual Product Aesthetics (CVPA). Because the primary objective of this research is to evaluate how the general consumer subconsciously reacts to mathematical aesthetic parameters as signals of product quality, the inclusion of design experts could introduce a significant bias. Therefore, their data will be isolated to prevent expertise bias and ensure the findings accurately reflect the true visual processing of the general consumer.

Chapter 3

Methodology

3.1 Research approach and procedure

To empirically test the hypotheses formulated in Chapter 2, a quantitative research approach was adopted utilizing an online survey methodology. The questionnaire was developed and hosted on the Qualtrics XM platform. This software was chosen because it effectively manages the complex randomization of visual stimuli. Additionally, it securely exports raw data in formats directly compatible with Python for statistical analysis.

3.1.1 Survey architecture and user flow

The survey was designed to be concise, requiring an average completion time of under five minutes to prevent cognitive fatigue and maintain the integrity of the respondents' intuitive visual processing. After an introductory screen detailing the academic purpose of the study and ensuring data anonymity, the questionnaire was divided into two distinct sequential blocks (see Figure 3.1):

- **Block 1: Visual pairwise comparisons (the duels):** In the primary experimental phase, respondents were presented with a series of side-by-side logo comparisons (A/B testing). To implement the research design without causing participant fatigue, the Qualtrics survey was programmed to randomly display exactly 6 duels from a predefined pool of 24 strategic pairings (as detailed in Section 3.4). Respondents were asked to instinctively select the logo they found visually preferable.
- **Block 2: Socio-demographic and behavioral metrics:** Following the visual assessment, all respondents were presented with an identical, fixed set of questions to collect quantitative data regarding their profile. This included standard demographic questions (age,

gender, education level), screening for professional design expertise, and self-reported measures assessing the respondent's Centrality of Visual Product Aesthetics (CVPA) and their sensitivity to brand design in daily purchasing decisions.

Placing the visual stimuli in Block 1 before the behavioral questions in Block 2 was a deliberate methodological choice. It ensured that respondents evaluated the logos purely on subconscious aesthetic fluency, without being primed to over-analyze their choices by the subsequent questions regarding design importance.



Figure 3.1: Mobile user interface of the Qualtrics survey displaying the two primary experimental blocks.

3.1.2 Sampling strategy and distribution

The distribution of the survey relied on non-probability sampling, specifically employing a hybrid of *convenience sampling* and *snowball sampling*. The primary survey link was initially distributed via social media platforms (predominantly Facebook) and personal networks. Initial respondents were then encouraged to share the survey within their own respective networks, creating a viral "snowball" propagation effect.

From an epistemological standpoint, it is important to clarify the boundaries of this sampling strategy. Because the respondents were not randomly selected from a centralized national database, this sample does not claim strict statistical representativeness of the entire global or national population. Rather, this research operates within an *exploratory framework*. The primary objective is to test the internal validity of cognitive processing mechanisms (e.g., how the human brain evaluates mathematically ordered design variations compared to a baseline logo under certain conditions).

Consequently, these statistical inferences serve to establish internal reliability rather than universal applicability. Digital snowball sampling naturally produces localized datasets. However, the high volume of collected data ensures strong statistical power within this specific subset. As noted in methodological literature, replicating this network-based methodology would yield highly consistent inferences and stable Bradley-Terry parameter estimations specifically for the observed demographic.

3.2 Stimuli development

To empirically test the influence of Birkhoff's 14 mathematical criteria on consumer preference, a custom set of visual stimuli was engineered specifically for this research. The complete dataset consists of 15 distinct logos: one baseline design and 14 mathematically altered variations.

3.2.1 Fictitious brand and baseline design

A fictitious corporate entity named "NovaCore" was conceptualized for this study. The decision to create a novel, virtual brand rather than utilizing an existing corporate logo was a critical methodological control. Utilizing a known brand would introduce severe confounding variables, such as prior brand equity, established consumer loyalty, and pre-existing emotional associations, which would heavily skew the aesthetic evaluation. By using "NovaCore", respondents were forced to evaluate the logos purely on their structural and visual merits.

An initial "Base logo" was designed to serve as the control stimulus. This baseline design was crafted to represent a standard, modern corporate identity, possessing moderate levels of complexity and order without heavily optimizing for any single mathematical aesthetic rule.

3.2.2 Mathematical variations and AI integration

Following the establishment of the baseline design, 14 variations were generated, each strictly isolating and amplifying one of the 14 aesthetic criteria (e.g., *Symmetry*, *Proportion*, *Unity*, *Rhythm*).

To achieve high-fidelity corporate designs, this study integrated Generative Artificial Intelligence (specifically OpenAI’s DALL-E 3 model) into the stimuli development process. Crucially, a Human-in-the-Loop (HITL) approach was employed rather than accepting default algorithmic outputs. Through iterative prompt engineering and strict manual verification, the generated designs were continuously refined to ensure they accurately embodied the targeted geometric rules without random algorithmic artifacts.

A rigorous methodological constraint was applied during this generative phase to isolate the independent variable. While the structural geometry and layout were systematically altered to reflect the target Birkhoff criterion, all extraneous visual elements were held strictly constant across all 15 stimuli. These fixed elements specifically included the color palette, typography, stroke weight, and the brand name (“NovaCore”). This control ensures that any variance in consumer preference, as calculated by the Bradley-Terry model, is exclusively attributable to the mathematical arrangement rather than arbitrary stylistic changes.

Figure 3.2 illustrates the baseline design alongside the visual translation of two mathematical criteria. The complete catalog of the 14 aesthetic variations used in the experimental duels is provided in Appendix A1.



Figure 3.2: Examples of the stimuli set, demonstrating the baseline control logo and the isolation of specific mathematical criteria while maintaining core brand identity constraints. The full set is available in Appendix A1.

3.3 Measures and variables

To empirically test the hypotheses formulated in Chapter 2, the Qualtrics survey collected a specific set of dependent, independent, and moderating variables, alongside strict methodological screening criteria. Each item was deliberately chosen to operationalize the theoretical constructs, enable precise dataset segmentation, and allow for targeted statistical analysis.

3.3.1 Dependent variable: pairwise preference

The primary dependent variable of this study is the binary preference choice made by respondents during the visual duels (Block 1). By forcing an instinctive choice between two

competing logos, the survey captures the subconscious aesthetic processing of the consumer. The aggregate of these binary choices forms the foundational dataset evaluated by the Bradley-Terry algorithm. This comparative choice is the core metric used to test all five hypotheses, establishing whether designs demonstrating mathematical order (the 14 Birkhoff variations) are systematically preferred over the baseline design under various consumer conditions.

3.3.2 Independent demographic variables

Standard demographic data were collected to evaluate how personal consumer characteristics influence aesthetic preferences.

- **Age:** Respondents were asked to input their exact age in an open-ended format. During the data processing phase, these continuous values were subsequently recoded into distinct age cohorts. This variable is strictly necessary to test Hypothesis 4 (H4). Segmenting the sample by these derived age brackets allows the Bradley-Terry algorithm to compute cohort-specific preference rankings.
- **Gender:** Data regarding gender was collected to evaluate potential variances in aesthetic processing. This serves to test Hypothesis 5 (H5), allowing the algorithm to stratify preferences based on the Selectivity Hypothesis.
- **Education level:** To capture the socio-educational background of the sample, respondents indicated their highest completed degree using a predefined categorical scale (Primary/CEB, Secondary/CESS, Bachelor's, Master's, or Doctorate).

3.3.3 Psychometric and behavioral variables

To assess the psychological importance respondents place on visual aesthetics, two self-reported behavioral measures were included.

- **Centrality of Visual Product Aesthetics (CVPA):** Respondents evaluated the statement: *“Generally speaking, I consider the visual appearance of a product to be just as important as its functionality”* (Original French: *“De manière générale, je considère que l'apparence visuelle d'un produit est tout aussi importante que sa fonctionnalité”*). Responses were recorded using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). This item acts as a proxy for CVPA, creating the necessary segmentation to test Hypothesis 1 (H1) and Hypothesis 2 (H2).
- **Design as a quality heuristic:** To assess Hypothesis 3 (H3), respondents were asked: *“On a daily basis, to what extent does a brand's logo design influence your purchasing*

decisions?” (Original French: “*Au quotidien, dans quelle mesure le design du logo d’une marque influence-t-il vos décisions d’achat ?*”). This was measured on a 5-point ordinal scale ranging from 1 (Not at all) to 5 (Very strongly). This item determines whether consumers whose purchasing decisions are strongly influenced by design evaluate aesthetics differently, providing the necessary variable to test the hypothesis.

3.3.4 Control variable: professional expertise

A critical methodological safeguard was the inclusion of a professional screening question. Respondents were asked if they currently work or study in fields related to graphic design, marketing, or visual arts (Original French: “*Travaillez-vous ou étudiez-vous dans un domaine lié au design graphique, au marketing, à la communication ou aux arts visuels ?*”).

This variable serves two analytical purposes. First, it acts as an exclusion criterion. Consumers with professional design training analyze visual stimuli using specialized cognitive frameworks, which differ drastically from the intuitive processing of a standard consumer. Isolating these experts from the primary dataset ensures that the main Bradley-Terry ranking represents the true mean of the general population. Second, provided the subsample of experts is large enough, this variable allows for a comparative analysis to observe whether professionals are systematically more sensitive to the underlying mathematical criteria than laypeople.

3.4 Experimental design

For this study, evaluating the complete set of pairwise comparisons across all respondents was mathematically and practically unfeasible. With 15 logos (one base logo and 14 variations), the total number of unique duels is determined by the combinations formula:

$$C(15, 2) = \frac{15(15 - 1)}{2} = 105 \text{ possible duels} \quad (3.1)$$

Submitting 105 duels to a single respondent would trigger severe cognitive fatigue, deteriorating data reliability and violating the threshold of intuitive visual processing required for this study. Furthermore, limitations within the Qualtrics survey architecture necessitated a streamlined approach. If a fully randomized presentation of all 105 duels was deployed, the data would become excessively sparse, as each specific pairing would receive too few views to achieve statistical significance within the sample size.

To optimize statistical power and ensure high data density around the most critical comparisons, a **Targeted Incomplete Block Design** was implemented. Rather than drawing randomly from all 105 possibilities, a curated set of 24 strategic duels was engineered.

3.4.1 The baseline duels (14 pairs)

The first 14 duels were designed to directly test each mathematical variation against the control stimulus. In these pairings, the Base logo was systematically pitted against *Balance*, *Equilibrium*, *Symmetry*, *Sequence*, *Cohesion*, *Unity*, *Proportion*, *Simplicity*, *Density*, *Regularity*, *Homogeneity*, *Economy*, *Rhythm*, and *Complexity*. This centralized structure ensures that every independent Birkhoff criterion is directly evaluated against a constant, neutral baseline.

3.4.2 The strategic variation duels (10 pairs)

To capture deeper theoretical nuances and test the boundaries of visual heuristics, 10 additional duels were constructed. These pairings specifically pit mathematical variations against one another. They were selected to compare criteria that are either mathematically adjacent (testing subtle differences) or diametrically opposed (testing extreme contrasts):

- **The clash of extremes (*Simplicity* vs. *Complexity*):** Pits absolute visual minimalism against mastered, maximal structural complexity.
- **The axes (*Balance* vs. *Equilibrium*):** Contrasts asymmetrical visual weight distribution against strict, centered symmetrical order.
- **The progression (*Sequence* vs. *Rhythm*):** Compares sequential progression driven by scale/size against rhythmic progression driven by visual fading (opacity).
- **The minimalism (*Simplicity* vs. *Economy*):** Evaluates the reduction of structural elements versus the reduction of graphical resources (e.g., ink/fill).
- **The structure (*Regularity* vs. *Homogeneity*):** Tests perfect linear alignment against perfect two-dimensional grid repetition.
- **The grouping (*Unity* vs. *Cohesion*):** Contrasts extreme proximity (Gestalt grouping) against structured alignment via bounding boxes.
- **The form (*Symmetry* vs. *Equilibrium*):** Compares the internal symmetry of an isolated shape against the global symmetry of the entire layout.
- **The space (*Density* vs. *Proportion*):** Evaluates the extreme manipulation of negative white space against the extreme manipulation of geometric size.
- **The geometry (*Homogeneity* vs. *Complexity*):** Contrasts structural order achieved via flat 2D repetition against order achieved through a complex 3D mesh structure.

- **The scale (*Sequence vs. Proportion*):** Compares dynamic, stepped scaling against static, proportional geometric scaling.

By curating these 24 highly connected duels, the Qualtrics platform was programmed to randomly assign a subset of exactly 6 duels to each respondent. This methodology ensures that the survey response time remains well under the five-minute mark, while generating a dense, highly connected bipartite graph of observations. This structural network is perfectly optimized for the Bradley-Terry ranking algorithm to converge and estimate accurate latent parameters for all 15 logos.

3.5 Mathematical framework: the Bradley-Terry model

The problem of evaluating and ranking individuals, teams, or objects based on pairwise comparisons arises in many contexts, ranging from sports competitions to consumer choice studies. To mathematically model these interactions, researchers frequently rely on the Bradley-Terry model. Historically, this probabilistic model was first introduced by Zermelo in 1929, before being rediscovered and popularized by Bradley and Terry in 1952 (Fageot et al., 2024; Glickman, 2025; Newman, 2023).

In its classical form, the Bradley-Terry model is designed to analyze binary outcomes, meaning a strict win or loss between two alternatives. The fundamental principle of the model relies on assigning a numerical score, or latent strength parameter, to each competitor. The probability of one individual defeating another is then modeled as a function of the difference between their respective scores. Most often, this relationship is expressed using a logistic function (Fageot et al., 2024; Glickman, 2025; Newman, 2022, 2023).

Although numerous generalizations of the model have been developed over time to account for complex scenarios like ties or contextual advantages (Davidson, 1970; Glickman, 2025; Rao & Kupper, 1967), this research strictly utilizes the classical binary formulation. This foundational probabilistic structure is perfectly suited for forced visual A/B testing, allowing raw comparative judgments from the survey to be transformed into a comprehensive and structured ranking.

3.5.1 Sampling and statistical power

For the ranking algorithm to work, it is not necessary for every person to see every logo, but it is imperative that the overall graph of duels is “connected”. If logo A faces B, and B faces C, the model can mathematically infer a relationship between A and C.

With a finalized sample of 307 respondents completing up to 6 duels each (following data cleaning and expert exclusion detailed in Chapter 4), the survey yielded over 1,800 valid ob-

servations. This volume is largely sufficient to estimate the parameters of the 15 logos in a convergent manner. This mathematical requirement for network connectivity also explains why certain small subgroups (such as specific influence levels or education categories with too few respondents) may create a “Singular Matrix” error and must be excluded from isolated analysis, as the internal graph of these subgroups is no longer sufficiently connected.

3.5.2 Probabilistic intuition

The model postulates that each logo i possesses a latent attractiveness “strength”, denoted p_i . The probability that logo i defeats logo j in a duel depends on the ratio of their strengths:

$$P(i \succ j) = \frac{p_i}{p_i + p_j} \quad (3.2)$$

3.5.3 Logit formulation (logistic regression)

In modern statistics, it is preferable to express this strength in an exponential form to ensure that the values remain strictly positive. We set $p_i = e^{\beta_i}$, where β_i is the parameter to be estimated (the attractiveness score). The formula then becomes:

$$P(i \succ j) = \frac{e^{\beta_i}}{e^{\beta_i} + e^{\beta_j}} \quad (3.3)$$

By applying the natural logarithm to the ratio of the probability of winning (the *log-odds*), we obtain a linear equation:

$$\ln \left(\frac{P(i \succ j)}{P(j \succ i)} \right) = \beta_i - \beta_j \quad (3.4)$$

It is exactly this difference in score ($\beta_i - \beta_j$) that our Python algorithm sought to maximize via the **Maximum Likelihood Estimation (MLE)** method.

3.5.4 Identifiability constraint (the base logo)

The original model presents a mathematical singularity: there is an infinity of solutions. Indeed, if a global constant (for example, +10) is added to all β scores, the score differences remain exactly the same, and the probabilities remain unchanged.

To solve this identifiability problem and allow the model to converge (matrix inversion during algorithmic calculation), it is imperative to set a reference parameter. In our case, we defined the score of the original baseline logo as a zero reference base:

$$\beta_{\text{base}} = 0 \quad (3.5)$$

Thus, the calculated score β_i for each variation directly represents its *relative* attractiveness compared to the reference logo.

3.6 Algorithmic processing

In order to translate the raw responses from the Qualtrics questionnaire into a format usable by the Bradley-Terry model, an algorithmic restructuring phase was developed in Python (via the *pandas* library).

3.6.1 Structural data transformation

The initial dataset was presented in a “wide format”, where each row represented a respondent and each column corresponded to a potential duel. The algorithm first performed a transformation into a “long format” so that each row in the database now corresponds to a unique observation, i.e., a specific duel evaluated by a user. Null values were automatically purged from the dataset. These null values correspond to duels not submitted to the respondent due to the targeted incomplete block design.

1. Wide Format (Raw Qualtrics Data)

ResponseId	Symmetry_Base	Sequence_Base	Equilibrium_Base
Respondent_01	1	NULL	2
Respondent_02	NULL	1	NULL

⇓

Restructuring (Melt) and purging of null values

⇓

2. Long Format (Observation Matrix)

ResponseId	Duel	Qualtrics_Response
Respondent_01	Symmetry_Base	1
Respondent_01	Equilibrium_Base	2
Respondent_02	Sequence_Base	1

Figure 3.3: Illustration of the algorithmic data transformation: transition from wide format to long format and exclusion of missing data.

3.6.2 The arbitration function

For each retained observation, the duel identification variable (e.g., named *Symmetry_Base*) was algorithmically split to isolate the two competitors: Logo A (presented on the left) and Logo B (presented on the right).

A conditional arbitration function was then applied to interpret the numerical response generated by Qualtrics:

- If the returned value is 1, Logo A is declared the *Winner* and Logo B becomes the *Loser*.
- If the returned value is 2, Logo B is declared the *Winner* and Logo A becomes the *Loser*.

Additional safeguards were integrated into the script to clean residual metadata (invisible spaces, decimal formatting .0, or possible textual responses), thus ensuring a strict and robust binary classification.

3.6.3 Construction of the design matrix

Once the winners and losers were identified for all duels in the sample, the algorithm generated the mathematical matrix X required for logistic regression estimation.

For each duel k pitting a winner i against a loser j , the corresponding row in the matrix is encoded as follows:

$$X_{k,m} = \begin{cases} +1 & \text{if } m = i \text{ (Winner)} \\ -1 & \text{if } m = j \text{ (Loser)} \\ 0 & \text{for all other logos } m \notin \{i, j\} \end{cases} \quad (3.6)$$

This vector encoding allows the mathematical solver (*statsmodels*) to map each row of data exactly to the score difference $(\beta_i - \beta_j)$ required by the log-odds equation (Eq. 3.4) detailed in the previous section.

Chapter 4

Results and discussions

4.1 Sample description and data preparation

Before executing the Bradley-Terry mathematical models, a rigorous data cleaning and restructuring phase was conducted using Python (via the *pandas* library) to transition the raw Qualtrics data into the bipartite tournament format required for logistic regression.

The initial dataset contained 359 total responses. During the algorithmic transformation from wide format to long format, all incomplete duels (null values inherent to the Targeted Incomplete Block Design) were purged, successfully generating a dense network of pairwise observations.

4.1.1 Expertise control and exclusion

As established in Chapter 3, a critical control check was performed regarding professional expertise. Respondents identifying as professionals or students in design, marketing, or visual arts were isolated. Initial algorithmic testing on this specific sub-group triggered a “Singular Matrix” mathematical error. This confirms two methodological expectations: an insufficient isolated sample size to form a fully connected graph, and a high degree of unanimity indicating specialized, top-down visual processing.

In strict accordance with the established exclusion criteria, these expert responses ($N = 40$) were permanently removed from the primary dataset (a detailed statistical validation of their divergent cognitive processing is available in Appendix A3).

Furthermore, to guarantee the absolute purity of the remaining sample, respondents who omitted the entire socio-demographic block and expertise screening question ($N = 12$) were identically excluded, as their cognitive processing style could not be verified. This conservative exclusion step guarantees that all subsequent aesthetic rankings strictly reflect the intuitive,

bottom-up visual processing of the general consumer ($N = 307$), completely free from analytical bias.

4.1.2 Handling missing data: pairwise deletion

Following the exclusion of experts and unknown profiles, the core dataset of general consumers consisted of $N = 307$ respondents. While this group yields a theoretical maximum of 1,842 duels (307×6), a detailed audit of the response matrix revealed minor data anomalies inherent to web-based survey distribution (such as network-induced rendering failures). A small subset of respondents exhibited partial attrition within the experimental block, missing a combined total of 12 visual comparisons despite forced-response parameters. Because the Bradley-Terry algorithm evaluates isolated pairs rather than complete respondent profiles, these partial responses were preserved. Consequently, the visual experiment generated exactly 1,830 valid pairwise comparisons. This massive volume of observations provides exceptional statistical power for the global Bradley-Terry ranking.

A secondary minor attrition rate occurred during the socio-demographic questionnaire (Block 2). While the remaining 307 respondents successfully completed the general behavioral and psychometric measures, a specific subset of 27 respondents omitted their exact age.

To maximize statistical power and preserve the integrity of the visual data, a pairwise deletion (available-case analysis) strategy was employed. The global aesthetic ranking utilizes the full refined sample ($N = 307$). For subsequent hypothesis testing, respondents were excluded strictly on a case-by-case basis only when the specific moderating variable (i.e., Age) was missing. This approach results in slightly fluctuating sample sizes for the sub-group analyses ($N = 307$ for CVPA and Influence analyses, and $N = 280$ for Generational analyses) while ensuring no valid visual duel data is unnecessarily discarded.

4.1.3 Demographic profile of the general consumer

Within the finalized general consumer dataset, the demographic distribution provides a solid foundation for cross-sectional analysis. The sample features a balanced gender distribution (57.7% Female, 42.0% Male, 0.3% Other) and a diverse educational background, with the largest proportion of respondents (41.7%) reporting a Bachelor's as their highest completed degree. The continuous age data was categorized into cohorts to facilitate robust generational comparisons between Generation Z, Millennials, and Generation X/Baby Boomers. Finally, the successful collection of psychometric data across this entire refined sample guarantees that subsequent evaluations of visual design sensitivity (CVPA) and purchasing heuristics are grounded in a highly representative consumer base.

4.2 General aesthetic preferences: the global Bradley-Terry model

To establish the foundational aesthetic preferences of the general consumer, the bipartite network of 1,830 valid visual duels was processed through the Bradley-Terry logit model. While the Elo rating system evaluates matches sequentially and is sensitive to chronological order, the Bradley-Terry model evaluates the entire dataset simultaneously. For this static cross-sectional experiment, it ensures a robust, order-independent calculation of global probabilities via Maximum Likelihood Estimation (MLE).

To ensure mathematical identifiability, the baseline "NovaCore" design was anchored as the reference parameter ($\beta_{\text{base}} = 0$). Consequently, the estimated parameters for the 14 structural variations represent their relative attractiveness compared directly to the control stimulus.

The comprehensive output of the logit regression, including the latent coefficients (log-odds), standard errors, and statistical significance levels, is presented in Table 4.1. A supplementary visual representation of these raw log-odds scores is available in Appendix A2.

Design Criterion	Coef (Log-Odds)	Std. Err.	z-score	P> z	95% Conf. Interval	
Base logo (Reference)	0.000	-	-	-	-	-
Equilibrium	-0.473	0.188	-2.515	0.012	-0.842	-0.104
Proportion	-1.011	0.178	-5.672	0.000	-1.360	-0.662
Regularity	-1.125	0.234	-4.801	0.000	-1.585	-0.666
Sequence	-1.256	0.189	-6.656	0.000	-1.626	-0.886
Unity	-1.362	0.258	-5.284	0.000	-1.868	-0.857
Symmetry	-1.588	0.224	-7.075	0.000	-2.028	-1.148
Rhythm	-1.883	0.238	-7.897	0.000	-2.351	-1.416
Complexity	-1.976	0.240	-8.248	0.000	-2.445	-1.506
Density	-2.225	0.250	-8.882	0.000	-2.715	-1.734
Economy	-2.428	0.426	-5.701	0.000	-3.262	-1.593
Homogeneity	-2.737	0.239	-11.444	0.000	-3.205	-2.268
Cohesion	-3.022	0.347	-8.719	0.000	-3.701	-2.343
Balance	-3.250	0.380	-8.550	0.000	-3.995	-2.505
Simplicity	-3.279	0.273	-12.019	0.000	-3.814	-2.744

Table 4.1: Global Bradley-Terry regression results ($N = 307$). Negative log-odds coefficients indicate a lower probability of defeating the baseline reference logo.

4.2.1 The baseline dominance (log-odds analysis)

The most immediate and striking observation from the regression model is the absolute dominance of the Base logo. Without exception, all 14 mathematical variations yielded negative coefficients. In the context of the Bradley-Terry model, a negative log-odds score signifies a lower probability of winning a pairwise comparison against the baseline.

Furthermore, 13 of the 14 variations present p-values of 0.000 ($p < 0.001$), indicating a highly significant, systematic rejection of strict mathematical order by the general consumer.

The data provides robust empirical evidence that isolating and maximizing specific aesthetic formulas (as postulated by Birkhoff's aesthetic measure) actively deteriorates the visual appeal of a modern corporate identity compared to a balanced, moderate baseline.

4.2.2 The *Equilibrium* refinement

The only mathematical variation that managed to compete closely with the baseline design was *Equilibrium* (coef = -0.473). The isolation of the pure novice sample ($N = 307$) establishes a definitive p-value of 0.012, which falls strictly below the standard $\alpha = 0.05$ threshold of significance. Therefore, while *Equilibrium* is statistically proven to be inferior to the Base logo, it represents the most tolerable form of strict mathematical order for the general consumer, likely because its centered *Symmetry* aligns closest with standard digital interface expectations.

4.2.3 Translating scores into probabilities

To contextualize these latent log-odds coefficients into actionable managerial metrics, the scores were transformed into direct probabilities of victory using the standard logistic function ($P = \exp(\beta)/(1 + \exp(\beta))$).

As visualized in Figure 4.1, the gap between theoretical math and actual preference is vast. While *Equilibrium* maintains a respectable 38.4% chance of defeating the baseline logo in a blind test, other prominent design heuristics fail drastically. For instance, strict geometric *Proportion* (often associated with the Golden Ratio) only secures a 26.7% win rate, and *Sequence* achieves a 22.2% win rate.

Most critically, the bottom of the ranking fundamentally challenges minimalist design trends. *Simplicity*, defined as the extreme reduction of structural elements, was the most heavily penalized variation, securing a mere 3.6% probability of victory. This confirms the limits of the Gestalt “Law of Simplicity” in modern branding: if a design is made too simple, it loses its visual appeal and appears completely empty to the average consumer.

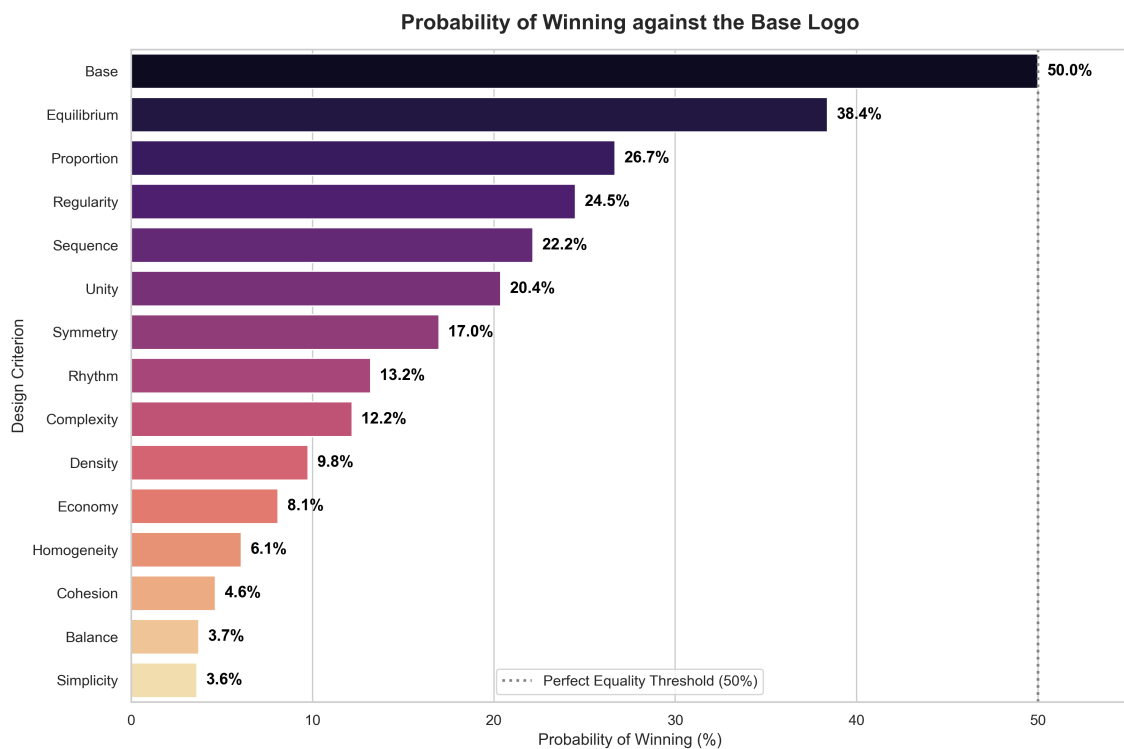


Figure 4.1: Probability of each mathematical variation winning against the Base logo in a blind pairwise comparison. The dashed line represents the 50% threshold of perfect equality.

4.3 Hypothesis testing through demographic and behavioral filters

While the global Bradley-Terry model establishes a definitive baseline preference for moderate complexity over strict mathematical order, it inherently assumes a homogeneous consumer base. As postulated in Chapter 2, visual processing is not uniform. The following subsections test the core hypotheses, systematically applying psychographic and demographic filters to the dataset to determine how individual consumer characteristics actively moderate the perception of mathematical aesthetic order.

Statistical inference framework for sub-group analysis

To test the subsequent hypotheses, the dataset was stratified based on relevant psychographic and demographic variables. While the Bradley-Terry logit model generates raw win probabilities for these cohorts, comparing these visual percentages directly can introduce analytical bias due to varying sub-sample sizes. To ensure scientific rigor, a Chi-Square Test of Independence (χ^2) was applied across the subgroups for each design criterion. This inferential test calculates a p -value indicating whether the variance in pairwise selection rates is statistically significant, or merely a byproduct of sample size and random noise. Given the number of criteria and

subgroup contrasts, these tests are exploratory; p-values are reported unadjusted and should be interpreted with caution.

The statistical significance levels, visualized via star notations on the Y-axis of all subsequent graphs, are defined as follows:

- *** $p < 0.01$: High statistical significance (very strong evidence of a difference between groups).
- ** $p < 0.05$: Statistical significance (strong evidence of a difference; standard scientific threshold).
- * $p < 0.10$: Marginal significance (suggestive evidence of a difference).
- ° $p < 0.20$: Directional trend (notable pattern, but weak statistical evidence).

Note on the directional trend threshold (°): Because the stratification of the dataset inherently reduces the sample size within certain specific cohorts (e.g., Boomers, or 'Strongly Agree' respondents), the statistical power of the Chi-Square test becomes highly conservative. The inclusion of the $p < 0.20$ threshold allows this exploratory research to identify and discuss robust, general behavioral trends that might otherwise be masked by the strict penalties applied to small sample sizes.

4.3.1 The impact of design sensitivity (H1 & H2)

The Centrality of Visual Product Aesthetics (CVPA) dictates the overall significance visual aesthetics hold for a consumer. To operationalize this construct and test Hypotheses 1 and 2, the sample was segmented based on respondents' self-reported aesthetic sensitivity, categorized by their level of agreement with the statement: "*De manière générale, je considère que l'apparence visuelle d'un produit est tout aussi importante que sa fonctionnalité*" (Generally, I consider the visual appearance of a product to be just as important as its functionality). The Bradley-Terry algorithm successfully converged for all five Likert subgroups. To determine the robustness of the variance between these cohorts, a Chi-Square Test of Independence was applied. The probabilities and significance levels are visualized in Figure 4.2.

The subconscious nature of geometric heuristics

The most prominent finding from the inferential analysis is the broad lack of statistical significance across major geometric criteria. Classic heuristics such as *Proportion*, *Equilibrium*, and *Regularity* yielded no significance stars. This indicates that a consumer's conscious valuation of design (their CVPA) does not systematically alter their pairwise selection rate for these structures. This suggests that certain mathematical layouts are processed sub-cognitively; the

human brain evaluates these geometric rules identically, regardless of whether the consumer consciously prioritizes aesthetic design.

High CVPA: Aesthetic acumen and structural binding

H1 posited that the preference for mathematically ordered designs would be significantly higher among respondents with high CVPA (Bloch et al., 2003). The inferential data provides targeted, partial support for this hypothesis, specifically regarding structural grouping.

When observing the 'Strongly agree' cohort (high design sensitivity), there is a statistically significant increase in the probability of victory for *Cohesion* ($p < 0.05$) and a marginally significant increase for *Symmetry* ($p < 0.10$). Individuals with high CVPA possess a higher degree of visual acumen; they actively search for, and derive pleasure from, underlying structural connections. While the baseline logo still maintains an overall advantage, the high-CVPA consumer is significantly more receptive to the specific "Order" variables that bind a design together compared to the average consumer.

Low CVPA: The cognitive load paradox

H2 anticipated that the positive effect of mathematical parameters would be mitigated among consumers with low design sensitivity, indicating cognitive disengagement (Bloch et al., 2003). The empirical data refutes this hypothesis, instead revealing a marginal trend rooted in processing fluency (Reber et al., 2004).

The "Strongly disagree" cohort (individuals who consider design entirely secondary to functionality) demonstrated severe, volatile spikes in preference for explicit mathematical order. Most notably, for this cohort, *Sequence* achieved a win probability approaching 60%. The Chi-Square test flags this as only a marginal trend ($p < 0.20$). This is likely due to the high variance and smaller sample size inherent to the extremes of a Likert scale. However, the directional behavior still aligns with processing fluency theory. Consumers with exceptionally low CVPA refuse to expend cognitive resources on visual evaluation. Consequently, they gravitate toward the most rigid, predictable mathematical structures available. For these users, extreme mathematical order acts as the ultimate cognitive shortcut, allowing them to process the stimulus with near-zero mental effort.

Conclusion for H1 & H2: H1 is partially supported; high design sensitivity significantly increases the appreciation of specific structural binding criteria (*Cohesion*, *Symmetry*) due to elevated aesthetic acumen, though it does not impact universal geometric ratios. H2 is rejected; low design sensitivity does not smoothly mitigate the effect of mathematical order, but rather triggers highly volatile preferences for explicit rigidity (*Sequence*) as a mechanism to minimize cognitive load.

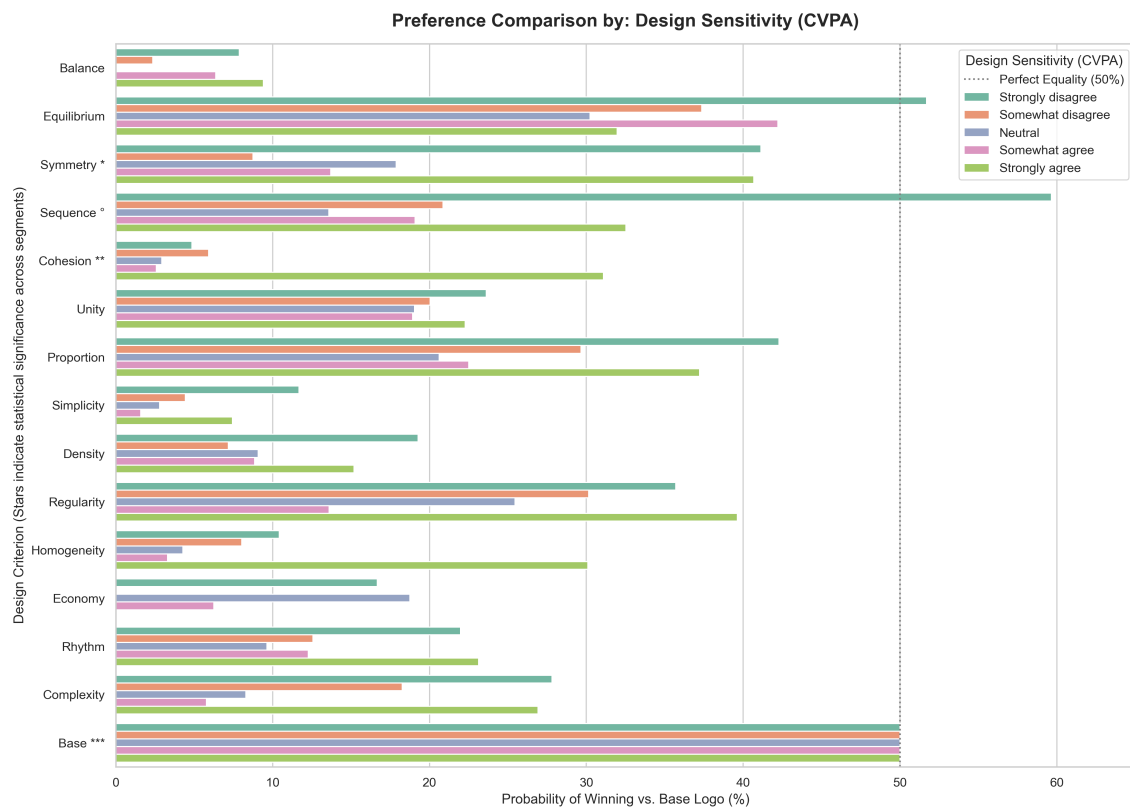


Figure 4.2: Probability of winning against the Base logo, segmented by Centrality of Visual Product Aesthetics (CVPA). Significance stars indicate the p -value of a Chi-Square test evaluating variance across segments. The dashed line represents the 50% threshold.

4.3.2 Design as a purchasing heuristic (H3)

Hypothesis 3 (H3) proposed that respondents who heavily rely on visual design as a daily purchasing heuristic would exhibit a significantly higher preference for mathematically ordered designs, utilizing formal criteria as a proxy for product reliability. To test this, the dataset was segmented by the self-reported influence of logo design on purchasing decisions. The "Very strongly" cohort was excluded from this iteration due to an insufficient sample size ($N \approx 3$, generating only 18 duels), preventing algorithmic convergence. The model successfully processed the remaining four cohorts. To determine the global robustness of these variances, a Chi-Square Test of Independence was applied (visualized in Figure 4.3).

Rejecting the heuristic: The sophistication of high-influence buyers

The empirical data decisively rejects H3. Contrary to expectations, the "Strongly" influenced cohort (those who actively use design to make buying decisions) did not systematically favor mathematical order.

The inferential analysis highlights *Proportion* ($p < 0.10$) and *Rhythm* ($p < 0.20$) as key

statistical dividers. For these criteria, the "Strongly" influenced cohort exhibited a drastically reduced probability of victory compared to less influenced groups. For example, strict *Proportion* (representing classic geometric scaling) plummeted to a win rate of under 8% for highly influenced consumers, whereas it maintained a robust 35% to 37% win rate among the "Moderately" and "Not at all" cohorts.

Rather than acting as a heuristic for quality, specific mathematical parameters appear to signal the opposite to design-conscious buyers. Consumers whose purchasing behavior is highly dictated by aesthetics are likely more visually sophisticated. To this demographic, logos governed by rigid mathematical rules are perceived not as reliable, but as generic or indicative of lower brand equity. Consequently, they heavily penalize these specific variations in favor of the moderate, nuanced complexity of the baseline design.

Corroborating the cognitive load paradox

Conversely, the data for these same significant criteria confirms the behaviors observed in the lowest design-sensitivity cohorts. The "Not at all" cohort consistently demonstrated the highest tolerance for strict structures like *Proportion* and *Rhythm*. This finding perfectly triangulates with the results of Hypothesis 2. It confirms that individuals who wish to bypass visual evaluation default to structurally rigid options when available, utilizing mathematical order as a mechanism for cognitive ease rather than a heuristic for premium quality.

The *Equilibrium* localized spike

While the high-influence cohort systematically rejected criteria like *Proportion*, a remarkable visual exception occurred with the *Equilibrium* criterion. For the "Strongly" influenced group, *Equilibrium* marginally surpassed the 50% threshold of perfect equality, indicating a probability of victory against the Base logo. However, the Chi-Square test reveals no global statistical significance for this criterion, indicating high variance and a lack of universal consensus across the cohorts. This means that while a localized sub-group of highly design-conscious consumers may occasionally view perfectly centered symmetry as a valid premium marker, it is a highly volatile preference that cannot be generalized as a strict heuristic rule for this demographic.

Conclusion for H3: H3 is rejected. Utilizing design as a strong purchasing heuristic does not globally increase the preference for mathematical order. In fact, for specific geometric criteria (*Proportion*, *Rhythm*), it actively decreases preference, as visually sophisticated consumers prefer nuanced complexity over rigid, predictable geometry.

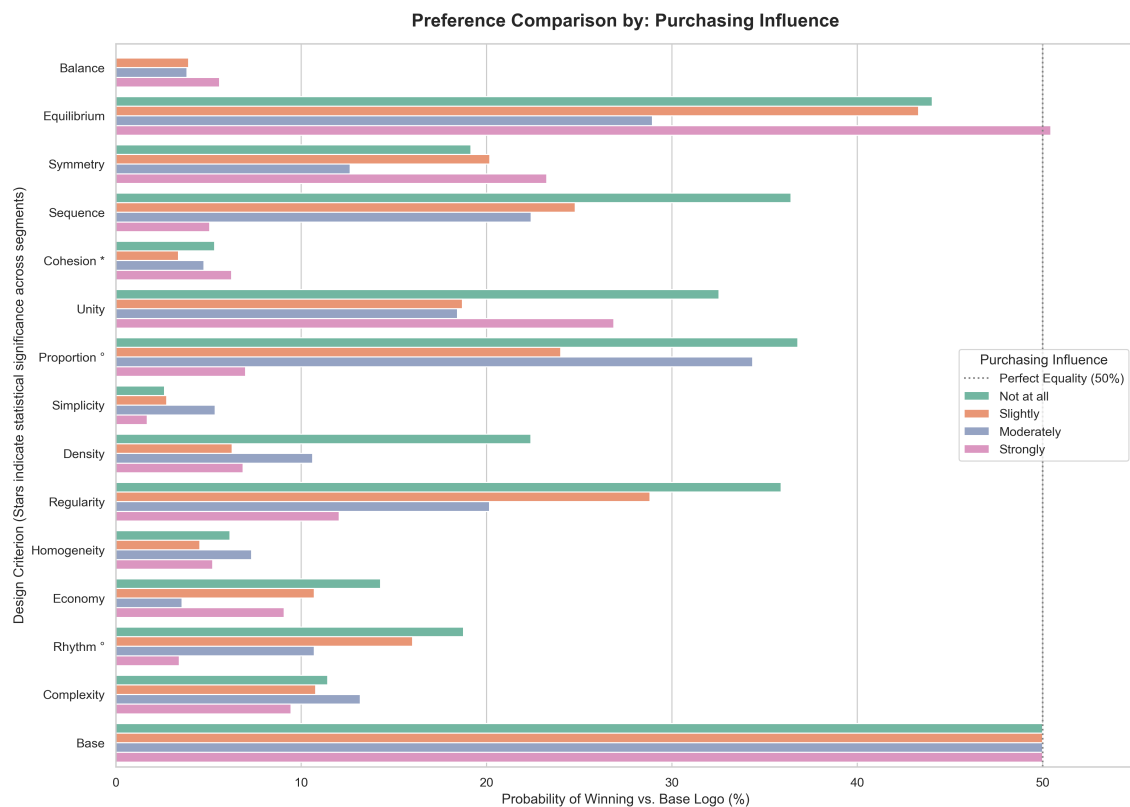


Figure 4.3: Probability of winning against the Base logo, segmented by the self-reported influence of logo design on daily purchasing decisions. Significance stars indicate the p -value of a Chi-Square test evaluating variance across segments. The dashed line represents the 50% threshold.

4.3.3 Generational differences and cognitive load (H4)

Hypothesis 4 (H4) posited that younger consumers, who habitually process digital information in high-distraction, high-cognitive-load environments, would exhibit a lower systematic preference for strict mathematical order compared to older generations.

To operationalize this test, the continuous age data was segmented into four distinct generational cohorts based on varying degrees of digital immersion during cognitive development: 18–25 years (Gen Z, generating 630 duels), 26–35 years (Millennials, 191 duels), 36–55 years (Gen X, 619 duels), and 56+ years (Boomers, 231 duels). The Bradley-Terry algorithm successfully converged for all four cohorts. To evaluate the statistical robustness of the generational variances, a Chi-Square Test of Independence was applied (visualized in Figure 4.4).

Generation Z: The rejection of structural rigidity

The inferential data strongly supports H4, specifically regarding explicit linear structure and visual mass. The Gen Z cohort (18–25 years), representing true digital natives, shows an

absolute rejection of rigid mathematical order. For this group, variations like *Sequence* and *Simplicity* fall to roughly a 5% probability of victory, and *Density* to under 10%.

Because this generation is acclimated to fast-paced, highly visual, and fluid digital environments, strict mathematical reduction does not appeal to them. Instead of seeing rigid order as a helpful cognitive shortcut, they perceive it as overly simplistic, static, or visually boring, heavily preferring the nuanced, moderate complexity of the baseline logo.

The strict order gradient (Gen X and Boomers)

A very clear, statistically significant generational gradient emerges specifically for rigid, repetitive structures. The most robust finding in this demographic analysis is the severe generational divide regarding *Sequence* ($p < 0.01$). While Gen Z entirely rejects it, the tolerance and active preference rise steadily with age, reaching its peak with the Boomer cohort (56+ years), who elevate *Sequence* to nearly a 53% win rate, effectively defeating the baseline logo in direct pairwise comparisons.

This upward generational trend is further supported by *Density* ($p < 0.10$), as well as marginal significance indicators for *Regularity* ($p < 0.20$) and *Simplicity* ($p < 0.20$). Older cohorts formed their aesthetic habits during an era of print media and early standardized digital interfaces, where explicit geometric structure signaled professionalism. Consequently, these consumers find high value and cognitive ease in explicit visual order and heavier visual density.

The illusion of classical heuristics (*Equilibrium, Proportion & Unity*)

Visually, the graph suggests that the Millennial cohort possesses a unique hybrid response, displaying massive preference spikes for classical layouts like *Equilibrium* (reaching 54%), as well as *Proportion* and *Unity* (both approaching 40%). However, it is crucial to note that the Chi-Square test yielded no statistical significance for these specific criteria.

This lack of global significance indicates that these visual peaks are subject to high sample variance, meaning classical geometric and structural heuristics (such as Gestalt unity, the Golden Ratio, or perfectly centered *Symmetry*) are evaluated inconsistently across all ages. Consequently, while rigid repetition (*Sequence*) is strictly dependent on age, the appreciation for classical spatial geometry and grouping (*Equilibrium, Proportion, Unity*) transcends generational boundaries and cannot be reliably generalized as a Millennial trait.

Conclusion for H4: H4 is supported. Younger consumers (Gen Z) systematically reject strict mathematical order. As age increases, the preference for explicit mathematical structure rises significantly. This is particularly true for rigid sequencing (*Sequence*) and visual weight (*Density*), which act as positive heuristics for older generations.

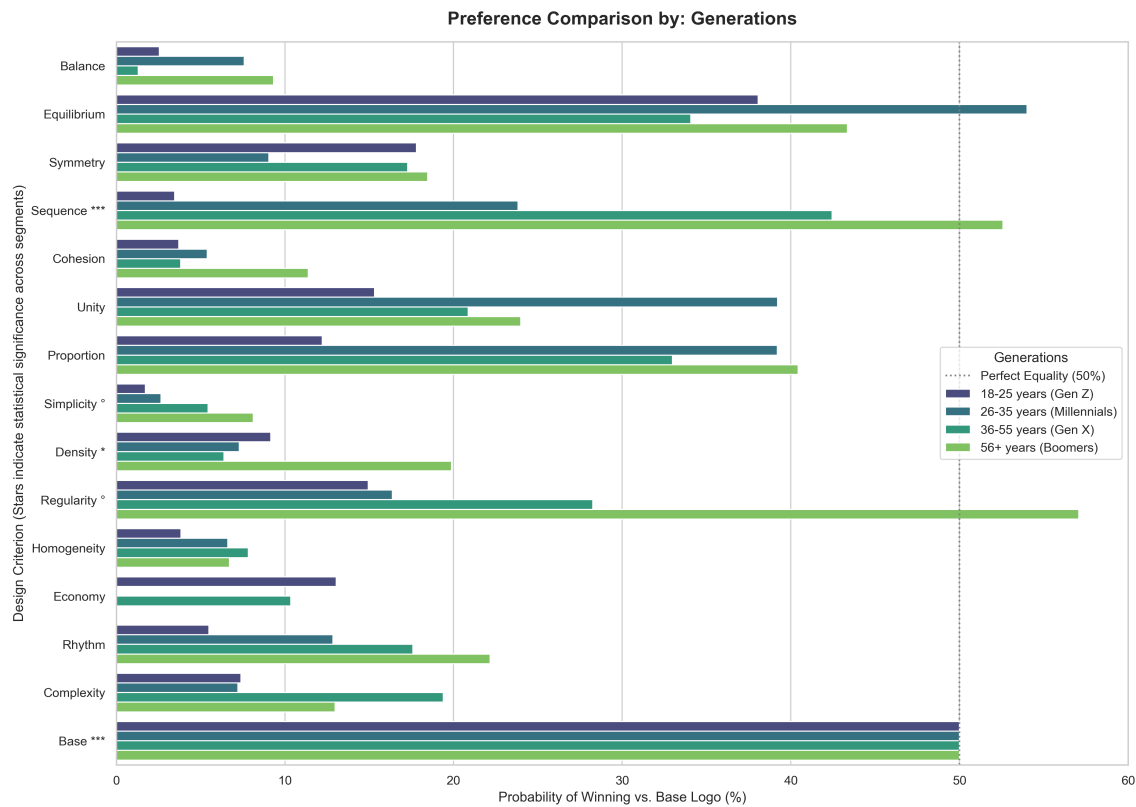


Figure 4.4: Probability of winning against the Base logo, segmented by four generational cohorts. Significance stars indicate the p -value of a Chi-Square test evaluating variance across the generational segments. The dashed line represents the 50% threshold.

4.3.4 Gender selectivity in visual processing (H5)

Hypothesis 5 (H5) posited that female respondents would demonstrate a stronger preference for mathematically ordered logos than male respondents. This prediction was grounded in the Selectivity Hypothesis Meyers-Levy and Sternthal (1991), which suggests that females are comprehensive processors with a lower threshold for elaborating on subtle structural cues, whereas males are selective processors who rely on highly salient, overall heuristics.

To test this, the dataset was segmented by gender. The algorithm successfully evaluated the male cohort (generating 772 pairwise duels) and the female cohort (generating 1052 pairwise duels). The "Other" category was excluded from this iteration due to an insufficient sample size (6 duels), which would trigger a complete separation mathematical error in the Bradley-Terry model. To determine if the variance in pairwise selection rates was statistically robust, a Chi-Square Test of Independence was applied. The resulting win probabilities and significance levels are visualized in Figure 4.5.

Comprehensive processing and female structural appreciation

The inferential data offers nuanced support for H5, revealing that female consumers do exhibit a statistically significant higher likelihood of selecting specific types of mathematical order in pairwise comparisons.

This divergence is most firmly established in criteria related to grouping and delicate spatial layout. The female cohort demonstrated a significantly higher win probability for *Unity* ($p < 0.05$) and *Proportion* ($p < 0.10$). Furthermore, *Symmetry* and *Complexity* both registered marginal significance ($p < 0.20$), indicating a strong directional trend where women favor these structured deviations more frequently than men. These specific selection rates align well with the Selectivity Hypothesis: because female consumers utilize comprehensive cognitive processing, they are more likely to consciously perceive, process, and reward the subtle visual harmony embedded in *Unity* and classical *Proportion*.

It is crucial to note that while criteria such as *Equilibrium* and *Sequence* display large visual gaps in their raw win probabilities, the Chi-Square test reveals these differences lack statistical significance. This indicates high variance within the sub-samples, meaning the preference (or rejection) of these specific layouts cannot be confidently generalized as a strict gender divide.

Selective processing and male heuristic reliance

The statistical analysis fundamentally challenges the notion that males simply "punish" all mathematical rigidity. Instead, the data reveals that male respondents actively and significantly select entirely different structural heuristics compared to females to win their visual duels.

The most statistically robust findings in this demographic analysis are the profound male pairwise preferences for *Density* ($p < 0.01$) and *Economy* ($p < 0.01$). Rather than being minor exceptions, these criteria act as primary aesthetic drivers for the male cohort. This behavior perfectly illustrates male selective processing. Male consumers are less likely to expend cognitive effort decoding subtle, relational alignments (like *Unity*). Instead, they rely on highly salient, immediate visual characteristics. Both *Density* (which maximizes structural weight) and *Economy* (which minimizes extraneous elements) offer high-contrast, easily digestible visual anchors. Consequently, male respondents consistently favor these high-impact structural traits during pairwise comparisons.

Conclusion for H5: H5 is partially validated and requires refinement. Gender undeniably plays a significant role in aesthetic evaluation; however, it is not a simple binary of women selecting structure and men rejecting it. Driven by comprehensive processing, female respondents demonstrate a statistically significant higher likelihood of selecting subtle relational structures (*Unity*, *Proportion*). Conversely, driven by selective processing, male respondents significantly favor highly salient, immediate structural heuristics (*Density*, *Economy*).

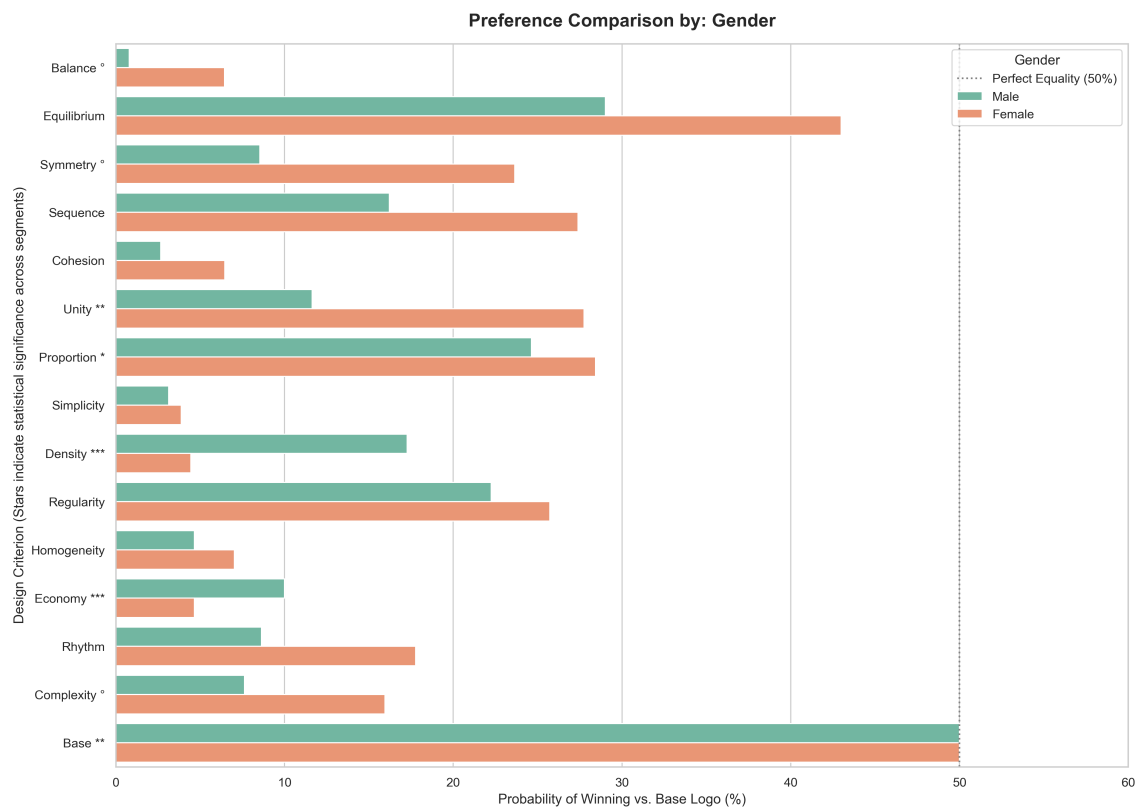


Figure 4.5: Probability of winning against the Base logo, segmented by gender. Significance stars indicate the p -value of a Chi-Square test evaluating variance across the gender segments. The dashed line represents the 50% threshold.

Exploratory analysis: education level

As outlined in the methodology (Chapter 3), the respondent's highest completed degree was tested as an exploratory demographic filter. A stratified Bradley-Terry analysis was conducted for the viable cohorts (High School, Bachelor's, and Master's). The 'Primary' and 'Doctorate' cohorts were excluded from algorithmic processing due to insufficient sample sizes, which prevented network convergence. The subsequent Chi-Square test of independence revealed no statistically significant variances ($p > 0.20$) across any of the 14 mathematical criteria between the remaining groups (see Appendix A4). This indicates that within this predominantly university-educated sample, formal education level does not act as a significant moderating filter for visual geometric processing.

Chapter 5

Conclusions and perspectives

The primary objective of this research was to challenge the assumption that pure mathematical formulas, such as George Birkhoff's aesthetic measure ($M = O/C$), serve as universal predictors of modern consumer preference. Through the algorithmic evaluation of 1,830 visual pairwise comparisons, this thesis demonstrates that strict geometric order is not an absolute heuristic for quality. The empirical findings actively validate D.E. Berlyne's psychobiological theory of aesthetics: consumers systematically reject extreme mathematical reduction (such as absolute *Simplicity*) in favor of the moderate complexity found in the baseline design. Furthermore, the data reveals a profound cognitive load paradox. Contrary to expectations, consumers with low design sensitivity (low CVPA) exhibited the highest preference for rigid, predictable structures like *Sequence* and *Equilibrium*. For these consumers, extreme mathematical order acts not as a marker of inherent beauty, but as the ultimate cognitive shortcut, allowing them to process the visual stimulus with near-zero mental effort.

These theoretical insights carry immediate strategic implications for brand management and corporate design. Marketing agencies must abandon the notion that classic geometric heuristics, such as strict adherence to the Golden Ratio or perfect linear sequencing, automatically generate premium brand equity. Instead, mathematical design must be deployed strategically as a tool to regulate cognitive load based on specific demographic profiles. Brands should adapt visual complexity to their target demographic. Highly design-sensitive groups, such as Generation Z or predominantly female audiences, utilize comprehensive processing and have a higher threshold for visual engagement. For these consumers, brands should embrace nuanced, moderate complexity. In contrast, older cohorts like Baby Boomers often rely on rapid, selective processing. For these audiences, integrating strict mathematical *Regularity* and *Symmetry* more effectively communicates organizational stability and reliability.

While these findings are statistically robust within the modeled subgroups, several methodological boundaries must be acknowledged. First, the use of a fictitious brand (NovaCore) suc-

cessfully isolated structural aesthetics from prior brand equity. However, this approach prevents an analysis of how mathematical changes interact with established emotional brand loyalty in real-world scenarios. Second, the stimuli were limited to two-dimensional digital logos. This format ensures mathematical proportions are processed without the interference of spatial depth or volume. Finally, the digital convenience sampling strategy yielded a predominantly Western European dataset. Consequently, the observed aesthetic preferences and heuristic behaviors cannot be reliably generalized to global consumer markets.

These boundaries present clear and necessary avenues for future academic exploration. To determine the true universality of these mathematical design penalties, cross-cultural replications should be conducted in East Asian markets. This will help observe how holistic visual processing alters the perception of structural order. Furthermore, research must transition from controlled survey environments to real-world behavioral testing. Implementing live A/B testing of digital advertisements or packaging would provide critical data on how aesthetic fluency directly impacts financial conversion rates. Ultimately, this structural analysis should be extended into three-dimensional product design. Utilizing physiological measures like eye-tracking could further decode the biological relationship between mathematical geometry, cognitive load, and consumer attraction.

Appendix A

Appendices

A1 Mathematical variations of "NovaCore" logo

This appendix presents the complete set of visual stimuli utilized in the empirical phase of this research (detailed in Chapter 3). The catalog includes the baseline "NovaCore" logo, which serves as the control stimulus, followed by the 14 structural variations. Each variation was systematically generated to isolate and amplify a specific mathematical aesthetic criterion defined by George Birkhoff, while strictly holding all other visual identity elements (color, typography, and stroke weight) constant.



(a) Baseline Design (Control)

Figure A.1: The baseline corporate logo serving as the control stimulus.



NovaCore

(a) Variation 1: *Balance*

NovaCore

(b) Variation 2: *Equilibrium*(c) Variation 3: *Symmetry*

NovaCore

(d) Variation 4: *Sequence*

NovaCore

(e) Variation 5: *Cohesion*

NovaCore

(f) Variation 6: *Unity*

NovaCore

(g) Variation 7: *Proportion*(h) Variation 8: *Simplicity*

Figure A.2: The visual catalog of the 14 structural variations (Part 1 of 2).



(a) Variation 9: *Density*



(b) Variation 10: *Regularity*



(c) Variation 11: *Homogeneity*



(d) Variation 12: *Economy*



(e) Variation 13: *Rhythm*



(f) Variation 14: *Complexity*

Figure A.3: The visual catalog of the 14 structural variations (Part 2 of 2).

A2 Visual representation of Bradley-Terry log-odds

This appendix provides a visual barometer of the raw latent coefficients (log-odds) estimated by the global Bradley-Terry model. It illustrates the attractiveness scores of the 14 mathematical variations relative to the zero-anchored baseline design ($N = 307$).

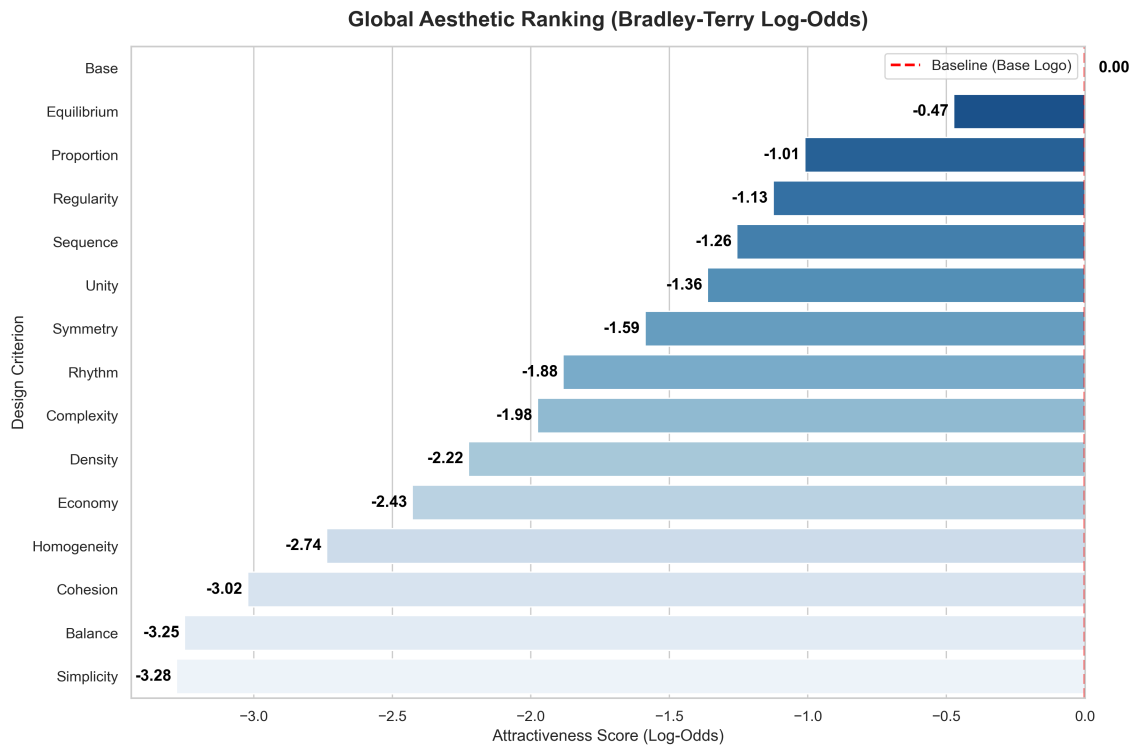


Figure A.4: Global aesthetic ranking based on Bradley-Terry log-odds scores.

A3 Exploratory analysis of professional design expertise

Rationale and methodology

As detailed in Section 4.1.1, a rigorous methodological control was applied to exclude respondents who identified as professionals or students in design, marketing, or visual arts ($N = 40$). This decision was grounded in the "Expert vs. Novice" paradigm, which posits that formally trained individuals utilize top-down, analytical cognitive processing, thereby skewing the intuitive, bottom-up aesthetic evaluations of the general consumer.

Furthermore, this exclusion was mathematically necessitated by the Bradley-Terry model. Initial algorithmic testing on this isolated expert cohort triggered a "Singular Matrix" error. Because the expert sample size was small and their aesthetic judgments were highly unified, the algorithm could not form a fully connected bipartite graph, preventing the estimation of log-odds probabilities.

Consequently, to empirically validate the divergent processing styles between experts and novices, an exploratory frequency analysis was conducted using Raw Win Rates (the total number of victories a design achieved divided by its total duel participations). To ensure scientific rigor and prevent over-generalization from the small expert sample, a Chi-Square Test of Independence (χ^2) was applied to these raw frequencies to determine statistical significance, utilizing the same thresholds established in Section 4.3.

Results: divergent cognitive processing styles

The inferential data reveals targeted, statistically significant divergences in how mathematical aesthetics are processed between the two cohorts, strongly validating the theoretical premise of the exclusion (see Table A.1).

1. **Universal validation of the control:** Both cohorts exhibited immense consensus regarding the Base logo, with experts awarding it an 88.32% win rate and novices an 84.39% win rate. The lack of statistical variance ($p = 0.2808$) confirms that the control stimulus was universally recognized as a high-quality corporate identity, regardless of formal design training.
2. **The penalization of explicit visual rules:** The most highly significant statistical divergence occurred with explicit, linear mathematical rules. Experts violently penalized *Sequence* (a -25.85% drop compared to novices, $p < 0.05$). A similar directional trend is observed for *Unity* (a -19.59% drop, $p < 0.20$). While novices rely on Gestalt principles like proximity (*Unity*) or linear progression (*Sequence*) for easy cognitive processing,

design professionals perceive these explicit layouts as static, predictable, and lacking dynamic visual tension.

3. **Top-down processing and structural appreciation:** Conversely, the data reveals a directional trend indicating that design professionals possess a higher tolerance for underlying, complex mathematical grids. *Cohesion* demonstrates marginal significance ($p < 0.20$), generating a +15.20% win rate increase among experts. Because experts utilize top-down processing, they actively search for structural logic. While the general public immediately rejects this variation as visually unappealing, trained designers recognize and reward the technical execution of alignment and precise spacing.
4. **The illusion of visual gaps (*Proportion & Rhythm*):** The inferential data further proves the necessity of the Chi-Square validation. While *Rhythm* exhibits a massive visual increase among experts (+16.32%), and *Proportion* shows a visual decrease (-5.46%), the mathematical test yields no statistical significance for either criterion ($p > 0.20$). This confirms that the expert evaluation of both classic scaling (the Golden Ratio) and rhythmic repetition is highly volatile. The observed visual gaps are artifacts of the small sample size ($N = 40$) and cannot be reliably generalized as strict professional heuristics.

Conclusion: This exploratory analysis mathematically justifies the methodology employed in Chapter 4. Design experts process visual stimuli fundamentally differently than the general public, exhibiting a statistically significant distaste for explicit linear sequencing and an elevated appreciation for subtle structural rules. Retaining this expert cohort in the primary dataset would have introduced a severe analytical bias, distorting the true heuristic processing of the general consumer.

Design Criterion	Expert Win Rate (%)	Novice Win Rate (%)	Difference (%)	Significance
Base (Control)	88.32	84.39	+3.93	-
Equilibrium	74.19	68.95	+5.24	-
Regularity	55.00	53.28	+1.72	-
Proportion	47.37	52.83	-5.46	-
Rhythm	41.67	25.34	+16.32	-
Unity	32.00	51.59	-19.59	[°] ($p < 0.20$)
Density	28.57	16.67	+11.90	-
Homogeneity	28.12	30.42	-2.29	-
Cohesion	26.32	11.11	+15.20	[°] ($p < 0.20$)
Symmetry	20.83	20.89	-0.05	-
Sequence	19.23	45.08	-25.85	** ($p < 0.05$)
Economy	18.18	8.11	+10.07	-
Simplicity	13.79	21.15	-7.36	-
Balance	0.00	4.79	-4.79	-

Table A.1: Raw Win Rates across pairwise comparisons, comparing design experts ($N = 40$) to general novices ($N = 307$). *Complexity* was excluded due to insufficient comparative data points within the expert cohort. Significance stars indicate the p-value of a Chi-Square test of independence.

A4 Exploratory analysis: education level

Figure A.5 visualizes the non-significant probability variances ($p > 0.20$) across the viable education cohorts.

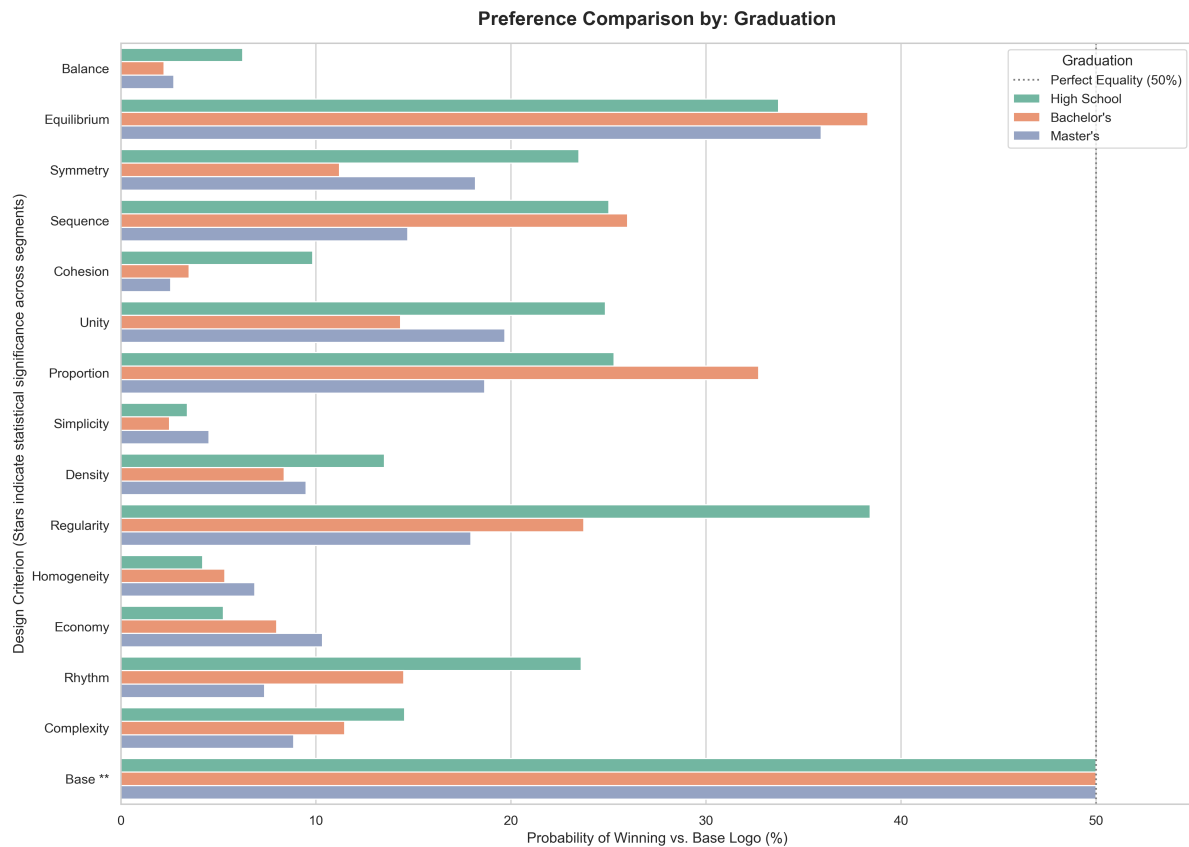


Figure A.5: Probability of winning against the Base logo, segmented by formal education level. The lack of significance stars indicates no statistical variance between cohorts.

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Mathematical aesthetics in marketing design: revising the role of formulas in shaping visual harmony and consumer attraction

Summary: Does strict mathematical geometry universally define a good corporate logo? Grounded in George Birkhoff's aesthetic measure, this thesis challenges the assumption that formal mathematical rules, such as symmetry and proportion, automatically generate consumer attraction. Through 1,830 pairwise visual comparisons analyzed via a Bradley-Terry logistic regression model, the research demonstrates that the general consumer systematically rejects extreme mathematical reduction in favor of moderate visual complexity. However, visual processing is not uniform. The study reveals that a consumer's design sensitivity, purchasing habits, generation, and gender act as critical perceptual filters. Notably, Gen Z and visually sophisticated consumers heavily penalize strict structural rigidity, whereas older demographics and low-involvement consumers utilize explicit mathematical order as a cognitive shortcut. Ultimately, this thesis proves that corporate design must be strategically adapted to specific cognitive profiles rather than relying on universal mathematical heuristics.

L'esthétique mathématique dans la conception marketing : réévaluer le rôle des formules dans la création de l'harmonie visuelle et de l'attrait du consommateur

Résumé: La géométrie stricte définit-elle universellement un bon logo d'entreprise ? Basée sur la mesure esthétique de George Birkhoff, cette thèse remet en question l'idée que les règles mathématiques formelles génèrent automatiquement l'attraction du consommateur. À travers 1 830 comparaisons visuelles analysées via un modèle logistique de Bradley-Terry, la recherche démontre que le public rejette systématiquement la réduction mathématique extrême au profit d'une complexité visuelle modérée. Cependant, le traitement visuel n'est pas uniforme. L'étude révèle que la sensibilité au design, les habitudes d'achat, la génération et le genre agissent comme des filtres perceptuels cruciaux. La Gen Z et les consommateurs sophistiqués pénalisent fortement la rigidité structurelle, tandis que les générations plus âgées et les acheteurs moins impliqués utilisent l'ordre mathématique explicite comme un raccourci cognitif. Finalement, cette thèse prouve que le design doit être stratégiquement adapté aux profils cognitifs spécifiques plutôt que de s'appuyer sur des heuristiques mathématiques universelles.

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