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THE IMPACT OF VISUAL COMPLEXITY ON REAL WORLD BANNER ADVERTISEMENT PERFORMANCE ON AN E-COMMERCE PLATFORM

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PREFACE

This master's thesis marks the end of my academic journey at the University of Twente. My time here involved diverse study programs and an enriching semester abroad at Washington State University. It has been a time of academic growth and personal development, that shaped who I am today. I am grateful for my experience as a student at the University of Twente. My sincere thanks go to the staff for their consistent openness and approachability.

I want to thank my supervisors for their guidance and valuable feedback throughout this research process. Dr. Raymond Loohuis, your curiosity for new ideas were consistently inspiring. Your ability to connect science with practice and emphasizing its real-world value provided clear purpose as I conducted this research. Furthermore, I extend my gratitude to Dr. A. van der Zeeuw for his insightful opinions and views, which consistently prompted me to consider the broader impact of this research on society and individuals.
In addition, I would like to thank the E-commerce platform for providing access to their performance data. This collaboration was crucial for my work and deeply enriching. It offered unique insights into the rapid evolution of E-commerce advertising, helping me develop practical skills and understand what truly matters in practice. The team's encouragement and passion for their work were a continuous source of inspiration.

Finally, I want to thank the many people who supported me throughout this journey: my family, friends, and fellow students. Their encouragement, companionship, and understanding were essential in keeping me grounded and motivated.

I hope this thesis is informative and enjoyable for anyone how reads it.

Selena Hof
June 2025

ABSTRACT

Purpose: This study was performed to investigate the impact of visual complexity (henceforth, VC) in static banner advertisements on advertising performance within E-commerce yielding theoretical implications and practical guidance for banner design strategies.

Method: Based on a literature review, VC was defined. The following indicators were used: text length, image count, colour variety, font variety, symmetry, and element overlap. Advertising performance metrics are automatically generated through the platforms internal analytics system. Advertising performance was assessed across three key metrics: click-through rate (CTR), brand cart additions, and promoted return on advertising spend (pROAS), corresponding to the attention, consideration, and conversion phases of the customer journey. **Study sample:** From an E-commerce platform's internal analytic system, the performance data of the year 2024 was retrieved for Fast Moving Consumer Goods campaigns (henceforth, FMCG). This dataset included 232 banner advertisements. After excluding banners with missing performance data, the final sample included 216 banner advertisements. **Data Analysis**: Of the 216 banner advertisements, manual content analysis was performed to assess VC. Next, multiple regression analyses were performed to investigate the effect of VC indicators on the three advertising performance metrics. Additionally, Exploratory Factor Analyses (EFA) were performed to investigate whether latent VC has an effect on advertising performance.

Result: Descriptive analyses revealed variation in banner VC, particularly in text length, image count, and font variety. Advertising performance metrics brand cart add and pROAS exhibited non-normal distributions. The impact of the VC indicators (i.e., text length, image count, colour variety, font variety, symmetry, and element overlap) on CTR, Bard Cart addition and pROAS was not significant; for CTR ($F(5, 210) = 1.67$, $p = .143$, $R^2 = .038$); Brand cart add ($F(5, 210) = 1.09$, $p = .369$, $R^2 = .025$); and pROAS logistic regression ($\chi2(7)=8.99$, $p=.253$). Additionally, exploratory factor analysis identified a latent VC factor comprising element overlap, image count, and font size variety. The impact of this factor was statistically significant on all three advertising performance metrics (CTR, $F(1, 214) = 10.42$, $p = .001$, $R^2 = .046$; brand cart additions, $F(1, 214) = 8.20$, $p = .005$, $R^2 = .037$; and pROAS, $F(1, 214) = 4.93$, $p = .027$, $R^2 = .023$). This indicates that higher element overlap, image count, and font size variety are associated with improved advertising performance, suggesting that banners with greater visual complexity tend to yield better outcomes. However, explained variance is low ($R^2 = .023–.046$), indicating other unknown variables can influence advertising performance.

Conclusion: This study investigated the impact of VC in static banner advertisements on advertising performance within E-commerce. The impact of the VC indicators individually was not significant. However, a latent factor, including element overlap, image count and font size variety did have an impact on advertising performance in each phase (CTR, brand cart additions, and pROAS). This indicates that banners perform better when these visual indicators are combined. Therefore, defining visual complexity in the E-commerce context should focus on element overlap, image count, and font size variety. These findings provide actionable guidance for banner design strategies.

Keywords: Visual Complexity, Banner Advertising, E-commerce, Click-Through Rate, pROAS, Brand Cart Add.

TABLE OF CONTENTS

PREFACE 2

ABSTRACT 3

ABREVIATIONS 6

1. INTRODUCTION 7
1.1 EMPERICAL PHENOMENON 7
1.2. RELEVANCE 8
1.3. PURPOSE & RESEARCH QUESTIONS 8
1.4. RESEARCH APPROACH 8
1.5. EXPECTED CONTRIBUTION 9

2. THEORETICAL BACKGROUND 9
2.1 LITERATURE REVIEW METHOD 9
2.2 DEFINITION AND MEASUREMENT OF VISUAL COMPLEXITY (VC) 11
2.3 CONSUMER INFORMATION PROCESSING 12
2.4 ADVERTISNG PERFORMANCE 13
2.5 THEORETICAL FRAMEWORK & HYPOTHESES 15

3. METHODOLOGY 16
3.1 RESEARCH DESIGN 16
3.2 RESEARCH SAMPLE 17
3.3 MEASUREMENT OF VISUAL COMPLEXITY (VC) AND ADVERTSING PERFORMANCE 17
3.4 MATERIALS & INSTRUMENTS 18
3.5 PROCEDURE 19
3.6 DATA ANALYSIS 19

4. RESULTS 20
4.1 DESCRIPTIVE STATISTICS OF VC INDICATORS AND ADVERTISING PERFORMANCE 20
4.2 CORRELATION ANALYSIS OF VC INDICATORS AND ADVERTISING PERFORMANCE 21
4.3 RELATION VC INDICATORS AND CTR 22
4.4 RELATION VC INDICATORS AND BRAND CART ADDITIONS 23
4.5 RELATION VC INDICATORS AND PROAS 23

5. DISCUSSION 24
5.1 SUMMARY OF KEY FINDINGS 24
5.2 INTERPRETATION IN CONTEXT WITH PREVIOUS RESEARCH 25
5.3 THEORETICAL IMPLICATIONS 25
5.4 PRACTICAL IMPLICATIONS 26
5.5 LIMITATIONS AND FUTURE RESEARCH 26
5.6 CONCLUSION 27

REFERENCE LIST 28

APPENDICES 31
APPENDIX A: CONCEPTS AND SYNONYMS OF SEARCH TERMS IN LITERATURE REVIEW 31
APPENDIX B: LIST OF PAPERS UPLOADED INTO RESEARCHRABBIT 31

APPENDIX C: REFERENCES USED FOR LITERATURE REVIEW 32
APPENDIX D: LITERATURE REVIEW OVERVIEW FINDINGS 34
APPENDIX E: CODEBOOK VC INDICATORS IN BANNER ADVERTISEMENTS 35
APPENDIX F: HISTOGRAM VC INDICATOR DISTRIBUTIONS FOR DATASET (N=216) 38
APPENDIX G: ADVERTISING PERFORMANCE METRICS BOXPLOT FOR DATASET (N=216) 39
APPENDIX H: SCREEPLOTS OF EIGENVALUES FOR EACH ADVERTISING PERFORMANCE METRIC 40
APPENDIX I: USE OF GENERATED CONTENT 41

ABREVIATIONS

VC = Visual Complexity

CTR = Click Through Rate

ROAS = Return on Advertising Spent

pROAS= Promoted Return on Advertising Spent

FMCG = Fast Moving Consumer Goods

S-O-R = Stimulus-Organism-Response framework

PX = Pixels

EFA = Exploratory Factor Analysis

KMO = Kaiser-Meyer-Olkin

TLI = Tucker-Lewis Index

1. INTRODUCTION

1.1 EMPERICAL PHENOMENON

Nowadays people face online information overload, reduced attention spans, and banner blindness (i.e., the tendency to ignore online advertisements) (Benway 1998, Resnick & Albert, 2015), leading to lower Click-Through Rates (CTR). While in 1990 online advertisements achieved CTRs exceeding 5%, with some reaching 44%, average CTRs have declined to between 0.1% and 0.5%, varying by format and industry (Cho & As, 2004; Dentsu, 2023). Banner advertising is a form of online advertising where visual advertisements are displayed on web pages, typically in rectangular formats (Peker, 2021). Static banner advertising refers to non-animated banners that use fixed images and text without motion. Banner design serves as a stimulus that captures consumers' attention, facilitates information processing, and can influence user behaviour. Despite the decline in CTR, banner advertisements remain prevalent to capture attention and direct users to landing pages (Peker et al., 2021). Investment in banner advertisements continues to grow, projected to reach US$227.4 billion by 2029 (Statista, 2024). However, as budgets expand, optimizing Return on Advertising Spend (ROAS) becomes imperative.

E-commerce platforms create a new environment for banner advertising. E-commerce refers to the buying and selling of goods or services through digital platforms, typically conducted via online marketplaces (Li & Ciu, 2023). The integration of advertisements on these platforms enables brands to promote their products directly within the digital shopping environment (Long, 2023). E-commerce platforms now serve as both sales environments and advertising channels. Through the use of the platforms' behavioural and transactional data, platforms can identify consumers with strong intent and deliver tailored advertisements that are more likely to drive conversions (Zenetti & Pauwels, 2024). Consequently, brands are allocating growing portions of their media budgets to banner advertisements on E-commerce platforms, recognizing the advantage of targeting consumers during the decision-making phase of the customer journey (Li & Chiu, 2023, Zenetti & Pauwels, 2024).

However, E-commerce environment raises concerns about user autonomy and ethical communication. Banners advertisements can affect brand awareness, purchase intention, and consumer attitudes (Yoo et al., 2004; Rosenkrans, 2010). To achieve this, banner advertisements must be visually optimized by managing their Visual Complexity (VC), the degree of visual detail and information they contain. While simplified and coherent advertisements designs can enhance user experience by reducing visual and cognitive overload (Gada et al., 2022), they also raise questions about how to balance persuasive intent with consumer well-being. Advertisers must navigate between maximizing attention and making banner advertisement user-friendly. However, advertising in E-commerce environments is unexplored in previous research.

Therefore, to add knowledge to this field, this study investigates whether the construct visual complexity (VC) in static banner advertisements influences advertising performance on an E-commerce platform. Offering theoretical implications and actionable practical insights for optimizing digital banner advertisements design in E-commerce environments. An exploratory research approach was adopted to define and uncover patterns and relations between VC and advertising performance, it examines naturally occurring patterns and associations in real-world E-commerce advertising environments, where variables are not experimentally manipulated but observed as they appear in practice.

1.2 RELEVANCE

Previous studies have examined isolated design elements in banner advertisements in controlled settings, but their combined visual impact remains underexplored (Bočaj & Ahtik, 2023). As a result, the influence of VC on advertisements' performance in real-world contexts remains underexplored. This study analyses how VC in banners influences advertising performance in real-world contexts. Furthermore, E-commerce is a rapidly evolving field characterized by continuous innovation in advertising formats, targeting strategies, and user interfaces (Peker et al., 2021). Studying banner performance within this context is essential for understanding how design effect advertising performance. CTR, commonly used to assess advertising performance, primarily reflects user interaction and neglects other critical dimensions, like business outcomes (Yang & Zhai, 2022). This study evaluates multiple advertising performance metrics, including brand cart advertisements as an indicator of customer consideration and promoted ROAS as a direct measure of financial performance. By incorporating these real-world metrics and focusing on VC, this research offers insights into how VC influences advertising performance in digital commerce settings.

1.3 PURPOSE & RESEARCH QUESTIONS

This study investigates the impact of VC in static display banner advertisements on advertising performance on an E-commerce platform. The main research question is: *"What is the impact of visual complexity in online banner advertisements on advertising performance on an E-commerce platform?"*

To explore this, the study addresses the following sub-questions:

- How can visual complexity in online banner advertisements be defined and operationalized?
- What is the relationship between visual complexity in banner advertisements and Click-Through Rates?
- How does visual complexity in banner advertisements affect the number of Brand Cart Additions?
- To what extent does visual complexity in banner advertisements impact promoted Return On Advertising Spend?

1.4 RESEARCH APPROACH

A literature review was conducted to explore key concepts and its relationships needed to define the multidimensional construct VC. Advertising performance data were collected from an E-commerce platform. The dataset included 232 banner advertisements. Data was retrieved of the most recent full year, which is the year 2024. After excluding banners with missing data, the final sample for analyses comprised of 216 banner advertisements with associated performance data. Manual content analysis was performed to assess the VC indicators of 216 banners. This is a method validated for quantifying visual attributes in advertisement design (Pieters et al., 2010; Saunders et al., 2016). Next, multiple regression analyses were performed to investigate the impact of VC indicators on advertising performance. Additionally, exploratory factor analyses were performed to investigate whether a latent VC influences advertising performance. Ethical approval for this research was obtained from the Ethics Committee of the University of Twente.

1.5 EXPECTED CONTRIBUTION

Previous studies on the relation between VC and advertisement performance have primarily focused on controlled lab settings. Analyses of VC's effect on real-word banner advertisement performance, within E-commerce, have not been conducted. This study contributes to advertising literature by using real-world secondary campaign data from an E-commerce environment. It examines how VC relates to advertising performance across multiple phases of the consumer journey: attention (CTR), consideration (Brand Cart Additions), and conversion (pROAS). Providing a more holistic understanding of VC and advertising performance. By using real-world data findings are relevant for marketing practitioners who seek to optimize real-time performance.

For marketers and designers, this study offers actionable design recommendations for optimizing visual indicators in E-commerce banner advertisements to enhance advertising performance. For a consumer, this study contributes to facilitating the creation of more relevant and user-friendly advertising experiences.

2. THEORETICAL BACKGROUND

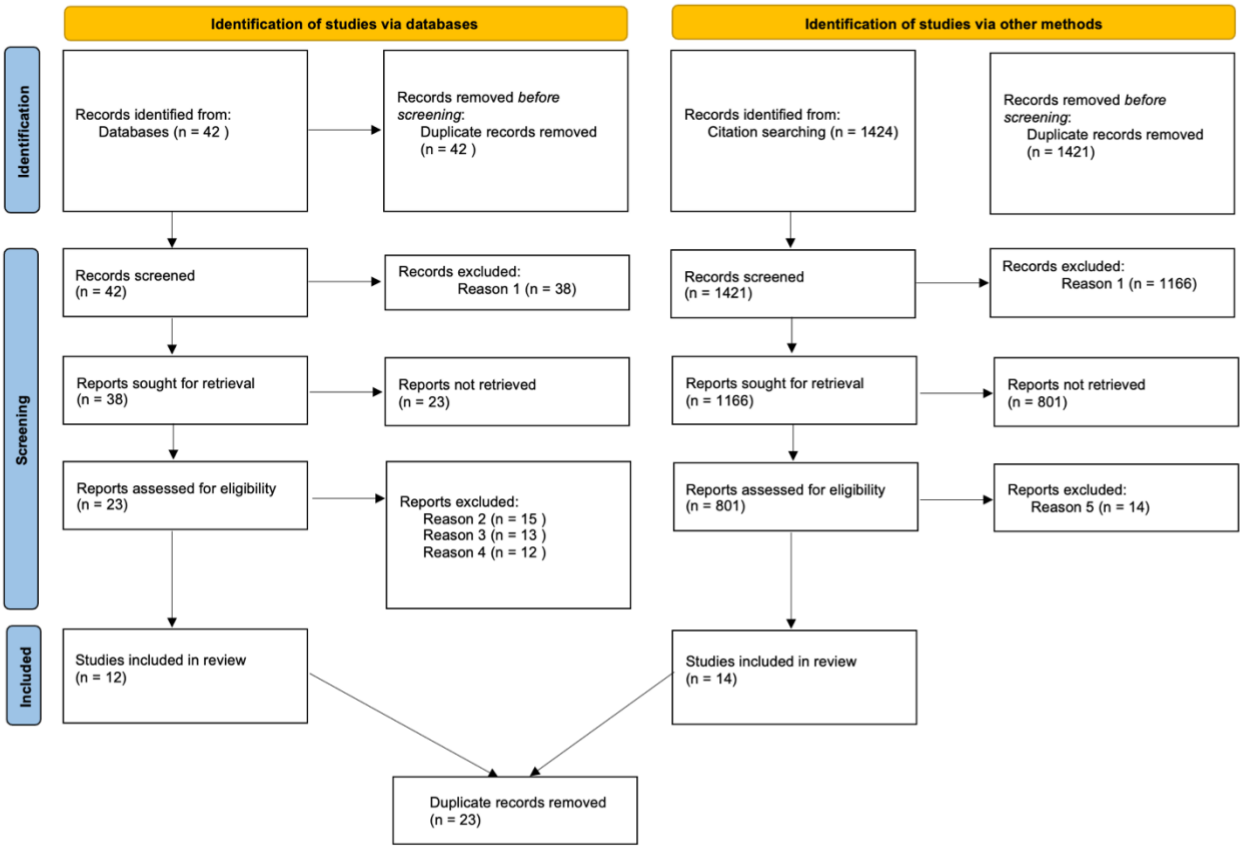
The chapter addresses the first research question: "How can visual complexity in online banner advertisements be defined and measured on E-commerce platforms?". This chapter begins with an overview of the literature review method. It then defines VC and outlines how it is measured. Next, theories of consumer information processing are discussed, followed by a section about advertising performance metrics. The chapter concludes by integrating these insights into a theoretical framework for the study.

2.1 LITERATURE REVIEW METHOD

This study started with a literature review, following guidelines from the PRISMA framework (Figure 1). PRISMA is a standardized framework designed to improve the transparency and completeness of reporting in systematic reviews and meta-analyses (PRISMA Statement, 2020). Relevant literature was identified through structured keyword searches in Scopus, a database of peer-reviewed literature (Elsevier, n.d.). The search strategy focused on: visual complexity, banner advertising, and E-commerce. Concepts and synonyms for each concept are listed in Appendix A. A search string was used in Scopus: ("visual complexity" OR "visual clutter" OR "design complexity") AND ("advertising" OR "banner ads" OR "display advertising"). This query returned n = 42 records in Scopus (Figure 1). To ensure comprehensive coverage, citation mapping was performed using ResearchRabbit, an AI-powered literature discovery tool (ResearchRabbit, 2025). In this tool five original relevant articles, used for the introduction of this research, were uploaded (Appendix B). Next this tool generated a network of n = 1,424 related publications through forward and backward citation tracing and thematic similarity (ResearchRabbit, 2025).

Figure 1

PRISMA overview



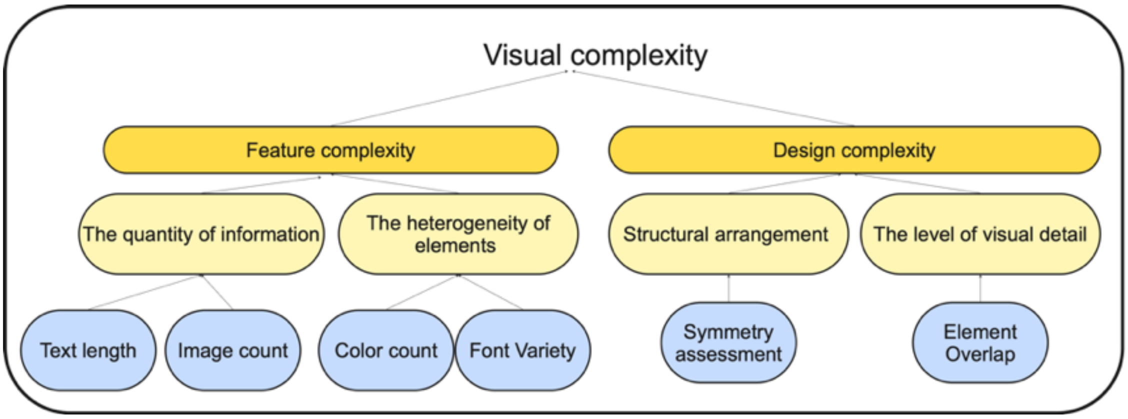
Following the identification phase, the screening process was conducted using multiple exclusion criteria to ensure academic rigor and relevance. The screening phase began with the removal of duplicate records (n = 42 & n = 1421). As the first exclusion step, book chapters were eliminated to focus on peer-reviewed journal literature (n = 38 & n = 1166) (Podsakoff et al., 2005). Articles not retrievable via the University of Twente's digital library, due to paywalls or indexing limitations, were removed (n = 23 & n = 801). Studies were excluded for the following reasons: (2) the study did not focus on digital, E-commerce or retail media contexts (n = 15); (3) the study did not address advertising performance (n = 13); and (4) the study did not involve banner advertisements (n = 12). In addition, titles from ResearchRabbit records were skimmed to assess thematic relevance (reason 5), this resulted in n = 14 articles. After removing duplicates between the two sources, a total of n = 23 articles were selected for inclusion in the literature review (Appendix C). An overview of the selected studies is provided in Appendix D, where key study characteristics such as research aims, methods, sample details, and theoretical perspectives are summarized. The studies were published from 2004 to 2025. The studies had a global representation, Europe (n = 8), North America (n = 7), Asia (n = 7), Oceania (n=1). Most are empirical and quantitative studies, employing experiments in a controlled setting (n = 10) and Eye-tracking methods (n = 7).

2.2 DEFINITION AND MEASUREMENT OF VISUAL COMPLEXITY (VC)

VC refers to the extent to which a visual stimulus contains numerous, varied, or detailed elements that require cognitive effort to process. VC in banner advertisements play a role in drawing attention, memory, and behavioural outcomes. The literature shows that definitions of VC vary across disciplines. Making VC as construct an underexplained phenomenon. Based on the literature review (Appendix D), this study defines the VC construct using six indicators derived from prior research, see Figure 2.

Figure 2

VC multidimensional construct



Note. Orange overarching dimensions, yellow dimensions, blue indicators

VC is commonly conceptualized through two overarching dimensions: feature complexity and design complexity (Pieters et al., 2010). Feature complexity refers to the number and type of visual elements present in an advertisement, such as images, text blocks, icons, or logos. It is typically assessed through two sub-dimensions:

- Quantity of information: The overall volume of visual and textual content, measured by the number of characters and the number of visual images (image count) (Miniukovich et al., 2018). Higher quantities can reduce processing ease of viewers, while simpler designs enhance clarity and engagement (Bočaj & Ahtik, 2023; Pieters et al., 2010; Pilelienė & Grigaliūnaitė, 2016). A greater number of characters and image count contribute to higher VC.
- Heterogeneity of elements: The diversity in the appearance of elements, including variations in shape, colour, font, and style. Moderate heterogeneity can enhance aesthetics, but excessive variation disrupts perceptual fluency and clarity for viewers, increasing cognitive load and diminishing engagement (Jylhä & Hamari, 2019; et al., 2023). Studies show that visual coherence tends to improve consumer responses (Jylhä & Hamari, 2019; Wang et al., 2023). Greater variation in colour and font sizes contributes to a higher VC.

Design complexity concerns the spatial organization and visual structure of visual indicators. It is commonly assessed through two dimensions:

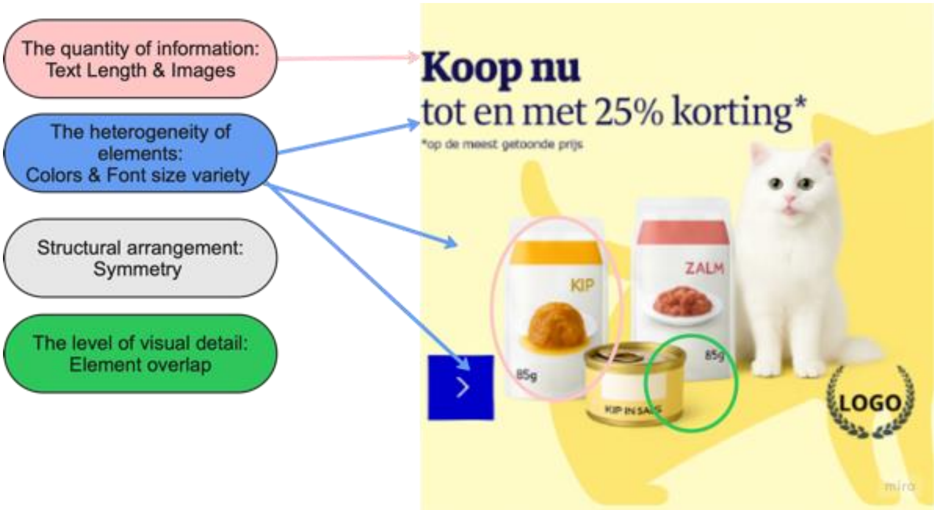
- Structural arrangement: The alignment and symmetry of visual components. Well-structured, symmetrical layouts reduce cognitive effort, while chaotic or misaligned designs fragment attention and hinder message processing (Bočaj & Ahtik, 2023; Miniukovich et al., 2018). In this study, spatial organization is measured by symmetry. An asymmetric structural organization contributes to higher VC.

- Level of visual detail: The clarity and separability of components, affected by overlap. It indicates how easily components can be distinguished. Overlapping components reduce legibility and distract from the message, while clearly separated components enhance visual fluency and interpretation (Bočaj & Ahtik, 2023; Nielsen Norman Group, 2021). A higher level of element overlap in components contributes to VC.

In Figure 3, an example banner illustrates VC in a banner. This demonstrates how multiple VC indicators can occur in a banner advertisement.

Figure 3

Example banner with VC



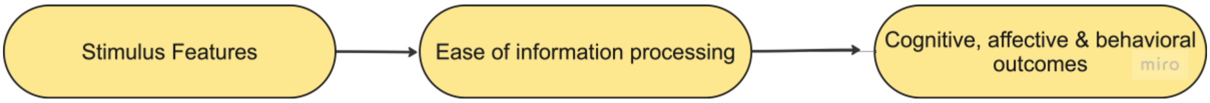
Note. Arrows point at VC indicators and circles. Note not all VC indicators are highlighted. In Appendix E an example banner with all VC indicators can be found.

2.3 CONSUMER INFORMATION PROCESSING

Understanding how VC in banner advertisements influences advertising performance requires understanding of how users perceive and process visual stimuli in digital environments. This section is based on psychological frameworks to explain how VC affects attention and behavioural outcomes. In Figure 4 an overview of user processing is shown. A visual stimulus, like a banner, initiates a processing response. Ease of processing influences subsequent cognitive evaluations, affective reactions, and behavioural outcomes.

Figure 4

Consumer information processing theory



Banner advertisements act as visual stimuli composed of various VC indicators, each contributing to the user's information load. As users navigate digital interfaces, their attention is guided by habitual scanning patterns and cognitive heuristics shaped by previous online experiences (Garaialde et al., 2020). Simpler advertisements often result in longer fixations and more attention, while overly complex designs may draw the initial gaze but fail to sustain it due to cognitive overload (Miniukovich et al., 2018; Pieters et al., 2010). This attentional filtering process can give rise to banner blindness, whereby users consciously or unconsciously ignore sections of a webpage typically reserved for advertisements (Benway, 1998).

Once a banner advertisement captures initial attention, it enters the user's perceptual and cognitive system. According to Processing Fluency Theory, individuals respond more positively to stimuli that are easy to process. When advertisements are fluently processed, they require less cognitive effort. This ease of processing enhances emotional response, improves visual and message clarity, and increases the likelihood of behavioural outcomes (Reber et al., 2004). In contrast, high VC can trigger disfluency, making advertisements harder to interpret and reducing their persuasive performance.

Alongside this, the Cognitive Load Theory posits that overly complex visual stimuli may exceed the limited capacity of working memory, leading to confusion and disengagement (Sweller, 1988). Conversely, visual clarity supports deeper information processing, particularly when users are motivated to engage with content. This processing enhances memory retention and contributes to behavioural outcomes (Sweller, 1988).
This can be further explained by the Stimulus–Organism–Response (S–O–R) framework (Peng & Kim, 2014). According to this model, the user's internal processes mediates the relationship between the stimulus and behavioural response. When a banner is fluently processed and aligned with user intent, it fosters favourable attitudes and drives behaviours. As such, VC can be considered a key design factor in digital advertising, with demonstrated effects on behavioural responses including purchase decisions, product preferences, and engagement (Jylhä & Hamari, 2019).

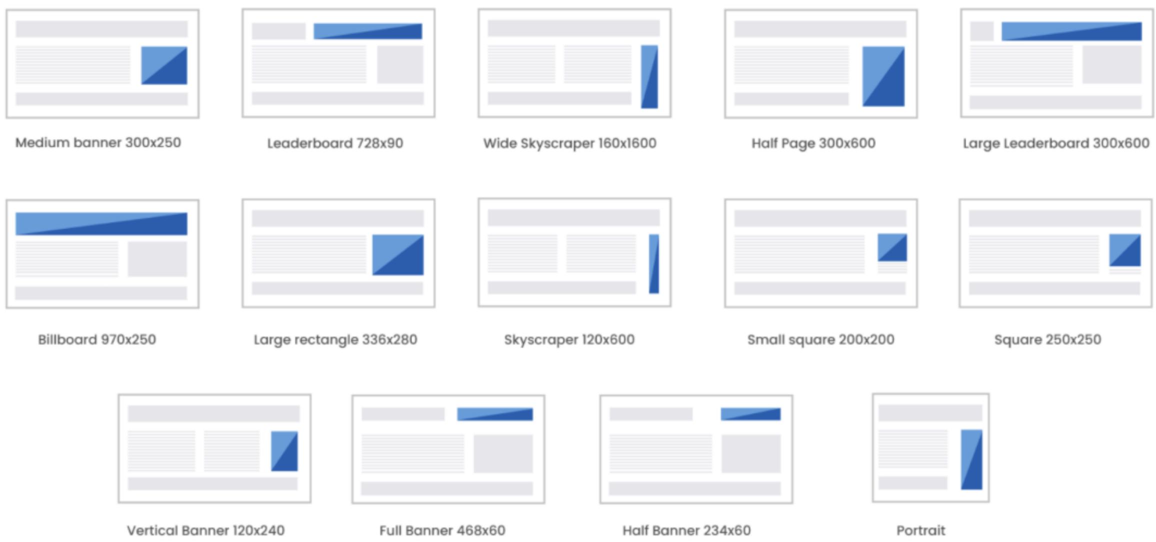
2.4 ADVERTISNG PERFORMANCE

To understand the behavioural implications of banners, it is essential to examine advertising performance metrics relevant to user actions within E-commerce contexts.
Advertising performance metrics are aggregated at the campaign level, so different banner formats. E-commerce platforms deploy uniform creatives across multiple advertisements formats, thereby preserving design and VC features regardless of format size variations (Pacvue, 2024). The banner formats used for aggregating performance data vary in sizes to suit different screen widths and placements. In Figure 5, common sizes of

banners are demonstrated. All banner formats include: 1152×250, 1152×150, 1152×100, 768×250, 768×150, 768×100, 764×148, 552×250, 480×250, 480×240, and 343×250.

Figure 5

Common banner advertisement formats



Note. Retrieved from: iDevAffiliate. (2023, May). *Common banner ad sizes* [Image]. iDevAffiliate Blog. https://www.idevdirect.com/blog/wp-content/uploads/2023/05/Common_Banner_Sizes-1-1536x854.png

Advertising performance is typically evaluated across distinct phases of the consumer decision journey, the awareness phase, consideration phase, and conversion phase. During the awareness phase, CTR is the indicator of initial attention. CTR is calculated by: (Number of Clicks/Number of impressions) x 100. Hence it captures the proportion of users who click on an advertisement relative to those exposed to it (Chaffey & Ellis-Chadwick, 2019). CTRs for E-commerce banners typically range from 0.3% to 0.5%, outperforming standard display formats (Dentsu, 2023). Design factors such as colour, imagery, and simplicity have been shown to influence CTR (Drèze & Hussherr, 2003; Pieters et al., 2010). However, CTR primarily reflects short-term interest and does not capture deeper engagement or conversion.

In the consideration phase, brand cart additions indicate purchase intent. Brand cart additions counts how often users add products from a specific brand to their shopping carts during banner advertisements campaigns. It captures post click (i.e., users click on an ad and later adds the product to cart) and post view behaviour (i.e., user sees the ad but does not click, yet still adds the product to cart). As such, brand cart addition serves as campaign-specific engagement and broader brand influence measure. A high brand cart addition rate indicates that users are not only interested in the product but also motivated to initiate the purchasing process. Conversely, a low rate may indicate barriers to conversion or a misalignment between user expectations and the brand's messaging. Behavioural eye-tracking studies suggest that brand familiarity and design structure affect gaze allocation and subsequently user behaviour (Bleier & Eisenbeiss, 2015; Pauwels et al., 2016).

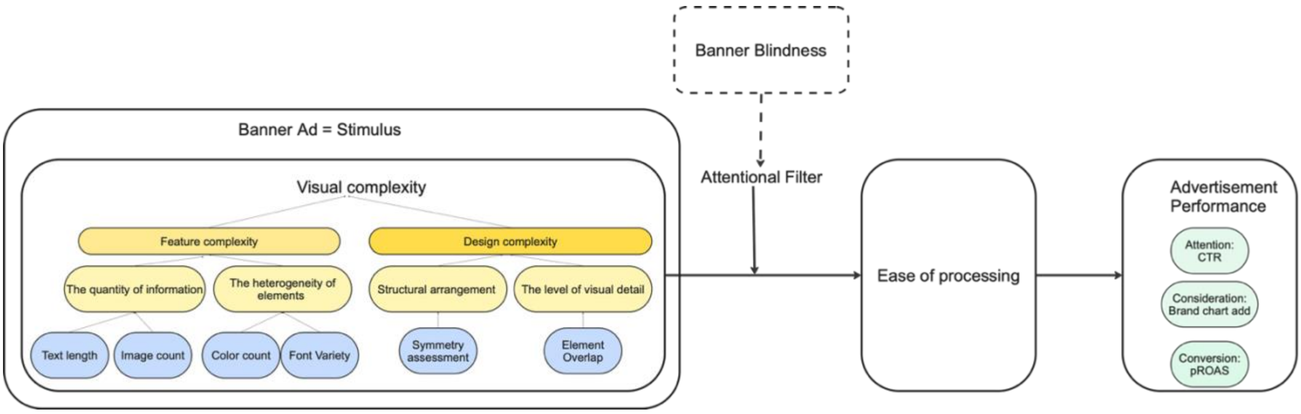
Finally, in the conversion phase, promoted return on advertising spend (pROAS) measures the financial efficiency of advertisements campaigns by quantifying revenue generated per euro spent on advertising (Kireyev et al., 2015). It is measured as: pROAS = Total Sales of Promoted Products / Total Advertising Spend. This metric indicates how effectively a campaign converts ad spend into sales for the promoted items in the banner advertisement campaign. A pROAS value greater than 1 indicates that the campaign is generating more revenue from promoted products than the amount spent on advertising, signifying a profitable investment. Conversely, a pROAS value less than 1 suggests that the campaign is not recouping its advertising costs through sales of the promoted items. PROAS is particularly useful for advertisers who want to assess the effectiveness of specific promotional offers or product highlights within a campaign. By isolating the sales of promoted products, marketers can determine whether the promotional investment is yielding the desired results.

2.5 THEORETICAL FRAMEWORK & HYPOTHESES

The conceptual framework guiding this research integrates the theories and mechanisms described. As shown in Figure 6, banner VC acts as the stimulus, which first activates the user's attentional system. The effect is moderated by banner blindness. VC is a multidimensional construct comprising six indicators: text length, image count, colour count, font size variety, symmetry assessment, element overlap (Figure 2). If the banner advertisement captures attention, it enters the user's cognitive system, where it is processed based on factors such as processing fluency and cognitive load. These evaluations influence behavioural responses: CTR, brand cart additions, and conversions. High VC banners can make the banner difficult to interpret, potentially negatively influencing behavioural outcomes. In contrast, advertisements with lower VC enhance fluency, making them easier to interpret and thereby improving overall performance.

Figure 6

Conceptual Framework



Based on this theoretical rationale, the following hypotheses are proposed:

H_0: There is no significant effect between Visual Complexity in banner advertisements and advertising performance.

H_1: There is a significant effect between Visual Complexity in banner advertisements and advertising performance.

The presumed effect is that higher VC in banners will generate lower advertising performance.

To further examine how visual complexity affects advertising performance phases, the following directional sub-hypotheses are proposed:

$H2_0$: There is no significant effect between Visual Complexity in banner advertisements and Click-Through Rates (CTR).

H2a: There is a significant effect between Visual Complexity in banner advertisements and Click-Through Rates (CTR).

The presumed effect is that higher VC in banners will generate lower CTRs.

$H3_0$: There is no significant effect between Visual Complexity in banner advertisements and the number of Brand Cart Additions.

H3a: There is a significant effect between the level of Visual Complexity in banner advertisements and the number of brand cart additions.

The presumed effect is that higher VC in banners will generate lower Brand Cart Adds.

$H4_0$: There is no significant effect between Visual Complexity in banner advertisements and promoted Return On Advertising Spend (pROAS).

H4a: There is a significant effect between visual complexity in banner advertisements and promoted Return On Advertising Spend (pROAS).

The presumed effect is that higher VC in banners will generate lower pROAS.

3. METHODOLOGY

3.1 RESEARCH DESIGN

This study employs a non-experimental quantitative research design using secondary real-world advertising data from a major European E-commerce platform. The dataset used in this study consists of banner advertisements from campaigns conducted in 2024, for Fast-Moving Consumer Goods (FMCG) categories such as personal care, household products, and pet food. The data used in this study is secondary, meaning that the data has already been collected by others for different purposes but is reused to address new research questions (Aocn, 2019; Wienclaw, 2021.).

A manual content analysis is used to systematically code VC indicators of static banner advertisements. Manual content analysis is a systematic research method used to identify, code, and interpret patterns, themes, or concepts in qualitative data, such as images (Columbia Public Health, 2023). This method, widely used in marketing and the social sciences, allows for both quantitative coding (e.g., counting images or font sizes) and qualitative interpretation (e.g., assessing symmetry) of visual data (Columbia Public Health, 2023; Krippendorff, 2019).

The study adopts a non-experimental observational design to investigate the impact of VC on advertising performance. Non-experimental and observational research is research where the researcher does not manipulate any variables (Çobanoğlu, 2023). Phenomena are observed as they naturally occur without any manipulation. This study collets data by measuring, analysing existing advertisement performance data of real-word E-commerce advertising campaigns.

From each individual banner, VC indicators and advertisement performance were measured. VC is defined the indicators text length, images count, colour count, font size variety, symmetry assessment and element overlap (Figure 2). Furthermore, from each banner the advertising performance was measured with the three phases (i.e., attention CTR, consideration Brand Cart Add, conversion pROAS, Figure 6).

3.2 RESEARCH SAMPLE

Advertising performance data was collected from a European E-commerce platform and comprised 232 banner campaigns from FMCG brands. Campaigns from 2024 were selected as it was the most recent full year, offering relevant insights given the ongoing changes in E-commerce advertising. Campaigns that employed contextual targeting strategies were eligible for inclusion. Contextual targeting matches advertisements to the content being viewed, and intent-based targeting uses user behaviour to deliver personalized content (Pacvue, 2024). For example, a diaper advertisement might be shown to users who are browsing baby-related pages (contextual) or to those who have previously searched for, viewed, or purchased diapers (intent-based).

Excluded were campaigns if they were cancelled, contained missing performance data, or lacked accessible ad materials. Therefore, the dataset for this study included 216 banner advertisements. The research relies solely on secondary data, with no access to personally identifiable information, ensuring compliance with data privacy and research ethics. Ethical approval was given by the University of Twente for this research.

3.3 MEASUREMENT OF VISUAL COMPLEXITY (VC) AND ADVERTSING PERFORMANCE

VC indicators were manually coded for banner advertisements. A codebook was developed to guide the content analysis of the VC indicators (Appendix E). The codebook was based on literature (Figure 2) and eyeballing of the banner advertisements to identify VC indicators. The VC indicators measured are listed below.

Quantity of information:

- Text character length: Total number of characters used in textual content. Higher values indicate more informational load.
- Image count: The number of distinct images present in a banner.

Heterogeneity of elements:

- Colour count: The number of dominant colours, indicating visual variety.
- Font size variety: The count of different font sizes, reflecting typographic heterogeneity.

Structural arrangement:

- Symmetry assessment: A coded measure of how symmetrical the layout is (0 = no symmetry, 1 = partial, 2 = symmetrical).

Level of visual detail:

- Element overlap: Degree to which elements visually overlap, affecting clarity and hierarchy.

Each banner is coded based on these indicators using the instructions in Appendix E.

Advertisement performance serve as dependent variable. For the attention phase, CTR was collected. CTR was calculated as clicks divided by impressions, reflecting user engagement. For the consideration phase Brand cart add measured the number of times users added a product of the brand to their shopping cart, indicating purchase intent and product interest. Lastly for the conversion phase, pROAS was calculated as revenue generated divided by advertisements spend, representing the efficiency of advertising investment.

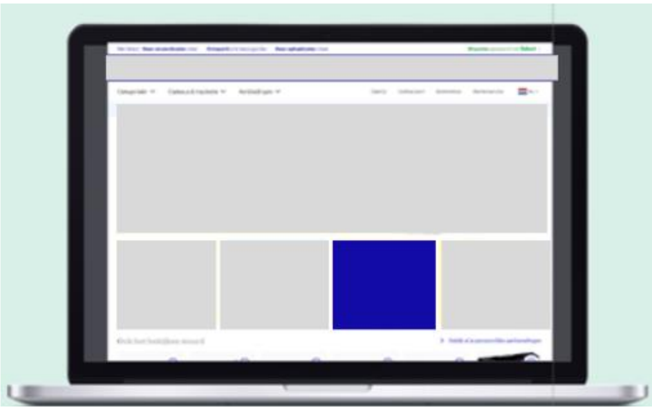
3.4 MATERIALS & INSTRUMENTS

The materials for this study include banner advertisements images and corresponding advertisement performance data, retrieved from an E-commerce platform.

For VC coding, banners with the 320×240 pixels format were used (Figure 7). E-commerce platforms standardize creative content across ad formats, preserving design and VC features regardless of size variations (Pacvue, 2024). This was verified by the researcher. All banner advertisements included in this study adhere to the E-commerce platform's standardized visual identity guidelines. All VC content coding was performed manually by the researcher by looking at the banners and add it to the dataset. To determine the number of characters in banner advertisements, the AI tool ChatGPT was used, with the researcher conducting random checks to verify the accuracy of the output. The instruction for measuring text length, as outlined in Appendix E, was provided to the AI tool to ensure alignment with the coding protocol.

Figure 7

Format Banner on E-commerce platform



Note. Dark blue is a 320x240 banner format.

Advertisement Performance metrics were automatically generated through the platform's internal analytics system. Data analysis was conducted in RStudio (Version 2023.09.1+494) to assess the effect of VC indicators on advertising performance.

3.5 PROCEDURE

Banner advertisements were selected for data collection and extraction based on predefined inclusion criteria and retrieved from the internal analytics system of an E-commerce platform. The dataset included static onsite display advertisements and their advertising performance metrics. First, the banners VC indicators were assessed. Second data preparation began with cleaning the dataset by removing entries with missing campaign performance data. Variables were then renamed and organized to facilitate clarity and consistency; this resulted in 216 banners suited for analysis.

3.6 DATA ANALYSIS

The aim of this study was to assess the effect between banner VC and advertising performance. To achieve this, a systematic data analysis approach was employed.

Initially, descriptive statistics (including mean, standard deviation, mean, minimum, maximum, skew, kurtosis) were calculated for all continuous variables from the banner VC and advertising performance phases. Skew measures asymmetry of the data around the mean (Chen, 2025). Kurtosis describes how the tails of the distributions are compared to the normal distribution (Kenton, 2025). These statistics provided an overview of the data distributions.

The internal consistency of the VC construct was evaluated using Cronbach's alpha. This analysis determined whether VC could be treated as a single construct or whether it required further subdivision into multiple dimensions. A Cronbach's alpha value above 0.70 was considered acceptable, indicating sufficient inter-item reliability (Field, 2024).

Background colour was included as a control variable to account for its potential influence on the relationships under investigation. Prior studies suggest that background colour can influence attention, aesthetic perception, and processing fluency (Drèze & Hussherr, 2003; Miniukovich et al. 2018; Pieters et al., 2010). Including this variable helped to isolate the effects of VC by controlling colour-based design variance.

Pearson's correlation coefficients were analysed to examine the bivariate relationships between the VC indicators and advertising performance phases. This step provided insight into the direction and strength of linear associations.

Multiple linear regression analyses were conducted to test the hypotheses and assess how each VC indicator contributed to advertising performance. Separate models were estimated for each advertising performance metric (e.g., CTR, pROAS, brand cart additions) with the VC indicators as independent variables. Prior to the regression analysis, model assumptions (i.e., linearity, multicollinearity, normality, homoscedasticity, and autocorrelation) were checked (Field, 2024). The Shapiro-Wilk test assesses whether a given sample of data was drawn from a normally distributed population (Malato, 2025). The Breusch-Pagan test checks for heteroscedasticity. It does this by regressing the squared residuals from the original regression model on the independent variables (Ten Tije, n.d.). The Durbin-Watson test is used to detect the presence of autocorrelation (i.e., correlation between an error term and the immediately preceding error term) in the residuals of a regression model (Kenton, 2024).

For the pROAS model, logistic regression was employed. The DHARMa package is used to simulate standardized residuals from the fitted logistic regression model (Hartig, 2022). This allows for a robust evaluation of crucial model assumptions for generalized linear models.

Exploratory Factor Analysis (EFA) was conducted on the VC indicators to identify underlying latent factors. Prior to conducting the factor analysis, the data's suitability was assessed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. For the dataset KMO = .64 and Bartlett's Test of Sphericity ($\chi^2(15) = 91.63$, $p < .001$) was significant. The number of factors to retain was determined by inspecting the screen plot and through parallel analysis. Both methods suggested the retention of factors, as indicated by the clear 'elbow' in the screen plot and the point where observed eigenvalues surpassed those from random data in parallel analysis.

Lastly, the interpretable factor scores derived from the EFA were used in subsequent regression analyses to test their effect on advertising performance metrics. Regression models are checked for their assumptions. Finally, robust regression models using the M-estimator were employed to address potential violations of regression assumptions and to ensure that the results were not influenced by outliers.

4. RESULTS

4.1 DESCRIPTIVE STATISTICS OF VC INDICATORS AND ADVERTISING PERFORMANCE

Descriptive statistics for the continuous variables are presented in Table 2. Except for symmetry, which was ordinal, all variables were continuous. This section summarizes the distributional properties and internal consistency among VC and advertising performance variables.

For VC indicators, text length and image count were skewed. Text length ranged from min = 24 characters to max = 659 characters (skew 9.63). Colour count, font size variety, and element overlap were normally distributed. Colour count (M = 4.46, SD = 0.94), Font size variety (M = 3.88, SD = 1.35), and Element overlap (M= 4.48, SD = 2.10). The variable symmetry was ordinal, 41.7% of banners exhibited no symmetry, 44.9% showed partial symmetry, and 13.4% were fully symmetrical. In Appendix F, a histogram with the VC indicators of distributions can be viewed. Overall, this reflects variation in VC in banner design. Although text length and image count showed positive skew, for further analyses they were retained in their original form given their theoretical importance.

Among the advertising performance, CTR was normally distributed (skew 1.14). Brand cart additions and pROAS displayed non-normality (skew = 3.95 & 3.65). Boxplots visualizing the distribution of advertising performance metrics are included in Appendix G. A log transformation was applied to the brand cart add. Promoted ROAS was analysed using a two-part modelling approach to account for its zero-inflated distribution.

Table 1

Descriptive Statistics Banners of VC indicators and advertisement performance (n = 216)

N = 216 banners

Variables	Mean	SD	Median	Min	Max	Skew	Kurtosis
VC indicators							
Text length	62.72	47.11	56.5	24.00	659.00	9.63	116.48
Image count	6.24	2.01	6	3.00	25.00	3.76	33.46
Colour count	4.46	0.94	4	2.00	7.00	0.37	–0.30
Font sizes variety	3.88	1.35	4	2.00	9.00	0.74	0.52
Overlap	4.48	2.10	-0.22	0.00	13.00	0.85	1.99
Advertisement performance							
CTR (%)	0.25	0.14	0.23	0.05	0.74	1.14	1.22
Brand Cart Add	61.55	109.07	9.5	0.00	877.00	3.95	20.26
Promoted ROAS	0.59	1.09	4.65	0.00	7.57	3.65	15.46

Note. SD = standard deviation; Median; Min = minimum; Max = maximum. For example of measures of VC indicators see Appendix E.

Internal consistency analysis using Cronbach's alpha indicated low reliability among the VC indicators (α = .021), as well as for the overarching dimensions feature complexity (α = .022) and design complexity (α = .002). These findings confirm that VC is a multidimensional construct, justifying the separate analysis of individual indicators in subsequent models.

The potential influence of background colour on advertising performance was examined. One-way ANOVAs indicated that background colour did not have a statistically significant effect on CTR ($F(7, 196) = 1.17$, $p = .323$), brand cart additions ($F(7, 196) = 1.29$, $p = .257$), and pROAS ($F(7, 196) = 0.39$, $p = .909$).

4.2 CORRELATION ANALYSIS OF VC INDICATORS AND ADVERTISING PERFORMANCE

To assess the relation between VC indicators and advertising performance, Pearson correlation coefficients were computed. Table 3 presents the correlation coefficients for all VC indicators with each advertising performance phase.

CTR showed the strongest and most positive associations with several VC indicators. Image count had the strongest correlation ($r=0.25$, $p<0.001$). Element overlap ($r=0.13$, $p<0.01$) and font variety ($r=0.10$, $p<0.05$) also demonstrated significant positive correlations with CTR. Text length, colour count and symmetry did not show significant associations with CTR.

For Brand Cart Additions, there are weak to moderate positive correlations. Image count ($r=0.15$, $p<0.01$), element overlap ($r=0.11$, $p<0.001$), and font variety ($r=0.15$, $p<0.05$) showed significant associations. Text length, colour count, and symmetry did not show significant associations with Brand Cart Add.

The correlations with pROAS were weaker and less consistent compared to CTR and brand cart additions. However, image count ($r=0.12$, $p<0.01$) and element overlap ($r=0.11$, $p<0.001$) still exhibited significant positive relationships, indicating a modest impact on advertising return.

These results indicate that certain VC indicators, particularly image count and element overlap, are consistently associated with higher advertising performance across multiple phases. Text length, colour count, and symmetry were not significant for any of the advertising performance phases.

Table 2

Pearson Correlation Analysis, VC indicators and Advertising Performance Phases

	Advertising performance metric		
VC Indicator	CTR	Brand Cart Add	pROAS
Text Length	-0.02	0.02	0.01
Image Count	0.23***	0.15**	0.12**
Color Count	0.09	0.06	-0.01
Font size variety	0.08	0.15*	0.13
Symmetry	0.03	0.04	-0.02
Element overlap	0.13***	0.11***	0.11***

Note. p < .05, ** p < .01, ***p < .001

4.3 RELATION VC INDICATORS AND CTR

To test the relation of VC indicators and CTR, a multiple linear regression was conducted. The model was not statistically significant ($F(5, 210) = 1.67$, $p = .143$, $R^2 = .038$).

Exploratory Factor Analysis supported a one-factor solution, with the first factor ($\lambda = 1.18$). The scree plot from the factor analysis is presented in Appendix H. In Table 3 the factor loadings of the VC indicators are presented. Factor loadings indicated that element overlap (.71), image count (.65), and font variety (.45) were the contributors to the latent factor. Text length (.02), colour count (.03), and symmetry (.001) showed negligible loadings. The extracted factor accounted for 20% of the total variance. The model had an acceptable fit (RMSR = .03, RMSEA = .00, TLI = 1.11). Factors score adequacy was satisfactory, with a regression score correlation of .82 and an R^2 of .67.

Table 3

Factor loadings of VC on CTR from Exploratory Factor Analysis

Indicator	Factor Loading
Element Overlap	.71
Image Count	.65
Font Variety	.45
Text Length	.02
Colour Count	.03
Symmetry	.001

Note. Loadings > .40 were considered meaningful.

A linear regression analysis was performed to examine whether the latent factor of VC predicted CTR. The model was significant ($F(1, 214) = 10.42$, $p = .001$, $R^2 = .046$). The unstandardized coefficient for the VC factor ($B = 0.00037$, $SE = 0.00012$, $t = 3.23$, $p = .001$) suggests that higher VC factor is associated with higher CTR.

4.4 RELATION VC INDICATORS AND BRAND CART ADDITIONS

To test the relation of VC indicators and Brand Cart Additions a multiple linear regression was conducted. Brand cart addition was log-transformed. The model was not statistically significant ($F(5, 210) = 1.09$, $p = .369$, $R^2 = .025$). Furthermore, not all assumptions were met. The assumption of normality was mildly violated (Shapiro–Wilk $p < .001$), the Breusch–Pagan test indicated heteroskedasticity ($p = .004$), and the Durbin–Watson statistic suggested positive autocorrelation ($D = 1.46$, $p < .001$). To address these violations, a robust linear regression was conducted using heteroskedasticity-consistent standard errors. The results remained that the model was not significant (all ps > .39).

Exploratory Factor Analysis supported a one-factor solution, with the first actor ($\lambda_1 = 1.11$). The scree plot from the factor analysis is presented in Appendix H. In Table 4 the factor loadings of the VC indicators are presented. Factor loadings indicated that element overlap (.80), image count (.63), and font variety (.41) were contributors to the latent factor. The model had an acceptable fit (RMSR = .02, RMSEA = .00, TLI = 1.14). Factor score adequacy was acceptable, with regression score correlation of .83, and an R^2 of .69.

Table 4

Factor loadings of VC on Brand Cart Additions from Exploratory Factor Analysis

Indicator	Factor Loading
Element Overlap	.80
Image Count	.63
Font Variety	.41
Text Length	.11
Colour Count	.03
Symmetry	.07

Note. Loadings > .40 were considered meaningful.

A linear regression analysis was performed to examine whether the latent factor of VC predicted brand cart additions. Model assumptions were violated Breusch–Pagan test was not significant ($p = .074$), visual inspection showed evidence of heteroskedasticity, and the residuals failed the normality test (Shapiro–Wilk $p < .001$). Additionally, positive autocorrelation was detected (Durbin–Watson $D = 1.50$, $p < .001$). To account for potential assumption violations, a robust regression using the M-estimator was performed. The effect was significant ($B = 12.05$, $SE = 3.49$, $t = 3.45$), and the residual standard error was reduced (from 107.3 to 40.0), indicating improved model stability.

4.5 RELATION VC INDICATORS AND PROAS

To test the relation of VC indicators and pROAS multiple tests were done. A two-part modeling strategy was employed due to the zero-inflated distribution of pROAS. Stage one involved a logistic regression predicting the likelihood of achieving a positive pROAS. The model showed adequate fit, as assessed via the DHARMa package. None of the VC indicators were significant ($\chi2(7)=8.99$, $p=.253$). However, while not included in the original hypotheses, a post hoc analysis revealed a significant quadratic effect for element overlap (B = –0.26, p = .030), suggesting that moderate levels of overlap may enhance performance more than very low or high levels.

Stage two used a Gamma regression to model the magnitude of pROAS among cases with positive values. Model fit showed minor violations via DHARMa package. The Kolmogorov–Smirnov test was significant (p = .006), and quantile residual plots revealed slight non-random patterns, particularly at the distribution extremes. However, dispersion (p = .08) and outlier (p = .077) tests were non-significant, supporting the appropriateness of the Gamma regression. The gamma regression model had no significant effect (all ps > .09).

Exploratory Factor Analysis supported a one-factor solution (λ_1 = 1.18). The scree plot from the factor analysis is presented in Appendix H. In Table 5 the factor loadings of the VC indicators are presented. Factor loadings indicated that element overlap (.76), image count (.77), and font variety (.56) were contributors to the latent factor. Other indicators (text length, colour count, symmetry) had negligible loadings. The model showed an acceptable fit (RMSR = .03, RMSEA = .00, TLI = 1.11).

Table 5

Factor loadings of VC on pROAS from Exploratory Factor Analysis

Indicator	Factor Loading
Element Overlap	.76
Image Count	.77
Font Variety	.56
Text Length	.02
Colour Count	.01
Symmetry	-.06

Note. Loadings > .40 were considered meaningful.

A linear regression was then conducted using the latent factor as a predictor of pROAS. Model assumptions were partially violated. Residuals were non-normally distributed (Shapiro–Wilk p < .001). A robust linear regression using the M-estimator was performed. This model was significant (B = 0.1125, SE = 0.0304, t = 3.70). The residual standard error dropped from 1.08 to 0.35.

5. DISCUSSION

5.1 SUMMARY OF KEY FINDINGS

This study explored the impact of VC in real-world banner advertisements on advertising performance within an e-commerce platform. The results of the study show that VC as defined by text length, image count, colour variety, font variety, symmetry, and element overlap did not have an impact on advertising performance. The three phases of advertising performance (CTR, brand cart additions, and pROAS) are not influenced by these indicators.

However, a latent factor of VC, characterized by element overlap, image count, and font variety, did have an impact on advertisement performance. This factor demonstrated a statistically significance impact on all three advertising performance phases. Meaning that banners combining overlapping elements, more images, and varied font sizes performed better in attracting clicks, encouraging cart additions, and generating returns. However, even though the factor was statistically significant the explained variance is low, indicating other unknown variables can influence advertising performance. Table 6 shows the study hypotheses and their results.

Table 6

Hypotheses tested and the outcome

H_1: VC → Advertising Performance (General)	Partially Supported	VC indicators were not predictive, but a latent VC factor (i.e., element overlap, image count, font variety) significantly predicted all advertising performance metrics
H_2a: VC → Click-Through Rate (CTR)	Partially Supported	Latent factor of VC was a significant positive predictor (R^2 = .046).
H_3a: VC → Brand Cart Additions	Partially Supported	Latent factor of VC significantly predicted brand cart additions (R^2 = .032).
H_4a: VC → Promoted ROAS	Partially Supported	Latent factor VC was a positive predictor of pROAS (R^2 = .023).

5.2 INTERPRETATION IN CONTEXT WITH PREVIOUS RESEARCH

Whereas researchers, particularly those aligned with Processing Fluency Theory (Reber et al., 2004), have found that simpler visuals enhance advertising performance due to ease of processing. This study found that banners with higher element overlap, image count, and font variety (associated with high VC), were positively associated with advertising performance on an E-commerce platform. These findings suggest that, in real-world E-commerce platforms, overlapping elements, rich imagery, and varied font sizes enhance consumer engagement and advertising campaign outcomes. The indicators Text length, Colour count, and Symmetry have no effect advertising performance.

5.3 THEORETICAL IMPLICATIONS

The study contributes to the conceptualization of VC in E-commerce advertising banners by identifying and analysing a set of indicators that influence different phases of advertising performance: attention (CTR), consideration (Brand Cart Add), and conversion (pROAS). Based on the literature review, six indicators of VC were identified (i.e., text length, image count, colour count, font size variety, symmetry assessment, element overlap). However, these indicators did not demonstrate a direct effect on advertising performance. Instead, only a latent factor, comprised of element overlap, image count and font variety, showed a significant effect on advertisement performance.

Contrary to prior literature, which suggests that high VC in banner advertisements can lower performance due to increased cognitive load, this study found no support for this theory. In fact, increased element overlap, image count, and font variety resulted in higher advertising performance on the e-commerce platform examined, indicating that some indicators of VC have impact on advertising performance.

Furthermore, the relation between VC and advertising performance was assessed in a new and rapid evolving E-commerce environment. Thereby this study indicates that, in real-world E-commerce environments, other theoretical factors beyond VC are likely to play a more critical role in determining advertisement banner performance.

5.4 PRACTICAL IMPLICATIONS

The findings of this study provide practical guidance for marketers and designers aiming to optimize their banner advertising strategies on a E-commerce platform. First, in the study six indicators of VC (i.e., text length, image count, colour count, font size variety, symmetry assessment, element overlap) were identified. They did not directly influence advertising performance. As such, marketers and designers should avoid focusing their strategies solely on these VC indicators. Instead, attention should be directed toward the VC factor identified (i.e., element overlap, image count and font variety) which was shown to have a significant effect on advertisement performance. Second, marketers and designers are encouraged to consider other factors beyond VC that may influence advertisement performance, such as consumer behaviour in different categories, brand familiarity, time and frequency.

From a consumer's perspective, this study facilitates the creation of potentially more engaging and user-friendly advertising experiences, as advertisements with specific forms of VC may be more attention-grabbing and memorable.

5.5 LIMITATIONS AND FUTURE RESEARCH

Certain limitations of this study could be addressed in future research. First, generalizability of findings is limited by the study's reliance on data from a single E-commerce platform and its focus on FMCG campaigns.

Given the diversity of E-commerce platforms, each with unique designs, layouts and user interfaces, as well as the existence of other product categories for campaigns beyond FMCG, future research should extend to additional platforms and product categories. This would help to determine whether the observed effect holds across different contexts.

Second, the content analysis was conducted by a single coder. Although a standardized coding scheme was used to minimize subjectivity, one coder can have subjective bias in classifying VC indicators. Future research should involve several coders to assure intercoder reliability, thereby strengthening the objectivity and robustness of the coding process.

Third, the relatively low explained variance observed across the statistical models suggests that additional factors, beyond the VC indicators, play a significant role in influencing advertising performance. Future research should seek to identify and incorporate other relevant variables, such as consumer demographics, brand familiarity, or factors like time of day and device type, to provide more comprehensive understanding of what drives advertising performance on E-commerce platforms.

Fourth, the use of secondary data, while efficient and reflective of real-world advertising practices, limits the ability to establish causal relationships. Unlike experimental designs, which allow for the manipulation and control of variables, secondary data analysis is inherently correlational. Although statistical controls were implemented to address potential confounding variables, these cannot fully substitute for the causal inference possible in experimental settings. Therefore, future research could benefit from controlled experiments simulating E-commerce environments, where VC in banners can be systematically manipulated and the effects of various indicators rigorously tested.

5.6 CONCLUSION

This study explored the impact of VC in banner advertisements on advertising performance within an E-commerce context. While none of the individual VC indicators significantly predicted performance outcomes, a latent factor comprising element overlap, image count, and font variety was a statistically significant predictor across all three advertising performance phases: attention (CTR), consideration (brand cart additions), and conversion (pROAS). These findings suggest that combining overlapping elements, more images, and varied font sizes performed better in attracting clicks, encouraging cart additions, and generating returns.

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APPENDICES

APPENDIX A: CONCEPTS AND SYNONYMS OF SEARCH TERMS IN LITERATURE REVIEW

Main concept	**Synonyms**			
Visual Complexity	Design density	Visual clutter		
Banner advertising	Display advertising			
Advertising performance	*Key performance indicators*	*(CTR)*	*(Brand Cart Add)*	*(pROAS)*
Retail Media	*Retail advertising networks*	*Commerce Media*	*E-commerce media*	*Onsite advertising platforms*

APPENDIX B: LIST OF PAPERS UPLOADED INTO RESEARCHRABBIT

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APPENDIX D: LITERATURE REVIEW OVERVIEW FINDINGS

n	Author	Year	Title	Goal	Research type	design/methodology	participant characteristics	sample size	dependent variable	independent variable	theory	country	VC definition/conceptualization	Perspective	key dimensions/notes
1	Banytė et al., 2025	2025	The role of consumers' visual attention stimuli in advertising	To explore how different visual stimuli (complexity, authenticity, attributes) impact attention and attitudes using traditional and neuromarketing methods.	Mixed methods	Survey (N=403) and eye-tracking experiment (N=26) with food ads.	General consumers (Lithuania)	403 (survey), 26 (eye-tracking)	Attitude toward advertising, gaze metrics (duration, frequency)	Design complexity, functional complexity, authenticity, content attributes	Cognitive-attentional frameworks	Lithuania	Design and functional complexity	Consumer psychological processing	Findings support design complexity increases attention; functional complexity can hinder attitudes
2	Bočaj & Ahtik	2023	Effects of visual complexity of banner ads on website users' perceptions	To investigate how banner ad complexity affects attention, preference, and visual perception	Quantitative (eye-tracking + survey)	Eye-tracking and user perception survey	Website users	50	Visual fixation, preference scores	Ad complexity (low vs high)	Gestalt principles, perceptual fluency	Slovenia	VC is the amount and arrangement of visual elements, affecting attention, cognitive load, and user perception of appeal.	Perceptual & Behavioral	Focus on text, image count, layout clarity. Simpler ads outperform complex ones.
3	Cuny et al.	2015	Can music improve e-behavioral intentions by enhancing consumers' immersion and experience?	To examine the effects of music on immersion, aesthetic experience, and e-behavioral intentions in a virtual art gallery.	Quantitative (Experimental)	Experimental design comparing conditions with and without background music in a virtual gallery website.	General consumers; average age ~29, 62% female.	250	e-behavioral intentions (revisit and recommend website)	Presence of music (stimulus), mediated by immersion and aesthetic experience	Stimulus–Organism–Response (S-O-R) model; Self-determination theory	France	Visual complexity linked to layout immersion and aesthetic experience; not formally defined.	Experiential and emotional design perspective	Immersion includes spatial experience; aesthetics tied to emotions (delight, stimulation) and contemplation.
4	Donderi	2006	Visual complexity: A review	To review definitions and measures of VC across disciplines	Theoretical review	Conceptual review of visual complexity models	Not applicable		Not applicable	Not applicable	Cognitive psychology, information theory	Canada	VC is the amount of information required to describe a visual stimulus. Bridges information theory and psychology.	Theoretical & Cognitive	Distinguishes between algorithmic complexity and perceptual load. Historical and foundational.
5	Farhat et al.	2024	High Visual Complexity or Low Visual Complexity	To examine how visual complexity in Instagram food ads affects arousal, pleasure, and purchase intention.	Quantitative	Online experiment with manipulated stimuli; PLS-SEM analysis	Instagram users	215	Pleasure, arousal, purchase intention	High vs. low visual complexity in ads	Stimulus-Organism-Response (SOR) model	Pakistan	Amount of visual elements and redundancy	Emotional-cognitive consumer reactions	High VC increases arousal and pleasure; low VC still positively impacts purchase
6	García-Madariaga et al.	2020	Revealing Unconscious Consumer Reactions to Ads with Visual Metaphors	To assess neurophysiological responses to metaphor complexity in advertising.	Experimental, neuroscientific	EEG, GSR, and eye-tracking; tested ads with different metaphor complexity	Consumers	43	Cognitive load, ad appreciation, preference	Level of visual metaphor complexity	Inverted U-curve of complexity-preference	Spain	Metaphor complexity as visual and conceptual load	Neuromarketi ng	Moderate complexity ads evoke best responses; supports inverted-U hypothesis
7	Im et al.	2021	Beyond visual clutter: the interplay among products, advertisements, and the overall webpage	To investigate how consumers allocate attention and evaluate ads/products on complex webpages during casual browsing.	Experimental	Two studies: eye-tracking (n=90), online experiment (n=121)	Undergraduate students	90 and 121	Attention, attitude toward webpage, product/ad evaluation	Webpage visual complexity (low/medium/high)	Berlyne's optimal stimulation theory, visual attention theory	USA	Overall visual clutter (display complexity) vs. target object complexity	Attentional spillover and contextual salience	Moderate complexity yields best attitudes (inverted U-curve); display vs. target complexity distinction
8	Jylhä, H. & Hamari, J.	2019	An icon that everyone wants to click: How perceived aesthetic qualities predict app icon successfulness	To investigate how aesthetic qualities of app icons influence consumer evaluations and behavioral intentions (e.g., clicking, downloading, and purchasing apps).	Quantitative	Vignette-based online experiment with semantic differential scales and randomized icon evaluations across 68 game icons.	General population; mostly young adults (mean age 26.9), mainly university students (61.7%) and smartphone users.	569 participants, 2,276 icon evaluations	con successfulness (evaluation, willingness to click, download, and purchase)	Perceived aesthetic qualities (22 adjective pairs including realistic-unrealistic, simple-complex, unique-generic, etc.)	Visual cognition and design theory; no singular theoretical framework but draws from user interface and semiotic theories.	Finland (majority of participants), with some from the US and UK	Visual complexity is assessed via semantic pairs like complex-simple, abstract-concrete, unique-generic; inferred rather than formally defined.	User-centered perceptual evaluation of icon design	Higher aesthetic icons are evaluated better; key dimensions of successful icons include uniqueness, realism, stimulation, and visual clarity. Complexity was discussed as a dimension (e.g., simple vs. complex icons), but results on this were inconclusive—simplicity not always linked to success.
9	Lin & Chang	2021	Influencing Consumer Responses to Highly Aesthetic Products: The Role of Mindsets	To study how consumer mindsets (abstract vs. concrete) affect evaluations of highly aesthetic products.	Quantitative (Multiple Experiments)	Series of lab and online experiments using mindset manipulation and product evaluation tasks.	General consumers; university participants; varied demographics.	5 studies, ~100–250 each	Product evaluation, brand choice	Visual aesthetics of products (high vs. low) and consumer mindset	Construal Level Theory (mindset: abstract vs. concrete)	Taiwan and USA	Aesthetics and visual complexity conceptualized through surface and shape details; not explicitly defined.	Cognitive and motivational consumer behavior	Visual simplicity/aesthetics interacts with mindset; effect stronger in utilitarian contexts.
10	Machado et al.	2015	Computerized measures of visual complexity	To propose automated VC measures and compare them with human perception	Quantitative (image analysis)	Edge detection, compression, machine learning	Not specified (image stimuli only)		Complexity ratings	Image properties (edge, compression)	Information theory, perceptual coding	Portugal	VC is the amount of information needed to describe a stimulus. Estimated through edge density, compression, and color distribution.	Computation al	Strong use of automated measures, aligned with subjective ratings.
11	Miniukovich et al.	2018	Visual complexity of graphical user interfaces	To propose and validate metrics for GUI visual complexity	Quantitative (GUI analysis)	Operationalization and validation of GUI metrics	GUI testers / web users	55	Perceived VC scores	GUI visual features (9 metrics)	GUI design theory, UX research	Italy	VC is a property of stimulus appearance, defined by four measurable facets: quantity, variety, spatial organization, and perceivability.	Perceptual & Computation al	Developed and validated nine indicators via GUI analysis. Strong multidimensional model.
12	Nadlifatin et al.	2024	Determinant of online purchase intention and corporate website contextual relevance	To analyze the impact of visual complexity and contextual relevance on trust and online purchase intentions.	Quantitative	2x2 factorial experiment with MANOVA, regression	Consumers (Indonesia)	160	Trust, purchase intention, web attractiveness	Visual complexity (high/low), contextual relevance	Biased competition theory, trust models	Indonesia	Amount and richness of visual information	Trust-building via design	High VC improves trust and attractiveness; context matters for interpretation
13	Obal et al.,	2017	Improving banner ad strategies through predictive modeling	To identify optimal banner ad strategies for different business metrics using predictive modeling	Exploratory, empirical	Predictive modeling (GLMM and k-fold cross-validation); data mining	Online users exposed to automotive banner ads	18,956 banner ad records (Jan 2011–Mar 2012)	Activities, Clicks, Effective Cost per Activity (eCPA)	Visual and temporal characteristics of banner ads (e.g., size, animation, content, timing)	Draws on advertising effectiveness literature and data science applications; includes visual complexity assumptions	USA (Data from american digital marketing firm)	Visual complexity conceptualized as banner features (e.g., animation, size, expandability, video)	Data-driven, managerial and theoretical	Visual factors (video, expandability, size, messaging); temporal factors (quarter, day, period) analyzed for impact on performance; predictive modeling identifies optimal ad formats for effectiveness and cost
14	Pieters, wedel, batra	2010	The Stopping Power of Advertising	To investigate how two types of visual complexity affect attention, attitude, and ad comprehensibility.	Quantitative, eye-tracking	Eye-tracking on 249 ads, analysis of gaze and recall	Ad viewers (university-based)	249 ads (participants not specified)	Attention to ad/brand, attitude, comprehension	Feature complexity, design complexity	Processing resources theory	Netherlands/ USA	Feature complexity (clutter, colors) vs. design complexity (creative structure)	Information-processing and ad design control	Feature complexity harms; design complexity helps attention
15	Pieters, wedel, zhang	2007	Optimal Feature Advertising Design Under Competitive Clutter	To optimize ad design to maximize visual attention under clutter using eye-tracking and Bayesian modeling.	Quantitative, optimization modeling	Eye-tracking on 1100+ feature ads; Bayesian hierarchical model	Consumers exposed to retail flyers	1100+ ads, sample size not directly stated	Attention (selection, gaze duration)	Size of brand, price, text, pictorial, promotion elements	Attention Engagement Theory	USA/Netherla nds	Surface element clutter and entropy	Optimization of ad layout under visual competition	Model balances brand vs. page-level attention; clutter moderates design effectiveness
16	Pilelienė & Grigaliūnaitė	2016	Effect of visual advertising complexity on consumers' attention	To analyze attention, recall, and behavioral outcomes across varying ad layout complexities	Experimental (EEG + survey)	Experimental EEG design comparing ad layouts	General consumers	26	Attention (EEG), recall, purchase intent	Ad layout complexity (3 levels)	Cognitive load theory, attention models	Lithuania	VC is linked to ad layout complexity, affecting attention, recall, and purchase intention.	Cognitive & Attentional	High VC demands more attention but harms recall and behavior.
17	Purchase et al.	2012	An exploration of visual complexity	To evaluate subjective vs computational measures of VC	Mixed-methods	User pairwise comparisons, metric testing	General users	54	Visual complexity ranking	Image features (color, edge count)	User-centered design	New Zealand	VC is subjective but consistent across users. Explored through computational and perceptual approaches.	Perceptual	Concludes that no single metric is sufficient; user perception matters most.
18	Putrevu, Tan & Lord	2004	Consumer responses to complex advertisements	To examine how ad complexity affects consumer attitudes and purchase intent	Experimental (survey-based)	Survey with manipulations of ad complexity	General consumers	210	Brand attitudes, purchase intention	Ad complexity, NFC, knowledge	ELM (Elaboration Likelihood Model)	USA	Complexity is defined as the amount and ambiguity of cues in an ad; includes both structural and semantic complexity.	Cognitive	Effects moderated by need for cognition, gender, and product knowledge.
19	Wan et al.	2021	A novel webpage layout aesthetic evaluation model for quantifying webpage layout design	To develop a model that evaluates the aesthetic quality of webpage layouts using quantitative feature extraction and machine learning.	Quantitative	Large-scale feature extraction and predictive modeling using an improved Adaboost algorithm on 13,017 webpages.	Not applicable (webpage data collected via Alexa API)	13,017 webpages	Predicted aesthetic score of a webpage	384 layout features (global, local, and aesthetic)	Gestalt principles, especially for aesthetic feature extraction	China (Wuhan University, Liaoning University) and New Zealand (Massey University)	Visual complexity is quantified using layout features like object count, size, position, symmetry, balance, etc.	Feature-based computationa l evaluation	Global features (object distribution), local features (9-grid mapping), and 14 aesthetic measures derived from layout symmetry, balance, etc.
20	Wang et al.	2023	Simple = Authentic: The effect of visually simple package design on perceived brand authenticity and brand choice	To examine how visually simple vs. complex packaging influences perceived brand authenticity and choice.	Quantitative (8 studies)	Series of experiments and IAT to validate the 'simple = authentic' lay theory and test its effects.	General consumers, various demographics	8 studies, total N=1941	Perceived brand authenticity, brand choice	Visual simplicity of packaging	Lay theory; associative learning theory	China	Visual simplicity = minimalism (fewer colors, shapes); visual complexity = detail, clutter	Cognitive branding and packaging psychology	Visual simplicity interpreted as authenticity signal; complexity undermines perceived sincerity.
21	Wu et al	2016	Complexity or simplicity? Designing product pictures for advertising in online marketplaces	To study the role of visual complexity and complexity contrast on buyer processing and preferences.	Experimental	Lab experiment on online shopping interface; visual salience test	General online consumers	Not explicitly stated	Pleasantness, visual salience	Visual complexity and complexity contrast	Processing fluency theory, biased competition theory	Canada/Chin a	Amount of visual detail; contrast to surrounding images	Consumer visual processing in C2C commerce	High complexity works only with distinct contrast; fluency mediates effects
22	Yegiyan et al.	2020	At the Intersection of Motivational Relevance and Website Visual Complexity	To examine how website complexity and emotional tone of media affect ad encoding and memory.	Experimental	Reaction time and memory recognition test across emotional video and ad density levels	Participants exposed to emotional video content	Not explicitly stated	Ad recognition, STRTs	Visual complexity (ad number), emotional tone (positive/negative)	Motivated Attention Theory, Memory Narrowing/Broadening	USA	Ad density as visual complexity	Cognitive load and motivational relevance	High VC reduces memory with negative tone; supports memory narrowing under aversive activation
23	Zanette et al.	2022	Re-arranging dressing practices: The role of objects in spreading ugly luxury	To explore how 'ugly' luxury objects (e.g., chunky sneakers) reshape consumer taste regimes and practices.	Qualitative	In-depth interviews (n=32) and visual analysis of 140 Instagram posts	Upper-middle-class consumers, majority millennials	32 interviews, 140 Instagram posts	Enactment of good taste	Materiality, design, and marketing of ugly luxury objects	Practice Theory; Extended Materiality	France	Visual complexity as aesthetic contradiction (ugliness + luxury); linked to material, design, and symbolic cues	Sociocultural practice-based perspective	Complexity includes bold shapes, colors, 'chunky' forms; impacts perceived structure and taste negotiations.

APPENDIX E: CODEBOOK VC INDICATORS IN BANNER ADVERTISEMENTS

This codebook outlines the definitions and measurement procedures used to assess VC in static banner advertisements. The aim is to provide a replicable framework for coding VC indicators. This codebook is structured by indicators of VC (i.e., text length, image count, colour count, font size variety, symmetry assessment, element overlap) (Figure 2). The coding was administrated using Excel. After which the columns were added to the dataset in RStudio. In Figure A an example banner is demonstrated used for coding examples.

Figure A

Example Banner Advertisement for coding (300x240 PX)

Note. Brand icons are removed for this example

Quantity of Information

This captures the overall volume of textual and visual content present. It is assessed through two indicators: text length and image count.

- **Text Length**: Total number of characters in all visible textual elements. Text within logos is excluded. Spaces are excluded from the character count. The coding involves a raw count of characters (e.g., 53, 108, 231), measured at the ratio level (continuous), with the unit of analysis being the number of characters.
  Example Figure A: Text: "Koopnu" (6), "totenmet25%korting*" (21), "*opdemeestgetoondeprijs" (26). Total: 53 characters
- **Image Count**: Number of discrete visual elements such as product images, logos, icons, and decorative graphics. Background objects and other visually distinguishable elements are included.
  The coding is based on the number of distinct visual elements, where 0 indicates a text-only banner, 1 represents one image, and n corresponds to the total number of distinct images. The measurement level is ratio, continuous.
  Example Figure A: Distinct images: White cat, Kip pack, Zalm pack, one cans, brand logo, background icon, blue button. Total Image Count: 7

Heterogeneity of Elements

This reflects the visual diversity within the ad, captured through colour usage and font sizes variety.

- **Colour Count**: Number of dominant colours. Subtle colour accents are excluded unless they occupy significant space. The coding consists of a raw count of dominant colours, measured at the ratio level (continuous).
  Example: Dominant colours: Yellow (background), White (cat, packaging), Blue (headline and button), Black (logo); Colour Count: 4.
- **Font sizes variety**: Number of distinct font sizes in text elements. Fonts in packaging or logos are excluded. The coding involves counting the number of distinct font styles or size variations, measured at the ratio level (continuous), with the unit of analysis being the number of font size varieties.
  Example: "Koop nu" (bold, large), "tot en met 25% korting"* (medium), "*op de meest getoonde prijs" (small). Font sizes variety: 3

Structural Arrangement

This refers to the spatial alignment and balance of elements within the banner, particularly their symmetry.

- **Symmetry Assessment**: Degree to which visual elements are evenly arranged along vertical and/or horizontal axes. The coding procedure involves visually assessing the spatial arrangement of elements within the banner. A grid overlay was used to assist in systematically assessing the visual balance and symmetry of banner layouts. Banners are categorized into one of three symmetry levels. First, no symmetry, where elements are asymmetrically distributed across both axes. Second, partly symmetric, where balance exists on only one axis. Third, symmetric, where clear mirroring is present along both vertical and horizontal axes. The measurement level is ordinal, and the unit of analysis is a categorical rating based on a three-point scale.

Figure B

Example Banner Advertisement with symmetry grid

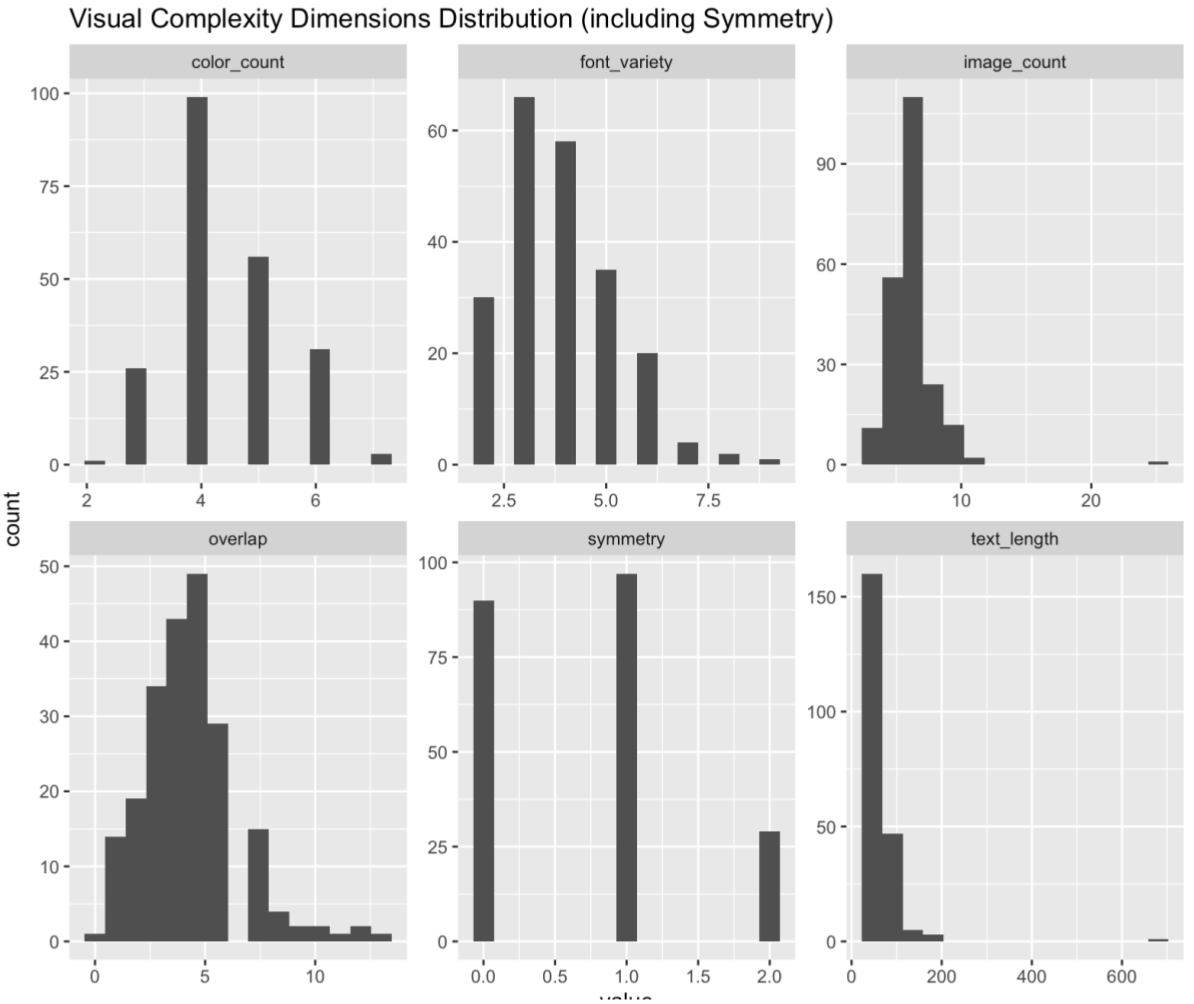
Example: Horizontal balance via central product positioning and logo & Blue box is partly symmetric

Level of Visual Detail

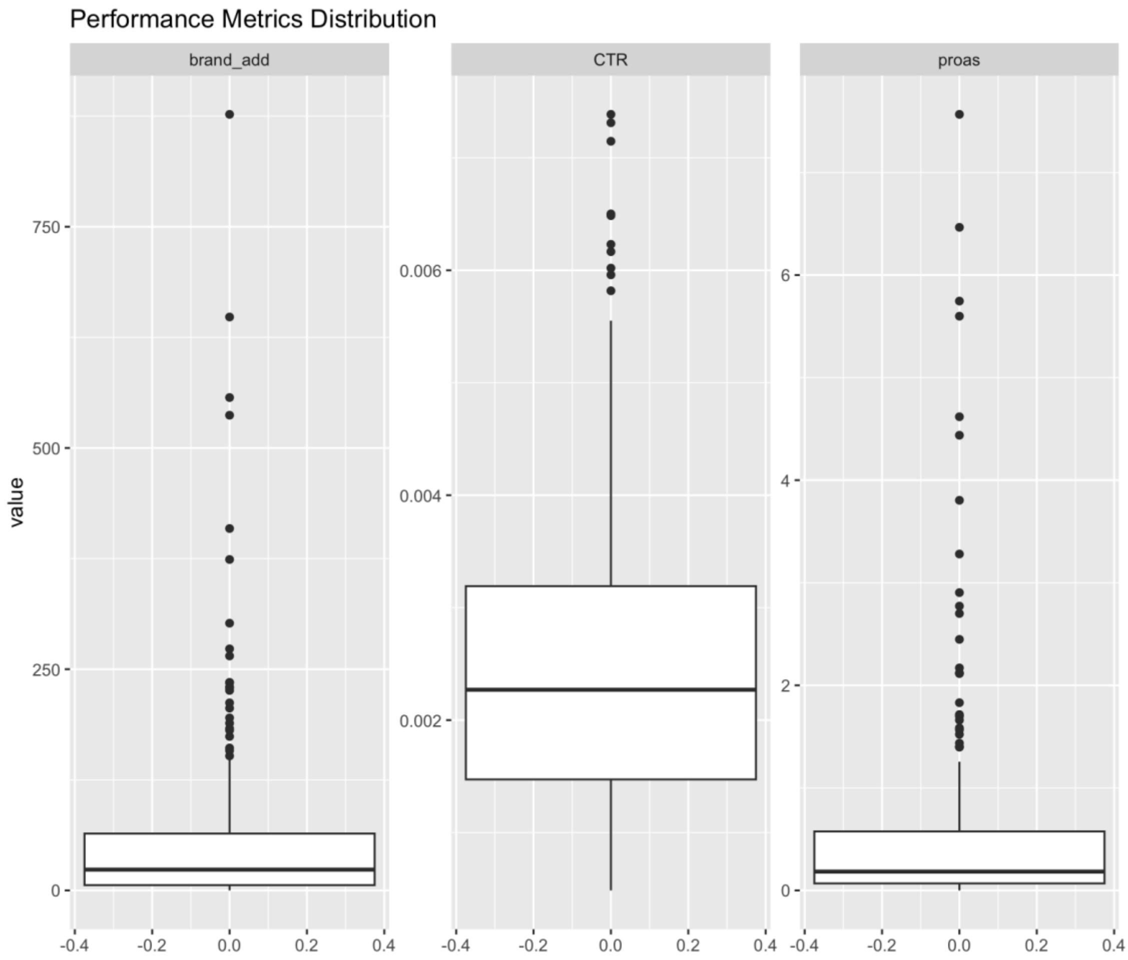
This evaluates the clarity and separation of visual elements, particularly in terms of overlap or visual crowding.

- Element Overlap: Presence of intersecting visual elements, such as text over images or image-on-image layering.
  Coding: number of overlaps
  Example: 6 instances of overlapping elements

APPENDIX F: HISTOGRAM VC INDICATOR DISTRIBUTIONS FOR DATASET (N=216)



APPENDIX G: ADVERTISING PERFORMANCE METRICS BOXPLOT FOR DATASET (N=216)



APPENDIX H: SCREEPLOTS OF EIGENVALUES FOR EACH ADVERTISING PERFORMANCE METRIC

Table A

Screeplot of Exploratory Factor Analysis of CTR

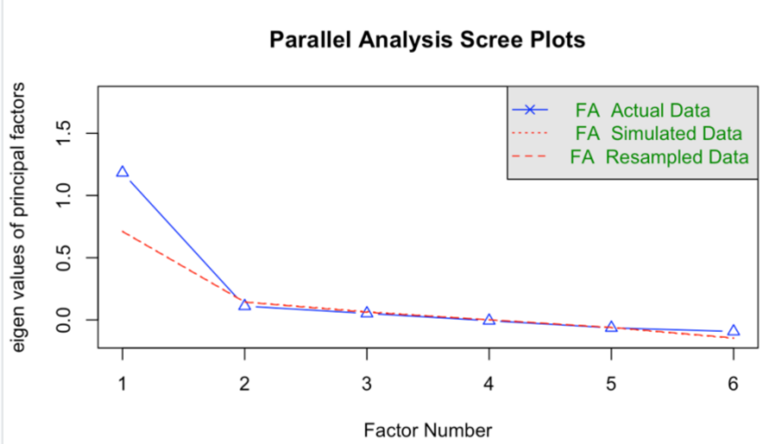


Table B

Screeplot of Exploratory Factor Analysis of Brand Cart Add

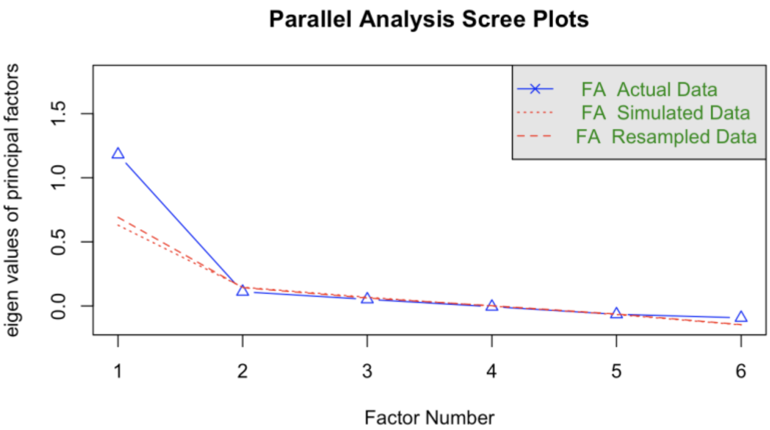
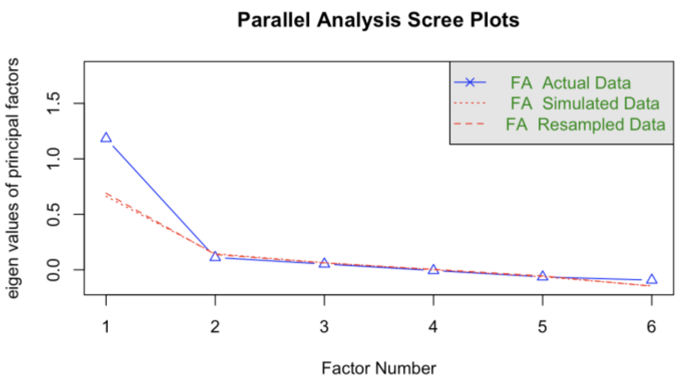


Table C

Screeplot of Exploratory Factor Analysis of pROAS



APPENDIX I: USE OF GENERATED CONTENT

During the preparation of this work, several AI-powered tools were utilized to enhance specific aspects of the research process. ChatGPT and Quillbott were used to refine the language, ensuring the use of formal and academic English. For the literature review, the AI tool Research Rabbit assisted in identifying and organizing relevant scholarly articles. Additionally, ChatGPT was used for the coding of VC indicator text length, with outputs subjected to critical assessment and verification by the author. Once these tools were used, I thoroughly checked and refined the content, ultimately taking full responsibility for the study's accuracy and integrity.

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