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Enhance the Perception in Viewing Business Data

by

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Certificate of Original Authorship

I, Yina Li, declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Computer Science, Faculty of Engineering and Information Technology at the University of Technology Sydney.

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ABSTRACT

A variety of computer graphics and visualization techniques for viewing business data on the screen are developed. Viewers' efficient and accurate perception of explicit and implicit business information relies on the interface design adaptive to the human eye-brain system. Human's attention, recognition, and semantic meaning interpretation are the keys to the perception of business data. This thesis discusses perception enhancement in three directions:

1) Enhance the perception (i.e., recognition) of visual networks through visual clutter reduction (or edge bundling).

2) Enhance the perception (i.e., attention) of a focal graphic object among similar others through the graphic saliency highlighting technique.

3) Enhance human capability in interpreting visualized temporal information through perception bias identification.

The thesis conducts experiments to examine how shape, color, location, orientation, and motion as the basic visual elements influence users' perception of business data displayed on the visual interface. We analyze the mechanisms in which visual elements are organized, perceived, and interpreted and indicate the opportunities to optimize users' experiences adaptive to the key stages of information processing when viewing business data.

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List of Publications

Journal Papers

J-1. Zheng Huang, **Yi-Na Li**, Jun Kong. (2022) "Investigating the Pointing Techniques in the Tabletop-Centric Cross-Device Interaction," Multimedia Tools and Applications, 82(7): 10077-10098
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J-2. Zhen-Bao Fan, **Yi-Na Li**, Kang Zhang, Jinhui Yu, Mao Lin Huang. (2022) "Measuring and Evaluating the Visual Complexity of Chinese Ink Paintings," The computer Journal, 65(8): 1964–1976.
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J-3. Kirlin Li, **Yi-Na Li**, Hong Yin, Yanpeng Hu, Peng Ye, Changbo Wang. (2020) "Visual analysis of retailing store location selection," Journal of Visualization, 23: 1071-1086.
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J-4. **Yi-Na Li**, Kang Zhang, Dong-Ni Hu, Mao Lin Huang. (2019) "The Influence of Edge Bundling on Visual Information Search," Information Sciences, 495: 234-246.
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Conference Papers

C-1. **Yi-Na Li**, Zhen-Bao Fan, Mao Lin Huang, Kang Zhang. "White space and Chromatic complexity: the predictors of the perceived complexity of Chinese Ink Paintings and their downstream consequences," (Paper ID S06203) Brain Informatics (The 1st International Workshop on Computational Neuroaesthetics), 2019, December, 1315, Haikou, Hainan, China

Papers Ready to Submit

J-1. **Yi-Na Li**, Mao Lin Huang. "Saliency Competition of Product Profile Images on E-commerce interface"

J-2. **Yi-Na Li**, Mao Lin Huang. "The speed of Visualized Time Elapsing: The Role of Horizontality in Temporal Perception"

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Chapter 1

Introduction

1.1 Business data

The digitalization of a firm's operations and performances has transformed analog information into a digital format. This has resulted in an abundance of easily processed, stored, and transmitted data about the firm's finance, sales, customers, employees, and product inventory. Such digitalization facilitates transparent business processes and the identification of opportunities to achieve business goals and ultimately drive profit [1, 2]. This accumulation of data mirrors real-world business facts in a virtual space, with business data referring to the digital representation of these facts and their attributes, such as stakeholders, events, time, location, quantity, and quality.

Business data is crucial for driving a firm's profitability. In this dissertation, the term "business data" refers to information that aids stakeholders in comprehending business performance and generating insights. While firms commonly utilize data they generate internally, they also extensively rely on diverse external data sources in various formats to enhance business performance. For instance, car manufacturers monitor social media sentiments to optimize product launches and schedule the announcement of defective product recalls, while logistics firms employ satellite cloud graphs to identify potential natural hazards that could disrupt their supply chains. In these examples, social media data and satellite remote sensing data that are collected outside the firm but both serve business objectives can be considered business data. In summary, the collection and inclusion of data in analysis are driven by business goals. Such goals define the scope of business data.

To achieve effective utilization of business data, a comprehensive understanding of the operational context is essential. Factors such as market volatility, competition, and political uncertainty pose challenges to business performance. Given limited resources, analysts must identify feasible actions and available opportunities within the current circumstances. They must also select few impactful indicators that indicate potential improvements in performance among many variables. Unlike data analysis in scientific and academic domains, business data analysis prioritizes actionable insights and emphasizes the adaptability of leveraging strategies for success in a dynamic business environment. Implementation effectiveness is a key consideration in this process [3].

The business data presentation greatly impacts the transition from business data analysis to business actions. The visual power of interfaces can effectively influence stakeholders' interpretation of business facts and guide them toward desired outcomes. A well-designed interface can facilitate reasoning, simplify causal relationships, and promote consensus among stakeholders with different perspectives [4]. For example, geographical information systems have been shown to assist in location-based decision-making, such as identifying suitable retail locations [5]. However, it is important to note that desired outcomes may not always be achieved, and misleading results can occur in certain boundary conditions [3, 6–8]. For instance, using visualization techniques can enhance decision-making and project portfolio success. The positive effect depends on users' familiarity with the technique and appropriate adoption of heuristic thinking [6]. The design of interfaces and their ability to harness visual power for improved business performance requires further systematic investigation.

Compared to other business activities such as supplier relocation, new product development, and market launching, optimizing visual interfaces based on individual visual perception is a relatively straightforward and less contentious process. This indicates that leveraging visual information has the potential to improve business performance. This dissertation focuses on network analysis for managers and consumer decision-making. Network visualization enables managers to gain an overview of the network, identify key players and their connections, and ultimately exercise better control. The e-commerce interface plays a crucial role in shaping consumers' choice architectures, directly impacting how choices are perceived, compared, and processed. By delving into users' interaction with business data, the dissertation aims to theoretically explore the perceptual lifting approach and contribute to ongoing optimization efforts for practically gaining business advantages.

1.2 Evaluation of business data visual interface

How people use graphic display as an instrument of communication and how people perceive visual information has been comprehensively discussed in Colin Ware, Edward Tufte and others' work [9–11]. Their work has established the underpinning foundation to evaluate visual interfaces. The evaluation of business data visual interfaces adopts comprehensive scales and measurement tools to assess users' experiences, including visual clarity, accuracy, learnability, aesthetics, and task-based performances [12]. These evaluations serve two purposes. The first type focuses on specific design, providing evidence to verify whether an interface meets human needs and provides effective solutions. The second type narrows the research focus to fundamental attributes of the interface. This evaluation highlights how visual attributes impact perception and decisions by studying users' recognition of shapes and colors, the organization of figurative graphics, and their interpretation in-depth [13]. Previous research has examined the influence of shading, shape distortion, and tokens showing proportion on cognitive bias, decision accuracy, and confidence levels under different task complexities, time pressures, and user capabilities [5, 14]. Such research identifies the advantages of specific visual attributes, explains their mechanisms in perception and inference, and provides generalized contributions applicable in similar situations. In the context of business data, the research addresses how visual attributes enhance decision-making success. For example, high saturation visual stimuli can increase consumers' willingness to pay for products with sentimental values [15], and circle visualizations lead to better decision-making than bars in geographical visualization for managers [5]. This stream of research provides actionable measurements to improve business performance and contributes to knowledge in management.

1.3 Interface view and visual representation

According to screen time statistics from DataReportal, worldwide, individuals spend 6 hours 57 minutes looking at a screen every day and 3 hours and 43 minutes on mobiles *. The increasing online time motivates building a metaverse as the mirror of the offline world and releases great power from images. In the interface-mediated world, new visual representations are created to map the tangible and intangible offline reality. The visual representations on the interface show business data, deliver information and convey knowledge. Consumers can browse products, make purchases, and track their orders through a user-friendly visual interface. Marketing managers can analyze consumer behavior, manage product listings, and run promotional campaigns. Suppliers can access real-time inventory data, update product information, and manage order fulfillment. Through a visual interface, the information on stakeholders, channels, products and services is organized and represented. The visual power is released when people access the information.

Business data visualization, despite its potential for visual complexity, can be understood through a four-level composition structure. This structure consists of visual features, elements, objects, and semantics. Visual elements encompass shapes, colors, orientation, positions, and other attributes, and are defined and measured by visual features. For instance, color in the HSV color system is defined by three values, while a curve is defined by its curvature and length. These basic visual elements are then organized to form visual objects, which can be interpreted as tangible entities. By combining

*www.comparitech.com/tv-streaming/screen-time-statistics/, 20220722 visual objects, relationships are implied, and the interpretation of complex and abstract concepts is enabled.

Visual representations deliver meanings by mapping visual stimuli to semantic meanings (see an example in Figure 1.1). The mapping relationships can be either arbitrary or based on widely recognized conventions. For instance, the representation of a cat concept can take the form of a hat symbol that bears no resemblance to the visual appearance of a cat, a composition of black shapes in the second image, or an arrangement of intricate visual elements in the third image. Clearly, the hat symbol is perceived as arbitrary when representing the cat concept, while the increasing visual resemblance in the subsequent images strengthens the perceived rationale behind establishing the mapping relationship. This example illustrates the varying levels of ease in interpreting images.

Designers or visual information senders encode meanings also through the mapping relationship. The mapping relationship occurs on the four levels mentioned above. For example, red colors in different lightness values at the visual feature level can be defined to refer to the level of emergency. Shapes at the visual element level can be used to refer to entities. The composition of visual elements can evoke the concept and denote recognizable visual objects (e.g., product profile images). The node-link diagram composed of many visual objects can reflect interactivities between individual entities (e.g., the number of conversation or the amount of financial trade) or reveals structural information (e.g., the density of population and the flight routes between cities).

1.4 The challenge in visual information processing research

It could be challenging for the viewer to interpret visual stimuli accurately. The interpretation can be achieved if human visual systems can successfully capture visual stimuli, organize them well as desired visual objects, and decode meanings appropriate to the context and environment. In familiar scenarios, the recognition of visual objects is perceived as spontaneous and effortless, which leads to an impression that the semantic meaning

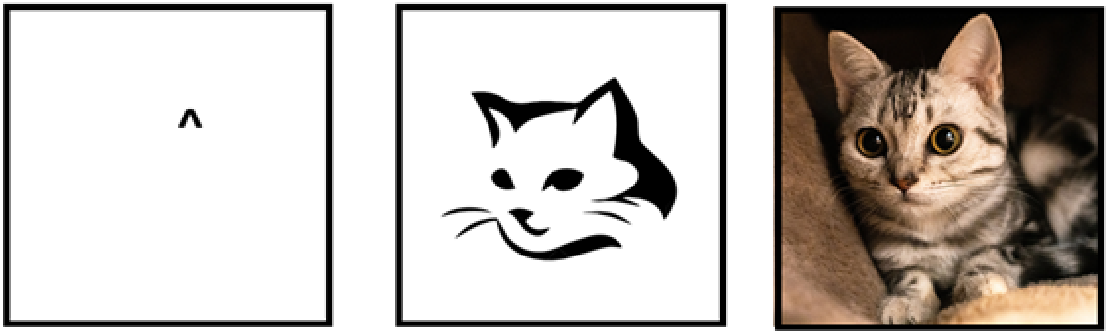


Figure 1.1 : Mapping relationships in visual representation

of visual objects is transparent and highly accessible. People seldom question in a view what information is failed to recognize, what visual object is ignored, and what is misunderstood. It is even mysterious why selected stimuli are perceived in a certain way. As the comprehensive uses of interface-mediated communication on mobile devices, computers, and other display devices, a tremendous number of images are created and updated daily to construct the interface of the digital realm. Firms endeavor to find out the efficiency of visual information communication, and they tend to gain more attention, earn the chance of elaboration, deliver accurate information and impress the viewers. Exploring the fundamental issues underpinning visual information communication may provide insightful solutions to optimize viewing and interaction techniques.

1.5 Visual information processing

Visual information processing is a complex task involving multiple steps. Initially, retinal cells in the eyes convert light stimuli into nerve impulses, while the brain encodes and registers various visual features such as shape, color, position, movement direction, and size. These features are then integrated to form a sense of closure, sequence, movement, distance, and figure-ground discrimination. Certain visual features are more attention-grabbing and receive longer fixation durations from viewers. The encoded features are compared with existing visual schema, leading to the detection, recognition, and memorization of visual objects. However, limited attention and incomplete information can result in failures in object detection and recognition.

When a visual object represents a tangible and concrete entity, its meaning is explicit. However, when it refers to an intangible and abstract concept, the interpretation of its meaning becomes more complex. Context-based rules, visual conventions, and existing knowledge need to be considered, which can amplify the ambiguity of semantic meanings and introduce significant biases. For instance, a visualized temporal interval could be perceived as fast or slow based on the perceived favorability of an upcoming event.

The process of visual information processing can be viewed as comprising three stages: attention, comprehension, and perception bias. These stages assess the level of attention, ease of recognition and comprehension, and presence of bias in conveying abstract meanings within visual objects. Figure 1.2 depicts these stages, illustrating their significance in evaluating the usability of interface design. By examining the allocation of attention to visual objects in the early stage of visual processing, visually salient elements can be identified, and the alignment of viewer attention with the designer's intentions can be assessed. Furthermore, comparing the comprehended meanings with the ground truth can uncover the ambiguity of visual representations and highlight areas for improvement. Ultimately, the analysis of perception bias allows for an understanding of how visual elements influence quantity estimation and how perceived information is utilized for inference.

In this thesis, our investigations focus on these three stages from a business-goal-driven perspective, specifically emphasizing transparency in representing complex relationships between entities and stakeholders over time. The following section provides a summary of these three focuses in concrete business scenarios.

The first focus of our research utilizes eye-tracking technology to analyze how product images in e-commerce interfaces attract viewers' attention. In the online shopping envi-

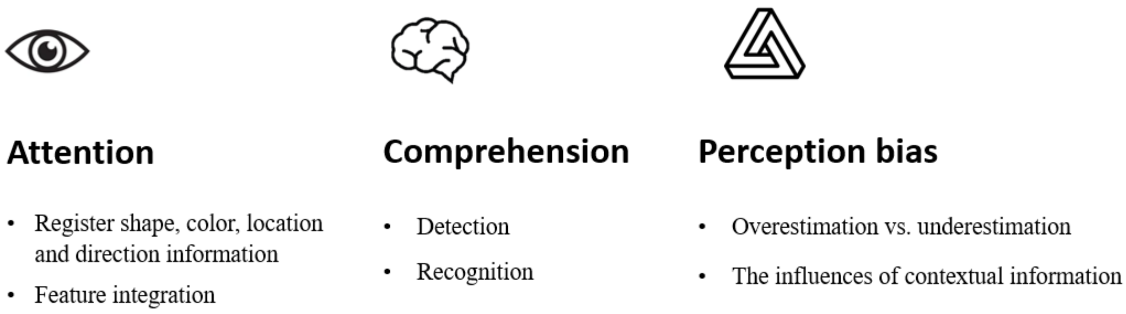


Figure 1.2 : Key stages of visual information processing

ronment, products within the same category compete for attention. The visually salient products have an advantage in attracting viewers' attention and increasing the likelihood of being evaluated and purchased. Understanding visual competition and its mechanisms can provide insights into the effectiveness of advertisements and the true value of display positions. This research explores how color attributes of the product profile image (saturation, lightness, and color complexity), their position on the e-commerce interface, and the color features of neighboring products influence users' perception of visual saliency. The findings identify color features that can be optimized for saliency and lay the foundation for optimizing the display order of recommended products.

The second focus of our research aims to determine whether a given visual pattern is detected and recognized accurately. Visualized networks are commonly used to analyze patterns in business ecosystems. Managers rely on these networks to identify key players, information flow and dependencies, and the dynamics of the ecosystem. Therefore, it is crucial to have an easy and accurate pattern recognition process. The edge bundling technique has been developed to address visual clutter and facilitate information access and analysis. We examine how increasing tension reduces visual clutter by viewing clustered edges, decreases visual complexity, and consequently affects users' speed-accuracy tradeoff in visual search. Our findings reveal an inverted U-shaped relationship between tension and accuracy, confirm the advantages of moderate tension in revealing skeleton information, identify the underlying assumptions, and propose an optimized tension parameter setting.

The third focus of our research investigates how given visual elements are interpreted in business contexts and how they cause perceptual biases in estimating quantity information. Specifically, we examine how physiological constraints and cultural factors contribute to an accurate representation of temporal information. Temporal perception is fundamental in scheduling and management, given that the proverb “time is equivalent to money” is widely accepted. The accurate transmission of time information significantly influences decisions regarding efficiency improvement. We consider temporal duration as quantity information and explore how time, as an abstract concept, is perceived when visualized in leftwards and rightwards directions under different temporal processing schemas. This research sheds light on the role of the business context in elaborating given visual information and adopting visual conventions.

1.5.1 Pattern recognition and Gestalt law of prägnanz

The Gestalt law of prägnanz explains how our perceptual organization occurs when we perceive the chaotic world [16]. The human brain has a tendency to recognize patterns by organizing individual and unrelated elements with the least amount of effort. Previous research has identified several visual cues for organizing visual stimuli, such as boundary or enclosure, similarity, connectedness, and proximity [17]. For instance, in the case of proximity, humans perceive separate or unrelated parts that are close to each other as being associated. The whole of a visual object is not merely the sum of its isolated parts, and judgments about the proximity are always comparative [18]. In Figure 1.3, the three lines that are close together in the middle are perceived as an entity in contrast to the other lines, and the six curves are organized into two groups based on their proximity and directions. Visual grouping through proximity suggests that the distance between visual objects determines the likelihood of perceiving them together, and neighboring visual

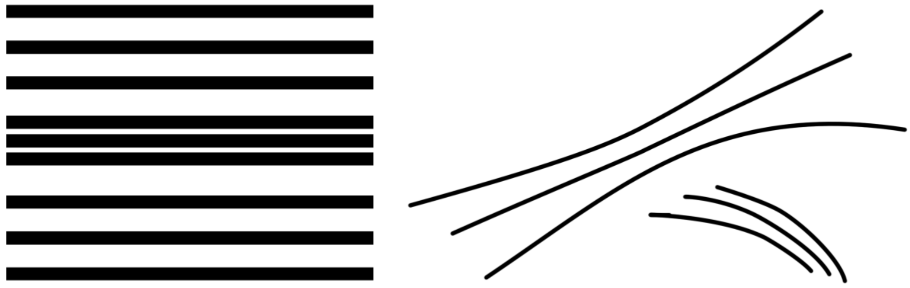


Figure 1.3 : The examples of visual grouping

objects may influence each other. The interactions between visual objects are equally important as the appearance of each individual visual object.

The organization of visual objects suggests that the combination of visual stimuli leads to the difference in the perceived saliency of a given visual object, in the cognitive effort to process the information, in the accuracy to reach the correct solution and interpretation. We then illustrate each dimension of the impacts.

1.5.2 Visual saliency in information browsing

The human's visual system integrates complex sensory stimuli and generates percepts of features, as explained by "feature integration theory" [19]. As a long-held view stated, merely in a single fixation, humans can extract semantic category, spatial layout, and object identities from a natural scene [20]. However, the downstream consequence of the fixation may not be equal for all visual objects due to the limited capacity in processing [21]. A visual object featuring specific attributes and occupying a spatial location may be more likely to stand out from the surroundings and gain visual conspicuity over other objects [22]. The perceptual quality of the location and attributes that can immediately grab people's attention and maintain a long gaze duration is called visual saliency [23–25]. The visual saliency of an area or an object can be measured by the total fixation duration spent on it [26].

Existing research explores saliency detection in both bottom-up and top-down models [10]. The bottom-up model focuses on the distinctive subjective perceptual quality which makes certain visual items stand out from the surroundings, such as the contrast in color and luminance, compactness, and contexture [19, 25]. Prior research established the saliency model [19, 24, 24, 27] based on natural scenes. The top-down model highlights the task-driven attributes (such as goal-oriented visual search) in processing visual stimuli, whereas the bottom-up model depicts the spontaneous process [23, 26]. Visual features determine the saliency of an image, including the variation of the spatial color pattern [28], the unfamiliarity of a visual object, high aesthetic quality, the area of high contrast, saturation, intensity, and lightness [29].

Applying the rule of visual saliency in shopping scenarios, Pieters et al. (2007) proposed the effect of competitive clutter in the retailers' advertisement design [26]. They revealed the influences of the size of design elements, including brand, text, pictorial, price, and promotion, on visual saliency. They manipulated the design elements' size and tested the impacts using retailers' print advertisements. When shopping moves online, search engines help to display target products in the same size on the same templates, which motivates our exploration of the attention competition relying on size-irrelevant features, such as saturation and color complexity.

1.5.3 Accuracy and fluency when processing visualization

Visual accuracy refers to the consistency between the ground truth based on the information from the dataset and the retrieved information from visualization by users. Perceptual fluency is the perceived ease when users process visual information to solve their problems. It could be measured by self-reported subjective experience and recognition speed [30]. Ideally, visualization optimizes both the performance in accuracy and speed [31]. However, there exist speed-accuracy tradeoffs. Users may slow down their response to reduce error or accelerate their speed but at the cost of inaccuracy. The tradeoff could be the users' choice or guided by the given visual stimuli, suggesting the approach to optimize the visualization usability.

The quantity of visual information impacts the tradeoff between accuracy and speed. Insufficient key information impedes accurate inference, but the impact of redundancy depends. The redundancy irrelevant to the solution may distract users, but the redundancy addressing the solution can enhance accuracy [32]. In contrast to its uncertain impact on accuracy, redundancy has a linear impact on fluency. A smaller amount of information is perceived as simple, clear, and processed rapidly and effortlessly [33]. In conclusion, the quantity of information can serve as a lever for optimizing visualization.

1.5.4 Perception bias and the denotation of visual feature

Individuals construct their subjective reality based on their perception of visual input. This constructed reality may deviate from objective reality and rational judgment, leading to biases. When processing visual symbols, individuals attempt to decode a discriminating visual feature as a semantic meaning [34]. A visual feature can potentially be interpreted as a series of utterances, more general and richer than the given meaning, which makes the semantic meaning ambiguous. Viewers capture the meaning that they believe the visual stimuli aim to convey. Therefore, we could observe the comprehensive bias when interpreting visualized information. Among rich visual information, this research focuses on visualized temporal information and investigates how horizontal orientation (left or right) influences time perception and related decision-making.

1.6 Thesis organization

Viewing and interaction techniques support managers' and practitioners' use of data through visualized information and help them in decision-making. The research takes a visual perception-based view to test how visual elements influence the perception of business data and propose approaches to optimize viewing and interaction techniques.

Table 1.1 lists the focal visual elements, outcome variables, and business scenarios.

The rationale behind organizing the research based on these visual elements and outcomes in their respective context is as follows. Through the three chapters, the chosen visual elements include shape, color, position, and orientation. These visual stimuli are selected to make a significant contribution to the current body of literature, aligning with the three stages of visual information processing illustrated in Figure 1.2. The examined outcomes consist of information processing accuracy, perceptual fluency, saliency, and context-based meaning interpretation. Detailed discussions on visual information processing are carried out in carefully chosen business scenarios to address the need of both managers and consumers. These scenarios aim to accurately illustrate the status of an event (such as the saliency of a given webpage), understand the relationships between entities in a network, and track changes in these relationships over time. The rationales for organizing the visual elements, outcome variables, and business scenarios and the research contributions are illustrated as follows.

Table 1.1 : Research Framework

Visual element	**Impact**	**Business Scenario**
1. Shape (e.g., curves) and proximity	Accuracy and recognition speed	Network information visualization
2. Color (e.g., saturation, lightness, and complexity) and position	Attention (visual saliency)	Product display on e-commerce interface
3. The horizontal orientations (leftwards vs. rightwards time flow)	Perception bias	Temporal perception

The first research examines the influence of edge bundling on users' information search performance, i.e., the accuracy, responding time, and perceptual fluency under various levels of bundling strength. It tested the effectiveness of edge bundling by comparing the ground truth with viewers' perceived information, indicated what information is distorted or hidden in boundary conditions, and discussed the mechanism of the influence. The research highlights the role of Gestalt law and the amount of information in the usability test. It provides insights into graph drawing in general and edge bundling in particular in fine-tuning parameters to maximize usability.

The second research adopts classical measurements of image features and indicates how the color attributes (saturation, lightness, and color complexity) of a displayed product, its position on a webpage, and its neighbor's color attributes influence its visual saliency. In an online-shopping scenario, this research highlights that sensory information, in parallel with the customer behavior data, can influence consumers' choices by enhancing the visual saliency of certain products in a bottom-up approach. The empirical results from eye-tracking data indicate the priority location on a webpage and show the impact of location and neighbor's attributes on the visual saliency of a given focal product. Our findings on the interactive influences of sensory features and locations shed light on the saliency map of multimedia interfaces composed of artificial images (vs. natural scenes). The research addresses the tradeoff between contrast and synergetic effects and sheds light on the visual saliency optimization strategies based on a local or holistic view.

The third empirical study focuses on the influences of horizontality on the perceived distance and speed of visual items. Unlike the presumption that horizontal position is processed equally, humans are inclined to process from left to right. The inclination leads to cognitive bias in perceived distance and speed when processing spatial information that is conveyed by horizontal orientation. The research findings show the downstream cognitive consequences of horizontal orientations and shed light on how human's asymmetricity in processing horizontal information influences interpretation and meaning generation.

1.7 Objectives

The research aims to reveal how visual objects are organized and processed and how the fundamental visual elements (i.e., shape, color, location, and orientation) interact with each other and semantic meaning delivery.

- Test the visual grouping of curves in edge bundling techniques of network visualization, and examine how the bundling strength influences information processing accuracy and speed.
- Examine how product profile images' saturation, lightness, color complexity, and position on e-commerce interface influence their saliency and discover how neighbors' attributes influence the focal product.
- Explore how the semantic assignment of horizontal orientation leads to the difference in temporal information interpretation in desired or undesired situations by adopting two metaphorical schemata.

1.8 The author's contribution

- Contribute to the puzzle of accuracy and speed tradeoffs in data visualization subject to clustering and overlaps.
- Optimize the saliency of focal visual objects among equal-size competitors.
- Discriminate the perception bias of time caused by visuospatial association.

1.9 Research Methodology

The research follows the procedures of experimental psychology to design experiments, collect user data, conduct statistical analysis, and draw conclusions. In the second Chapter, we developed an edge bundling visualization system along with an experimental interface to assess its usability. Analysis of variance (ANOVA) was employed to gather evidence supporting our conclusions. In the third Chapter, we utilized well-established graphic measurement techniques to depict the color characteristics of product profile images. Additionally, eye-tracking technology was employed to capture users' visual processing. To analyze individual users' responses to each product image, a generalized linear mixed model was employed. In the fourth Chapter, we manipulated the visual stimuli by altering their horizontal orientations. Analysis of variance (ANOVA) was then used to examine any significant differences in viewers' reactions. Such findings were used to establish a causal relationship between horizontal orientations and the generation of semantic meaning.

Chapter 2

The Influence of Edge Bundling on Business Data Perception

This chapter aims to improve graph drawing in general and the edge bundling technique in particular. Millions of nodes and edges in a node-link diagram representing the network structure of big data may clutter the space, which reduces the aesthetic quality of the visualization and hinders users' information search and comprehension. Edge bundling offers an approach to solve this problem. However, to what extent that edge bundling can solve the problem remains unclear. This research examines the influence of edge bundling on users' visual information recognition performance, including the accuracy, responding time, and perceptual fluency, compares the ground truth with viewers' perceived information, indicates the information distortion, and instructs the approach of usability optimization.

An earlier version of the research work presented in this chapter was published in the journal Information Sciences in 2019 (see J-4 in the Publication list). The inclusion of this publication in the thesis is based on its relevance to the common applications of business network analysis, as well as its evidence regarding the effectiveness of visual interface design in enhancing perception. The experiment and findings from the publication remain unaltered.

2.1 Introduction

Big data necessitates the utilization of sophisticated visualization technologies to extract concealed information from intricate and voluminous datasets [35]. Among the visualization techniques, networks serve as exemplary node-link diagrams that depict the interconnections among various entities. The visual elements of a network can be classified into two categories: nodes and edges. Nodes symbolize the entities under scrutiny, such as individuals, businesses, and accounts. Conversely, edges, represented by lines connecting two nodes, signify the associations between the aforementioned entities.

When large quantities of nodes and edges are presented within a limited interface space, overlapping, occlusion, and visual clutter may arise, thereby diminishing the aesthetic appeal of the visualization and hindering the efficiency of information retrieval. To address these challenges, edge bundling, as a technique for visual compression, groups edges into bundles based on predefined rules, to help revealing underlying structure of the diagram while preserving the original information [36].

To address the specific requirements of visualizing data, scholars have proposed various edge bundling techniques to ensure clarity in overall structure, path direction, and bundle strength. These techniques include hierarchical edge-bundling (HEB) [37], geometry-based edge-bundling (GBEB) [38], and force-directed edge-bundling (FDEB) [39], winding roads (WR) [40], and layered edge-bundling (LEB) [41]. Among these techniques, our experiment focuses on the LEB method. LEB divides edges into layers based on their directions to minimize interference between different bundles. Figure 2.1(a) illustrates the unbundled representation and bundling results of a citation dataset. Comparing the unbundled effect in Figure 2.1(a), the edge bundling effects shown in Figure 2.1(b)-(d) can reveal an apparent skeletal structure. The different levels of bundling strengths, referred to as tensions, result in varying thicknesses of bundles.

In addition to routing similar edges into bundles, LEB minimizes interference between dissimilar edges and generates bundles with less curvature and high traceability [41]. These characteristics highlight the advantages of edge bundling methods and their support for visual analytics. This research focuses on evaluating the effectiveness of visual infor-

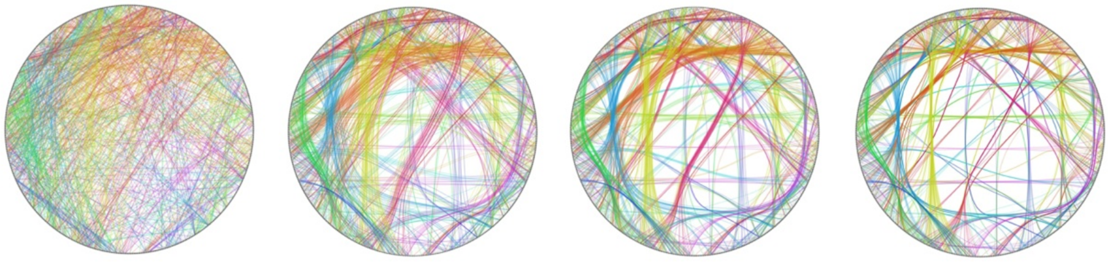


Figure 2.1 : Visualized citation dataset
(a) unbundled graph; (b) (c) and (d) LEB bundling results under low, medium and high tensions

mation communication using the LEB approach. We believe that the conclusions drawn from this study can be applied to other types of edge bundling techniques. Previous research has demonstrated that the technique used to display biclusters effectively reduces low-level perceptual problems and enhances high-level inferences [42]. Inconsistent with the findings, another empirical study found that edge bundling techniques hinder users' accuracy and reaction time when tracing paths between nodes, but can effectively reduce reaction time and aid in recognizing high-level connectivity [43]. Therefore, within the research framework of edge bundling techniques [36], further empirical evidence is needed to control for confounding factors and understand the influence of edge bundling techniques.

Our research makes the following contributions. This study empirically examines the effectiveness of edge bundling by comparing the ground truth with viewers' perceived information. Previous research has acknowledged the ambiguity of a diagram's semantics when edge bundling is applied [44]. However, it assumes that users can accurately process visual information with edge bundling. Our experiment data confirms the disparity between the ground truth and perceived information, shedding light on the distorted or concealed information and its impact on viewers' information processing. Additionally, this research evaluates the effects of edge bundling on accuracy, speed, and perceptual fluency in visual information searching under different bundling tensions. While edge bundling aims to reduce visual clutter, its influence on intuitive navigation at varying tension levels has not been examined. Furthermore, this research seeks to elucidate the mechanism behind the influence of edge bundling, considering visual complexity, Gestalt law, and perceptual fluency. It investigates perceptual fluency as a subjective sense of ease resulting from the clarity and simplicity of visual stimuli in the context of information visualization.

The subsequent sections of this chapter are structured as follows. Section 2 provides a review of the relevant literature. In Section 3, four hypotheses are proposed for empirical evaluation. Section 4 presents a detailed account of our empirical study, while Section 5 presents the obtained results. Finally, Section 6 offers discussions on the results and outlines future research.

2.2 Literature review

2.2.1 Network visualization

One of the important big data analyses is to demonstrate the network. The nodes and links in a network are not equally free of drawing. Figure 2.2- 2.4 are three typical examples of network visualization. Figure 2.2 shows the times each pair of users on a social network platform talk with each other. A node refers to a user, and the edge refers to the interactivities between the users. The location of each node doesn't encode any information. Designers could change the node's position and optimize the edge's length, direction and color. Both the node and the edges are free of drawing. Figure 2.3 shows the citation between papers. Node has fixed sequences, predefined as the publication time. The nodes' positions are fixed, and the edges drawing are flexible. Figure 2.4 shows the frequency of flights between two cities. Nodes refer to cities, each defined by latitudinal and longitudinal values. The edges refer to flight frequency, with a fixed route as the constraint of drawing. Neither nodes nor edges are free of drawing, making clutter very

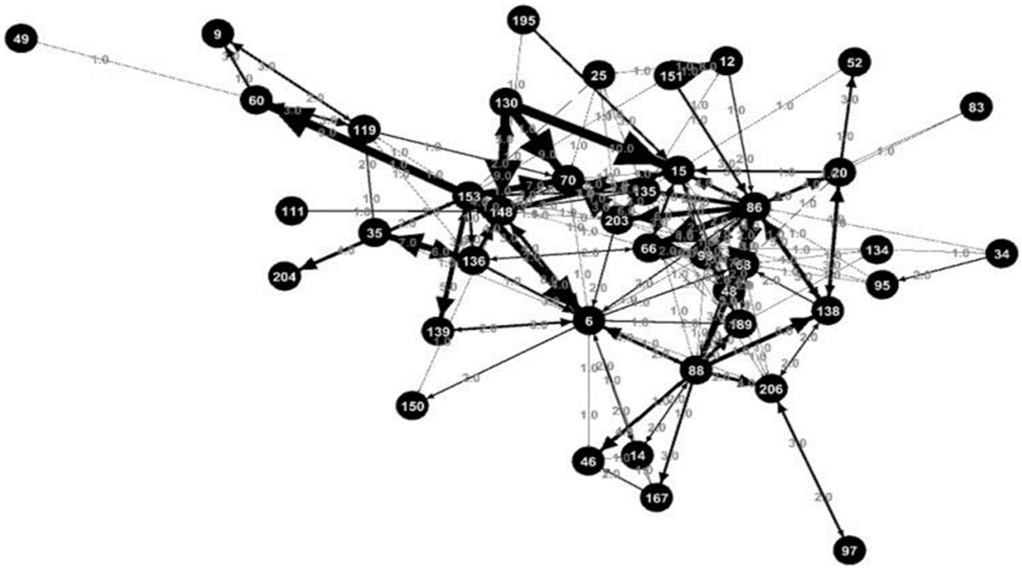


Figure 2.2 : A group of users' interactivities on a social network platform within a week, visualized using Gephi software default setting

common. When a data set has a great number of nodes and edges, they may overlap and cover each other, making it challenging to find any structural information.

2.2.2 Solutions to the visual clutter of network visualization

Filtering and clustering are fundamental methods for addressing visual clutter. Filtering enables users to select a subset for analysis while concealing the rest, providing an easy and straightforward approach [45, 46]. However, when the criteria for selection are ambiguous or highly correlated, and the objective is to identify causal relationships, the adoption of dependency network analysis, in collaboration with filtering, can enhance inference-making [47]. This analytical method can effectively discern the causal relationship between two closely related variables and determine the superior criterion. For instance, socioeconomic status and income often exhibit a strong correlation. Through dependency network analysis, it is revealed that socioeconomic status influences income, but not vice versa, confirming that socioeconomic status is a more suitable filter for analysis.

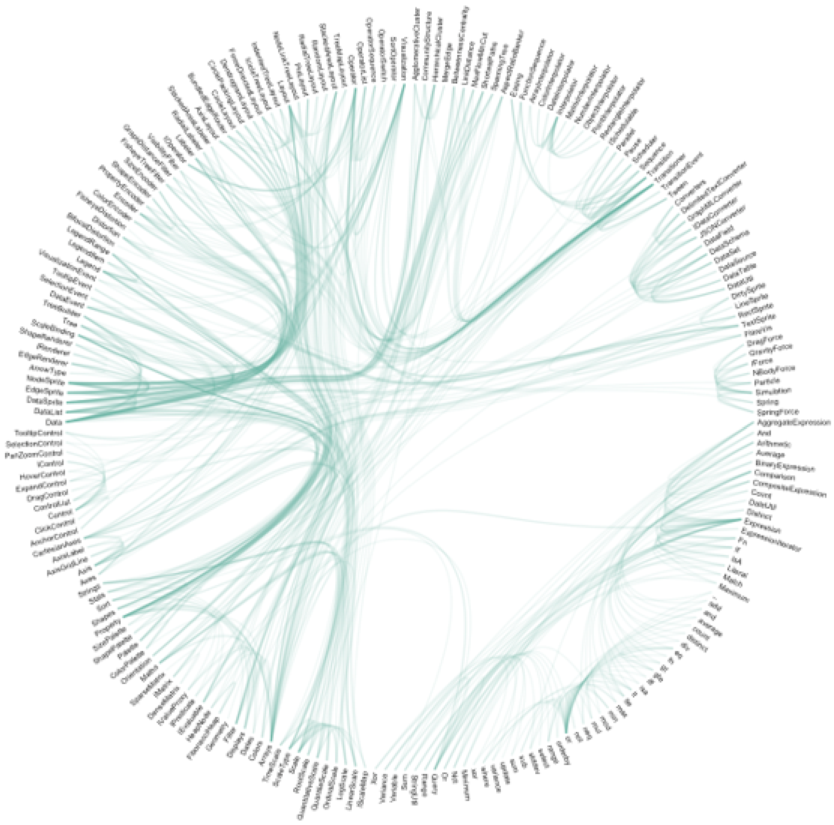


Figure 2.3 : Visualization of adjacency relationship (citation) in hierarchical data, IEEE TVCG by D. Holten 2006

Figure 2.4 : Flight paths edge bunding by Sophie Engle, updated 2020, From bl.ocks.org

Clustering algorithms group entities or elements that are similar and aid in identifying clusters with similar properties. Similarity is determined using topological criteria, such as node location or graph structure. Both entities and lines can be clustered. For example, social network users are classified into subgroups, which is a typical illustration of entity clustering [48–50]. Polylines in parallel coordinates can also be clustered, resulting in visually similar features to edge bundling [42, 51, 51, 52]. Filtering and clustering can be employed together, enhancing clarity in data presentation.

Given the position of the entities is fixed, edge bundling is the most feasible and powerful method to reduce visual clutter in information visualization [51]. It has been widely used in graph visualization [53–55] and flow map visualization [56,57]. Multiple types of edge bundling approaches have been developed pertaining to various task features [51]. LEB classifies edge bundling algorithms into three categories according to the underlying paradigms. The first category, geometry-based techniques, including HEB [37], GBEB [38], ambiguity-free edge bundling (AFEB) [58], sets appropriate control points on curve edges. The second category is cost-based approaches, which adopt either a self-organizing physical system or saving ink, consisting of FDEB [39], divided edge bundling [59], and multilevel agglomerative edge bundling (MINGLE) [60]. The third category uses image-processing techniques, including kernel density estimation graph bundling (KDEEB) [61] and skeleton-based edge bundling (SBEB) [44]. Research has shown that LEB can reveal the skeleton or backbone structure of any graph by minimizing the intervention between dissimilar edge bundles and diminishing the tangle at bundle intersections. LEB can be considered a representative method.

Many edge bundling techniques have showcased their effectiveness in various scenarios. For instance, HEB [37] offers an interface with interactive operations, allowing participants to adjust bundling strength and switch between different tree layouts. Informal evaluations have shown that HEB can effectively help gain quick insights into adjacency relations in hierarchically organized systems. GBEG [38] applies a geometry-based edge-clustering method and features a complex algorithmic pipeline to provide a display solution. To address concerns about potential connectivity inaccuracies caused by spatial proximity in edge bundling, recent research proposes using a confluent drawing method [62]. This method maximizes the accuracy of perceived connectivity, reducing the risk of misleading interpretations. FDEB [39]'s force-directed approach excels in faster generation of bundled graphs and exhibits more pronounced "webbing" and reduced curvature variation compared to GBEB. Other techniques, such as WR [40], have prioritized clutter reduction and computational performance improvements without relying on experimental evaluation methods. Notably, approaches like MINGLE [60], SBEB [44], AFEB [58], and KDEEB [61] differ significantly in their visualized graphs and algorithmic complexity. Nevertheless, these techniques have not undergone formal statistical evaluations of their merits and drawbacks. LEB [41] prioritizes providing an overview rather than obtaining precise answers. Experimental evaluations on three datasets demonstrate LEB's superiority over previous approaches when visualizing data patterns.

The existing assessment methodologies test the usability of information visualization using a set of tasks based on benchmark datasets [63] and low-level tasks in recognizing or discriminating detailed information [64]. The standard low-level tasks are not applicable for assessing edge bundling because edge bundling aims to depict the fundamental structure or pattern of a diagram rather than emphasizing detailed elements. A task taxonomy specifically designed for graph visualization supplements these low-level tasks by encompassing graph-specific and general tasks, offering capabilities such as locating adjacent nodes, performing scanning, and setting operations [65]. This taxonomy also provides a comprehensive list of tasks for analyzing graph data, including topology-based, attribute-based, browsing, overview, and high-level tasks [65]. To address these considerations, we conducted a controlled experiment based on this task taxonomy, focusing on topology-based tasks, overview tasks, and high-level information search tasks.

Previous studies have examined the effectiveness of edge bundling through assessments of participants' response time and accuracy in tasks related to low-level connectivity, path tracing, and high-level inter-cluster connectivity. Findings suggest that while edge bundling can enhance response time in recognizing high-level cluster connectivity, it can have detrimental effects on both response time and accuracy in tracing paths between nodes [43]. Building upon these insights, our research places emphasis on visual search, a crucial aspect of usability. We aim to elucidate the impact of edge bundling on visual search by focusing on the underlying mechanism of visual grouping.

2.3 Hypotheses

Visual objects are comprised of numerous components that interact with each other. The complexity of an object is influenced by factors such as the number of components, their level of detail, and their arrangement [66]. Visual complexity measures an object's information richness, with more complex objects containing a greater amount of information [16].

Different representations of information exhibit varying degrees of complexity. In the case of edge bundling, connections between components are distorted from straight lines to curved paths. This curvature introduces additional information, such as its radius and curvature, thereby displaying more attributes beyond a simple connection between two points. By aggregating the information carried by each line, without accounting for any overlapping lines, a bundle of curves encompasses more information than the same number of straight lines. With the inclusion of curvature via edge bundling, the additional information aims to assist users in identifying relevant information. Accordingly, we propose the following hypothesis:

H1: Edge bundling can enhance users' accuracy in conducting visual information searches.

Edge bundling techniques offer the flexibility to apply varying tension levels. Extremely low tension barely captures the underlying skeleton, whereas increasing tension facilitates the grouping of approximate connections and reveals the skeleton, accompanied by an increase in overlapping edges. On the other hand, employing extremely high tension may result in a dense concentration of overlapping edges within each bundle, leading to less distinguishable connections. By utilizing an appropriate tension, users can effectively group visual stimuli and enhance their performance in terms of both the accuracy and speed of information search. Thus, we propose the following hypothesis:

H2: Edge bundling under moderate tension is capable of revealing a clearer skeleton compared to bundles formed under extremely low or high tensions.

Human beings have inherent limitations in processing information in given time [67]. When attempting to comprehend a simple image, individuals typically perceive a sense of purity and clarity [68], resulting in a subjective experience of ease [64]. Simplicity, in this context, represents the absence of hardship, effort, or confusion [33]. The perceived subjective ease or difficulty during interpretation is referred to as processing fluency, which encompasses perceptual fluency, related to the ease of processing physical features such as the number of visual objects, modality, and shapes, and conceptual fluency, relating to the subjective ease of processing semantic knowledge [16, 33]. Edge bundling techniques aim to reveal the skeleton of visual information, enhancing clarity and simplicity and providing an intuitive interpretation, without reducing the cognitive load involved in reasoning and inference. Therefore, edge bundling serves to reduce visual complexity and increase perceptual fluency in the processing of visual information [16]. On this basis, we can propose the following hypothesis:

H3: Edge bundling can enhance users' perceptual fluency.

The Gestalt law of prägnanz explains how we perceptually organize a visually chaotic world [16]. The human brain has a tendency to recognize cohesive patterns by organizing individual and disparate elements with minimal effort. Previous research has identified various visual cues, including boundary or enclosure, similarity, connectedness, and proximity, as key factors in organizing visual stimuli [17]. Grouping by proximity specifically refers to the human ability to associate separate or unrelated parts that are close to each other. When it comes to judging the proximity of visual elements, our brains make comparative assessments according to the relative distances of a visual item from one another. Items that are closer to each other as being more associated or related, while those that are farther apart are seen as separate or unrelated [18]. Through the manipulation of edge proximity and the facilitation of prominent bundling tendencies, edge bundling enhances the grouping of separate visual stimuli, promotes the recognition of cohesive forms, and reveals underlying structures amidst vast quantities of edges.

Additionally, information theory offers a different perspective on the impact of edge bundling on the speed of information search. Psychologists have incorporated information theory into visual research since the 1950s. In this context, a collection of visual forms is considered an ensemble of messages, with each message possessing varying degrees of distinctiveness based on the amount of independent information conveyed. The greater the amount of information, the faster it can be discriminated from other messages [69]. Thus, we can hypothesize: H4: Edge bundling can enhance the speed of information search.

2.4 Main Study

To examine the impact of edge bundling, we have conducted an empirical experiment to find evidence.

2.4.1 Experiment design

Stimuli

We created four sets of visual stimuli for an experiment using a citation dataset. The stimuli contain four version of information visualizations, utilizing no tension, low ten-

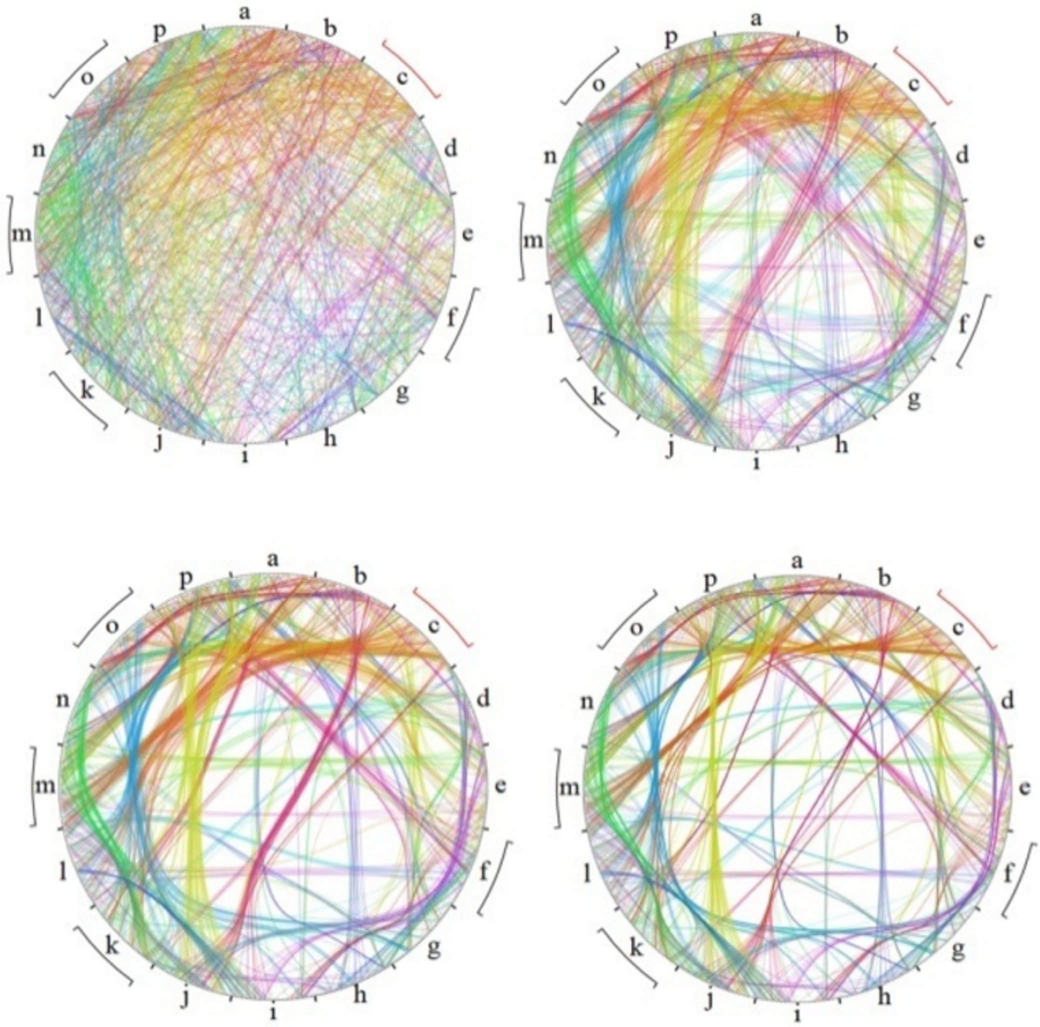


Figure 2.5 : Graphs of the expert version

sion, medium tension, and high tension in the edge bundling technique, as depicted in Figure 2.5. In this citation visualization, the tension of the edge bundling technique ranges between 0 and 1. We assigned tensions of 0, 0.3, 0.7, and 1 to the four sets of experimental stimuli. As the tension increases, the resulting bundles become tighter and thinner.

2.4.2 Questionnaire

Figure 2.5 displays different graphs, each representing the paper citation relationships within the InfoVis domain [70]. The papers are positioned along a ring composed of 16 equal intervals. To minimize the influence of existing semantic knowledge, we assigned meaningless letters instead of using actual years of the publication. Each interval comprises a combination of lines with different numbers and colors. To apply edge bundling technique, we clustered the lines (i.e., edges) based on their primary directions, using a histogram and grid-based methodology described in detail in our technical report [41]. The edges that fall within the same cluster are referred to as ”similar edges.”

Regarding the edge coloring, we employ a method similar to the tree coloring technique proposed by Tennekes and de Jonge [70]. This method assigns unique colors to different bundles while ensuring that nearby bundles are colored with the most distant colors on the color wheel, creating a strong contrast between them. For instance, if bundles are colored #F00 (0,° red) and # 0F0 (120,° green), a nearby bundle would be colored #00F (240,° blue). We exclude the impact of edge coloring by applying the same coloring method to the stimuli set of four tension levels.

2.4.3 Pretest

Prior to our formal tests, we conducted a pretest to establish expert consensus and ensure each question with a clear and definitive answer. Seven graduate students specializing in information visualization were asked to indicate whether 13 descriptions were true or false, based on pre-calculated ground truth, across the four stimulus versions. Out of the 13 questions, ten were correctly answered by the experts, while the remaining three received only 50% correct responses. Consequently, we excluded these three questions from our formal tests.

The decision to exclude the three questions from our experiment was primarily due to the inherent challenges presented by intervals c and o, characterized by significant blurriness, overlap, and clutter. Specifically, upon careful examination of interval o, we observed that the endpoints of edges were dispersed throughout the interval, rather than concentrated at one or two positions. Additionally, some bundles within interval o were colored similarly, posing difficulties in discrimination. Considering the nature of edge bundling, where bundling strength weakens as one approaches the edges of the ring, it became evident that these three questions could not effectively gauge the influences of edge bundling. The ambiguous display of bundle ends significantly diminishes the impact of edge bundling and adversely affects users' performance in high-level tasks. The experts' inability to answer these questions highlights the boundary conditions for the effectiveness of edge bundling. It is important to note that our assessment of the effectiveness of edge bundling is contingent upon the assumption of clearly displayed bundle ends.

We employed a Java-based questionnaire interface that facilitated double-blind trials. Among the four versions of visual stimuli, the control group was presented with an unbundled graph, while the three experiment groups were exposed to bundled effects at low, medium and high levels of tension. Each participant was randomly assigned to one of these versions. The questionnaire consisted of ten questions designed to assess participants' accuracy, efficiency, and perceptual fluency in information search across different tension levels. All questions and corresponding images were provided in Table 2.1.

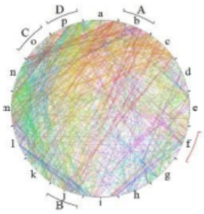
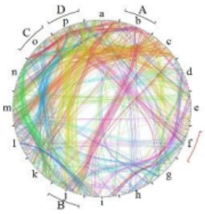
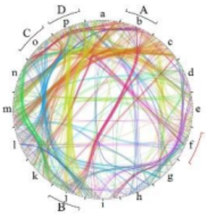
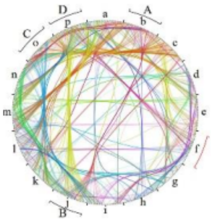
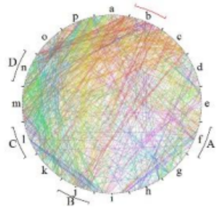
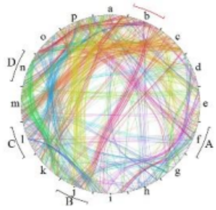
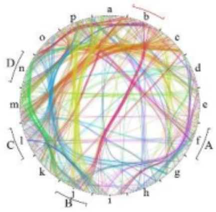
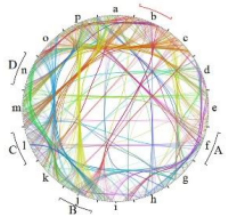
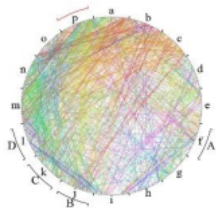
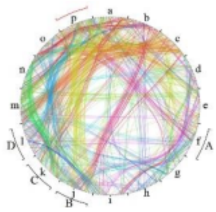
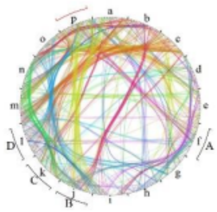
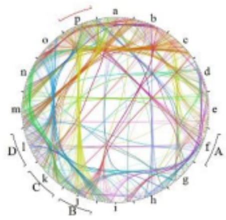
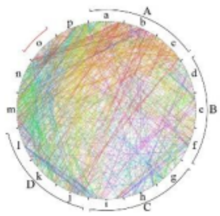
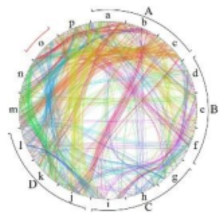
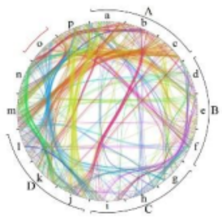
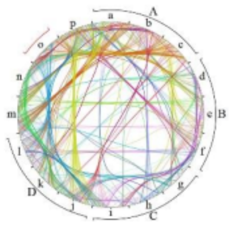
2.4.4 Procedure

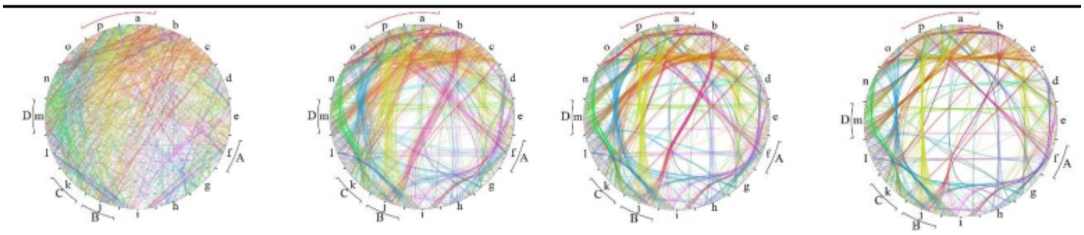
The questionnaire encompassed topology-based, overview, and high-level tasks. Questions 1-7 focused on topology-based tasks, and required participants to identify the most connected intervals. The first three questions examined relationships between two individual intervals, while the subsequent three questions explored relationships between one individual interval and multiple adjacent intervals. The seventh question involved two sets of intervals, each composed of three adjacent intervals.

Questions 8-10 involved overview tasks. Question 8 resembled Question 7 but included a set of four adjacent intervals instead of three. Question 9 asked participants to select the area traversed by the highest number of lines.

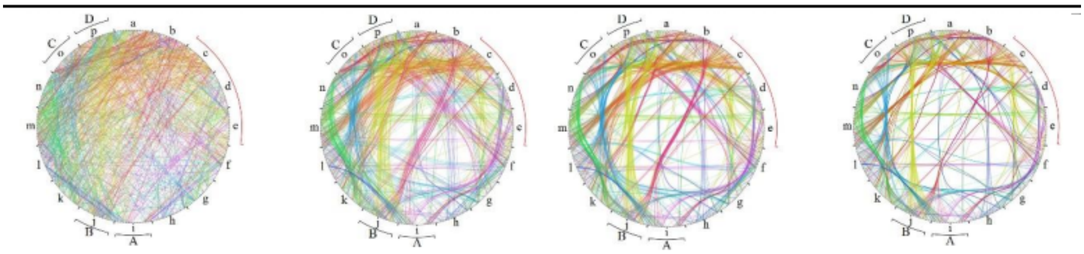
Question 10 was designed to assess participants' ability to make simple inferences

Table 2.1 : The Questionnaire Design

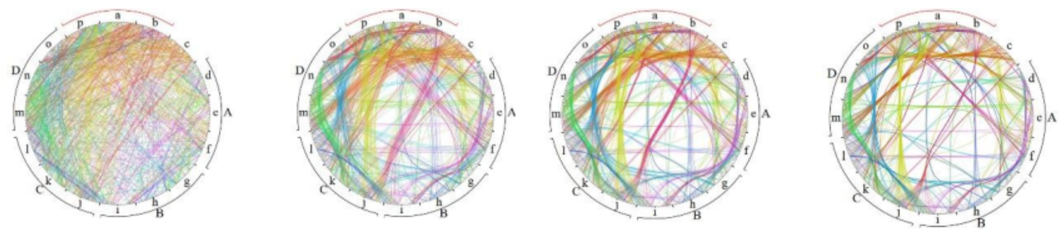
Version 1: Control group	Version 2: Experiment group 1	Version 3: Experiment group 2	Version 4: Experiment group 3
Topology-based tasks			
			
1. Which of the following intervals is the most connected to the interval f? Choices: A. b B. j C. o D. p Correct answer: D			
			
2. Which of the following intervals is the most connected to the interval b? Choices: A. f B. j C. l D. n Correct answer: B			
			
3. Which of the following intervals is the most connected to the interval p? Choices: A. f B. j C. k D. l Correct answer: B			
			
4. Which of the following intervals is the most connected to the interval o? Choices: A. abc B. def C. ghi D. jkl Correct answer: A			



5. Which of the following intervals is the most connected to the interval pa?
Choices: A. f B. j C. k D. m
Correct answer: D

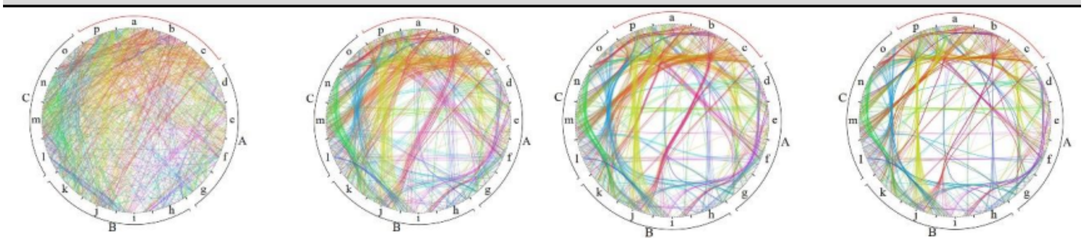


6. Which of the following intervals is the most connected to the interval cde?
Choices: A. i B. j C. o D. p
Correct answer: C

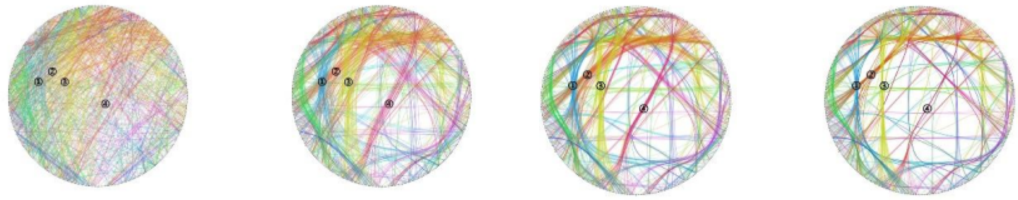


7. Which of the following interval is the most connected to the interval pab?
Choices: A. def B. ghi C. jkl D. mno
Correct answer: D

Overview tasks



8. Which of the following intervals is the most connected to the interval pabc?
Choices: A. defg B. hijk C. lmno
Correct answer: C



9. Please choose the area through which the largest number of lines pass.
Choices: A. 1 B. 2 C. 3 D. 4

Correct answer: B

10. If an interval has two-thirds or more lines connecting to another interval, then:

A. those two intervals are far from each other.

B. those two intervals are closely related.

C. the lines connecting the two intervals are colored the same.

D. the lines connecting the two intervals overlap.

Correct answer: B

High-level tasks
Please tell us what you feel about this information visualization exercise.

regarding the semantic meaning of thick edges, serving as a measure of their comprehension of the stimuli and attentiveness to the questions. Participants who failed to answer this question correctly were excluded from further analysis due to the unreliability of their responses. A total of four, four, two, and six participants were removed from Groups 1-4, respectively. Question 10 is unrelated to edge bundling.

After completing each question, participants were asked to rate their perceptual fluency in accordance with Hypothesis 3, utilizing a 7-point scale ranging from very easy(=1) and very difficult(=7) [71, 72]. Question 11 represented a high-level task, prompting participants to provide feedback on their experiences during the experiment and offer any additional comments.

The experiment system recorded the time participants spent on each question. The timing for each question began when a new page was displayed and concluded when participants clicked the "Next Page" button. The duration spent on each question served as an indicator of information search speed.

We developed a testing system that enables randomization. Each participant was exposed to a specific edge bundling display of citations with a fixed bundling tension. Participants were unable to zoom in for more detailed viewing. The study was conducted in a controlled lab environment, using individual tablets and one of the authors overseeing the process. Participants were recruited through advertisements and in-person invitations, with cash rewards provided for participation.

A total of 200 graduate and undergraduate students (98 females and 102 males) from various academic disciplines, including software engineering, mathematics, material engineering, computer science, and education, participated in the experiment. We adopted a between-subject design, with 50 individual participants in each of the four groups. Random assignment distributed participants in each group to the visual stimuli of a fixed tension among the four levels.

All participants successfully passed the color blindness test, as failing to do so would result in exclusion from the study. Prior to commencing the questionnaire, we provided a brief introduction to the stimuli, explaining that the graphs depicted the citation relationships among a set of papers. Dots on the ring represented papers, and lines connecting the dots indicated citations. Colors were used to distinguish bundles. Participants were then asked to answer the questionnaire without a time limit. Most participants were able to complete the task within 15 minutes. A total of 200 records were collected. Subsequently, we excluded 17 participants' records due to incorrect responses to Question 10.

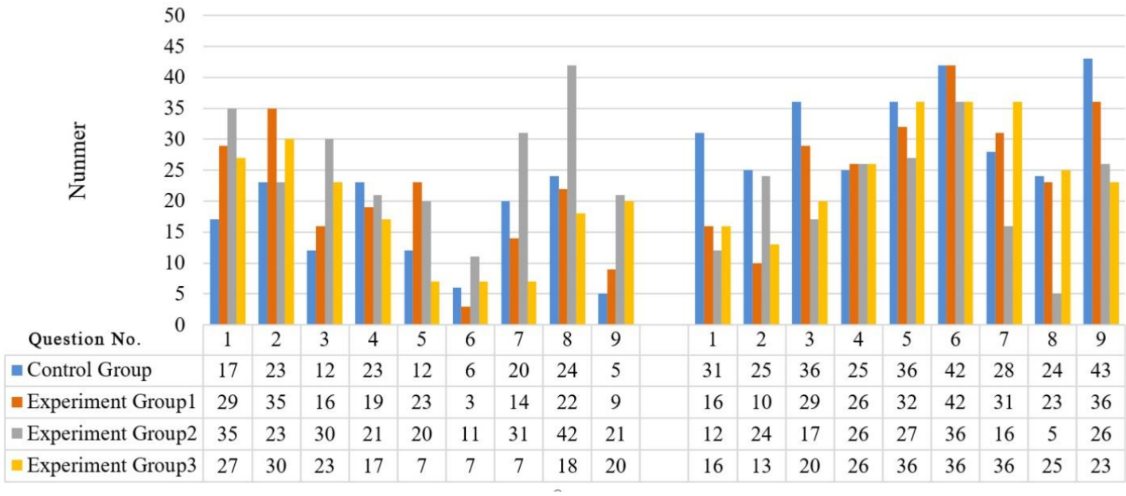


Figure 2.6 : The number of correct (left) and wrong (right) answers to the questions

Table 2.2 : The accuracy of information search

	1	2	3	4	5	6	7	8	9
Sig.	.001	.005	.001	.871	.046	.144	.000	.000	.000

* The degree of freedom is 3, and Sig. indicates the significance value, i.e., *p*-value. The signs are also applicable to Figure 2.7 and 2.9.

2.5 Results and Analysis

2.5.1 Accuracy of information search

The accuracy of information search was assessed by calculating the rate of correct answers for each question. Figure 2.6 presents the numbers of correct and incorrect responses for each question across the four groups. To analyze the differences in accuracy rates, we conducted a chi-squared test, and the results are summarized in Table 2.2.

With the exception of Questions 4 and 6, there were statistically significant differences in accuracy rates among the four groups. Interestingly, both Questions 4 and 6 involved intervals c and o, which were also mentioned in the descriptions explaining the exclusion of questions in the pretest. It is plausible that the overlaps and clutter within these intervals

Table 2.3 : The accuracy difference between the control group and three experiment groups respectively

Question Number	Experiment Group 1 vs. Control	Experiment Group 2 vs. Control	Experiment Group 3 vs. Control
1	.005	.000	.009
2	.003	.921	.035
3	.267	.000	.005
5	.672	.070	.307
7	.291	.018	.008
8	.915	.000	.437
9	.197	.000	.000

* The numbers in Table 2.3 are the *p*-values.

interfered with information processing. Although edge bundling cannot entirely eliminate overlaps, it does help reduce ambiguity.

We further applied the chi-squared test to compare the three experiment groups with the control group (Table 2.3). In Group 1, Questions 1 and 2 demonstrated significant differences in accuracy compared to the control group (both p-values $<.05$). In Group 2, Questions 1, 3, 5, 7, 8, and 9 exhibited a significant difference in accuracy from the control group (p-values for questions 1, 3, 7, 8, 9 $<.05$; p-value for question 5 $<.1$). In Group 3, Questions 1, 2, 3, 7, and 9 showed significantly higher accuracy rates compared to the control group (all p-values $<.05$). Excluding Questions 4 and 6, at least one group consistently achieved significantly higher rates of correct answers. Thus, we can confirm that edge bundling improves the accuracy of information search as hypothesized (Hypothesis 1).

There were no significant differences among all four groups in answering Questions 4

Table 2.4 : The differences of accuracy between experiment groups

Question Number	Experiment Group 1 vs.Experiment Group 2	Experiment Group 2 vs. Experiment Group 3
1	.296	.232
2	.004	.045
3	.007	.391
5	.172	.007
7	.001	.000
8	.000	.000
9	.012	.862

* The numbers in Table 2.4 are the *p*-values.

and 6. Upon further analysis, participants' answers to Questions 4 and 6 displayed different patterns compared to that of the other questions. Both questions involved intervals c and o, as discussed in the pretest section, indicating that the impact of edge bundling was diminished by the indiscernible ends of the bundles.

Subsequently, we compared the three experiment groups to evaluate the advantages of edge bundling specifically under medium tension. The results of the chi-squared test, as presented in Table 2.4, indicate that for the majority of questions, experiment Group 2 outperformed experiment Groups 1 and 3 significantly in terms of accuracy. Additionally, users were able to observe the underlying skeleton as hypothesized in Hypothesis 2. These findings provide support for the advantages of edge bundling in terms of accuracy, particularly at the medium tension level.

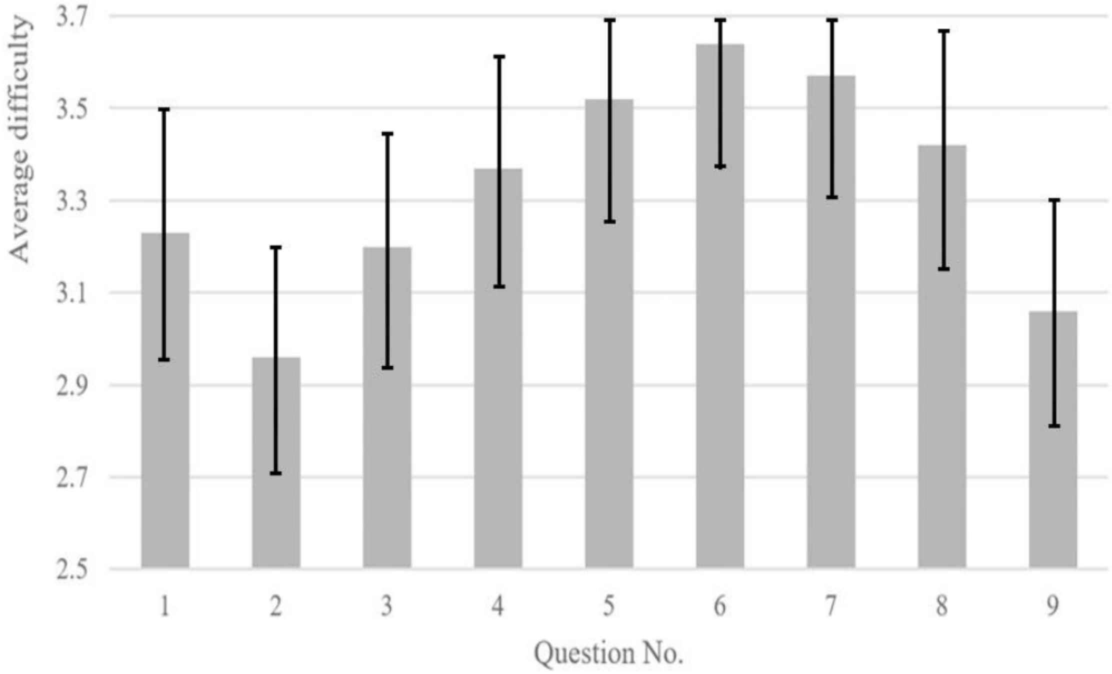


Figure 2.7 : The perceived difficulty on average for each question

2.5.2 Perceptual fluency

The assessment of perceived difficulties in Questions 1-9 served as an indicator of the perceptual fluency in information processing. To analyze these results, we conducted a one-way ANOVA with Tukey's HSD post hoc test, utilizing the four versions (zero/ low/ medium/ high) as independent variables and perceived difficulty as the dependent variable. The mean values and standard deviations of perceived difficulty can be observed in Figure 2.7.

The results of the ANOVA indicate a statistically significant difference among the four versions (as shown in Table 2.5). The average difficulty levels for each question can be observed in Figure 2.7. Note that Questions 6 and 8 did not exhibit a significant difference in perceived difficulty across the four groups, as indicated in Table 2.5).

We compare the perceptual fluency between the experiment groups and the control group, as presented in Table 2.6. The Tukey's HSD post hoc test revealed the following

Table 2.5 : The difference of perceived difficulty of each question between four groups

	1	2	3	4	5	6	7	8	9
F	7.348	2.258	5.841	3.652	7.083	1.244	3.090	1.337	5.319
Sig.	.000	.083	.001	.014	.000	.295	.028	.264	.002

* F in the table indicates the result of the F test.

findings: (1) The perceptual fluency of Questions 1, 3, 5, and 7 in experiment Group 2 differed significantly compared to those in the control group ($p < .05$); (2) The perceptual fluency of all questions in experiment Group 3 differed significantly compared to those in the control group (all p-values $< .05$); (3) The perceptual fluency of Questions 1, 2, 3, 4, 5, and 7 in experiment Group 4 differed significantly compared to those in the control group ($p < .05$). These results confirm Hypothesis 3, supporting the notion that edge bundling can enhance users' perceptual fluency.

Based on the participant reports, in experiment Group 3, 8 out of 9 questions (excluding Question 2) were perceived as more difficult compared to experiment Group 2. While the difference was not statistically significant, these results indicate a potential disadvantage of high tension and an advantage of medium tension. This observation aligns with the hypothesis that edge bundling at medium tension yields the most favorable outcomes.

2.5.3 Speed of information search

Efficient information search is desirable when users interact with information visualization systems. To assess this aspect, we conducted a one-way ANOVA analysis followed by Tukey's HSD post hoc test, with the four versions serving as independent variables and the total time as the dependent variable. The average total time spent on all questions for each group is presented in Figure 2.8. On average, participants required approximately four to six minutes to answer all the questions. The ANOVA revealed a significant dif-

Table 2.6 : The difference of perceived difficulty between the control group and three experiment group respectively

Question No.	Control vs. the 1st Experiment Group	Control vs. the 2nd Experiment Group	Control group vs. the 3rd Experiment Group
1	.002	.000	.002
2	.103	.039	.019
3	.024	.000	.001
4	.439	.004	.022
5	.005	.000	.001
7	.046	.003	.097
9	.499	.000	.615

* Numbers in Table 2.6 are the *p*-values.

ference in the total time spent among the different versions ($F(3, 179) = 4.888$, $p = .003$). Notably, less time was required as the tension level for edge bundling increased until an excessive tension was reached.

Tukey's HSD post hoc test revealed that experiment Groups 2 and 3 spent significantly less time compared to the control group (all p's-values = .001). The average time spent on each question is displayed in Figure 2.9. Experiment Group 1 did not exhibit significant differences in total time compared to the control group.

We utilized independent sample t-tests to examine the specific differences in time durations, as outlined in Table 2.7. The results demonstrate that for most questions, both experiment Groups 2 and 3 exhibited significantly shorter time durations compared to the control group. Notably, edge bundling at medium tension (stimuli for experiment Group 2) yielded the best performance. Only Question 7 in this version did not show a significant

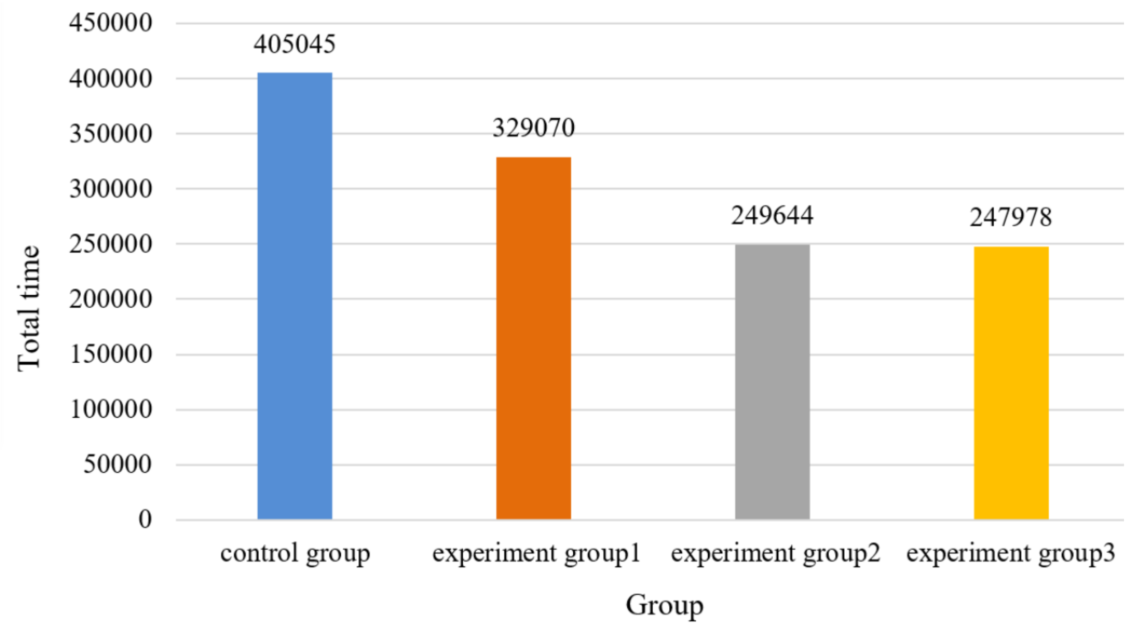


Figure 2.8 : Total time spent on answering all questions on average for each group

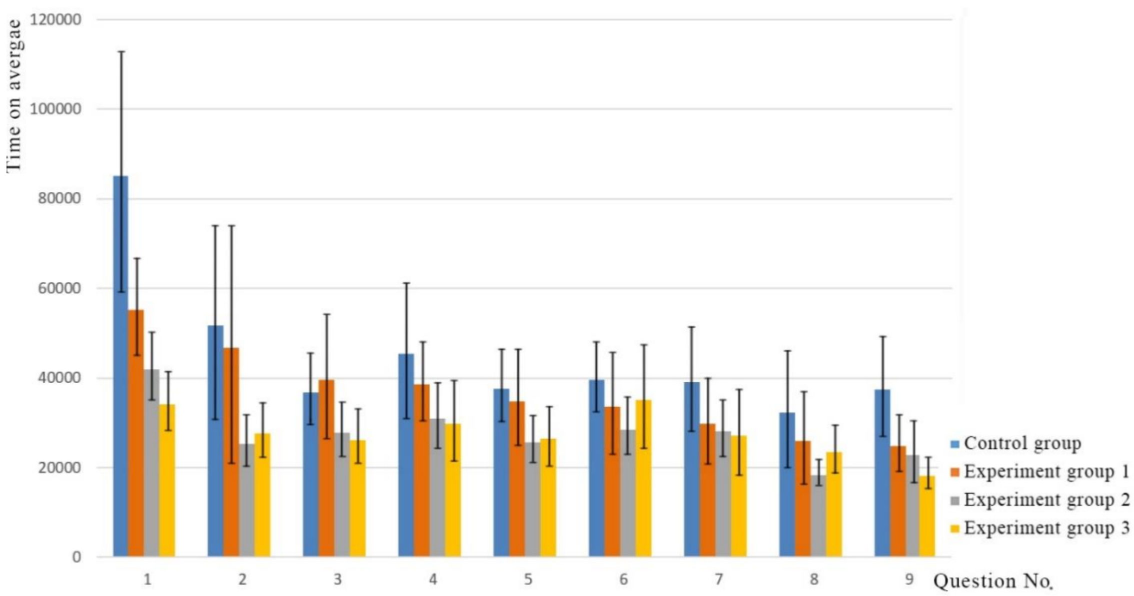


Figure 2.9 : The time spent on each question on average for each question

Table 2.7 : The difference of the time spent on each question between control group and three experiment groups respectively

	Control vs. Expt. Group1		Control vs. Expt.Group 2		Control vs.Expt.Group 3	
	F	Sig.	F	Sig.	F	Sig.
1	3.582	.050	5.884	.003	6.519	.001
2	.006	.777	5.821	.026	4.493	.042
3	1.622	.727	.014	.085	.141	.047
4	.983	.456	2.819	.096	1.900	.090
5	.587	.682	3.818	.017	.674	.042
6	.005	.393	2.246	.034	.426	.522
7	.576	.231	1.495	.108	.752	.130
8	.000	.455	2.849	.046	.572	.238
9	.914	.059	1.071	.032	4.336	.002

difference in time spent. Under high tension, Questions 1-5 and 9 in experiment Group 3 had significantly shorter time durations compared to the control group. Within the low tension (experiment Group 1), only Questions 1 and 9 required significantly less time compared to the control group.

The implementation of edge bundling, specifically the LEB method, allows users to interactively adjust the tension and fine-tune other parameters to attain optimal visual effects. Through tension adjustments, users can optimize the visualization to better suit their needs. Thus, edge bundling offers a distinct advantage in terms of information search speed when compared to an unbundled graph, which supports Hypothesis 4.

2.6 General Discussion and Future Works

Our experiments have provided empirical evidence supporting the effectiveness of edge bundling in revealing high-level skeletons, improving the speed of information search, and enhancing users' perceptual fluency. This research represents comprehensive exploration of the impact of edge bundling using different levels of tension on users' performance. A moderate level of tension was proven to be optimal compared to extreme tensions, offering insights for fine-tuning parameters in graph drawing and edge bundling to optimize usability. Although our analysis was conducted within the context of citation visualization, we expect that the mechanisms observed would apply to other edge bundling techniques.

It is important to acknowledge that our conclusions rely on the assumption that the connection of each edge to the corresponding entity is discernible. Prior studies have made efforts to optimize the clarity of edge ends, recognizing the importance of this aspect [62]. However, the previous literature has not fully addressed the influence of detailed information on high-level tasks. As exemplified by intervals o and c in our study, the heuristics provided by edge bundling can be confusing when users struggle to interpret the meaning of bundle ends. Exploring the effects of diverse connections and the interactive influences between high-level and low-level tasks could be a valuable avenue for future research.

This chapter has examined the effects of edge bundling under different levels of tension. The results indicate that tension does not have a linear relationship with accuracy. Experiment Group 2 demonstrated significantly higher accuracy than the other groups. Visual complexity may mediate users' information processing; however, the relationship between tension and visual complexity remains unclear. Further research in this area can offer more precise predictions regarding the impacts of edge bundling and suggest optimal methods for setting default tension based on usage conditions.

While edge bundling is proposed as a solution for reducing information clutter, our research has not quantified the effect of edge bundling at different levels of edge density. Future studies should explore the interactive effects of edge intensity using visual stimuli of varied layouts, and propose methods for maximizing the usability of edge bundling.

In the experiment, we selected four static frames as experimental stimuli. However, in practical applications, users are allowed to interact with edge bundling functions and adjust tension parameters according to their preferences. The effects of user interactions on information processing performance have not been explored. Future research should investigate users' spontaneous interpretations of the semantics of edge bundling during interaction, as well as design browsing tasks to test the operational performance of the interface.

While this study has demonstrated the impacts of the LEB technique using citation datasets, it remains unclear whether other types of bundling techniques, such as HEB, GBEB, FDEB, and WR, would influence information search in a similar manner. The validity of intuitive conclusions drawn from edge bundling techniques applied to other geographical information visualizations, such as immigration and airline data [44], has not been empirically proven. Further research is needed to compare conclusions derived from precise information processing and intuitive inferences to establish the robustness of the findings on edge bundling.

Prior research has suggested that LEB could enhance traceability [41], which is associated with color, an influential factor in our study. Future exploration should investigate color schemes and their impacts on user experiences. While many visualizations involving edge bundling showcase directed graphs, our studies did not emphasize heuristics related to edge directions. Future research could select appropriate visual stimuli to examine users' perception of edge directions.

Chapter 3

Saliency Competition of Product Profile Images on E-commerce interface

Product profile images are crucial in attracting consumers' attention and potentially increasing click-through rates and purchases during online shopping. This chapter presents research that measures product profile image features using classical graphic methods, performs an eye-tracking experiment, and systematically analyzes how color attributes (i.e., saturation, lightness, and color complexity) of a product profile image, its position on a webpage, and its neighbor's color attributes influence its visual saliency. The empirical findings form the basis for providing strategies to optimize visual saliency, taking into account both local and holistic perspectives. Moreover, the research underscores that sensory information and customer behavior data can influence consumers' perceptions in a bottom-up approach.

3.1 Introduction

Consumers surf on online-shopping websites or apps (such as Amazon, eBay, and Taobao) and immerse themselves in the information deluge of products image. Aggregated results of a customized search by consumers or recommended products are shown in designed banners compete for consumers' limited attention. Whether a product image can attract consumers' attention is the key to initiating the following chain of clicking through, comparison, selection, and purchase decision [73, 74]. Product display can impact advertisement recall, brand recognition, and brand awareness [75]. Even small increments of attention can influence memory, attitude towards the product, and preference [76, 77]. Visual influences are considered a promising marketing tool [78, 79] and

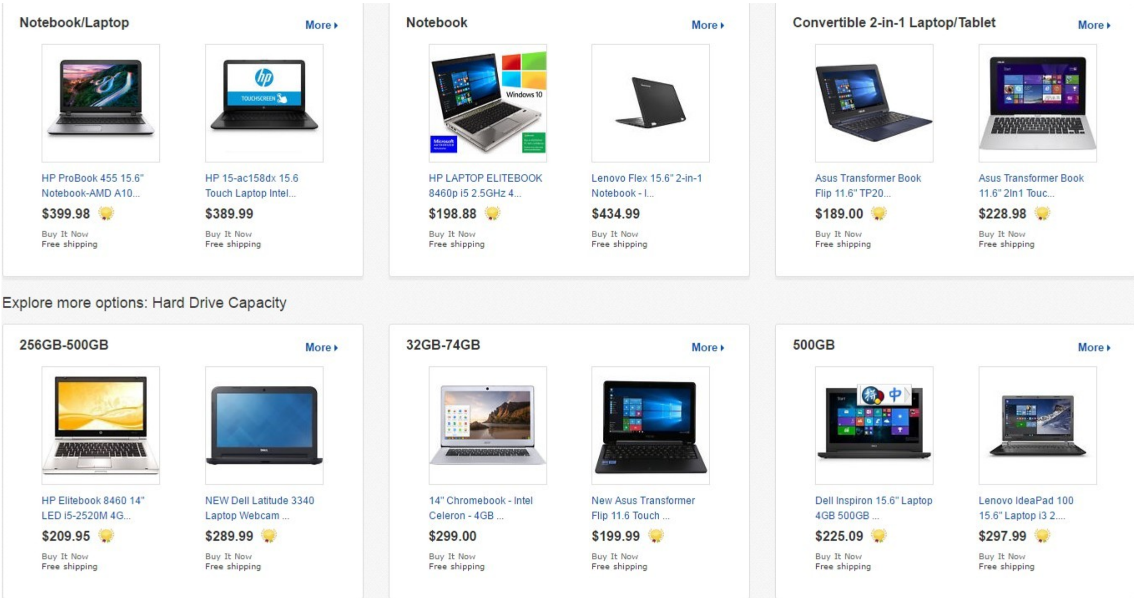


Figure 3.1 : Example of an original web page

motivate the research of the competition of saliency among product displays [26, 80].

Online shopping platform recommends products based on the relevance to the searched keywords and the predicted consumer preference inferred from the saved customer data, such as browsing behavior and purchase records [22]. The recommended products are displayed in each slot on the e-commerce interface from left to right by lines following the text reading approach. A typical interface is shown in Figure 3.1. Within each slot, a product profile image occupies the primary space above the texts and icons about the product model and features, price, shipping, users' rating, quality guarantee, and promotion. Neighbor products surround a given target product, shaping the environment in which the target product gains attention. The order of the product display assumes consumers read images as they read texts. However, the visual processing of images is different from that of text. We attempt to find out how the products displayed on a webpage can match the priority of recommendation and optimize the salience of a given target product.

This research first discriminates the advantage in attention attraction for each location and then studies how color attributes influence attention attraction. Color attributes are the foundation of the bottom-up processing route and are processed in universal types of products. As consumers show increasing concern for privacy and algorithm recommendation manipulation [73], color attributes that influence consumers' choices in a non-intrusive manner can be considered a complement to recommendation algorithms and the new power to improve product sales. Taking the interaction of color attributes and location on a page simultaneously into consideration, we attempt to reveal the way of optimization, i.e., how marketers of a product can strengthen the advantage of a given location or attenuate the disadvantage of a given location by adjusting the color attributes of displayed products.

At last, we analyze the impact of surrounding products on the visual attraction of a target product. Conflicting inferences can be drawn from Gestalt laws. On the one hand, the contrast between a target product and its neighbors may enhance its visual attraction and lead to the advantage of attracting attention [81]. On the other hand, the opposite prediction might also be true. Similar stimuli are inclined to group as a large visual entity that is processed simultaneously. Each product as a part of the group may gain an advantage over those visually independent. The conflict requests reconciliation and empirical evidence. Therefore, we analyze how a target product is influenced by its neighbors and examine how the attention attracted by a target product is influenced by its neighbor products.

Our research makes several contributions. First, we highlight the advantage of product positions on a webpage and emphasize the discrepancy between recommended best-relevance products and perceived prioritization of recommendations. We argue that incorporating a strategy of visual saliency competition, taking into account position and surrounding products, can complement algorithmic recommendations and ultimately boost product sales.

Second, we provide empirical evidence that demonstrates the influence of three color attributes on a product's ability to attract attention. Our findings indicate the involvement of bottom-up visual information processing during consumers' early stages of decision-making.

Third, this research sheds light on the interaction between horizontal and vertical positions and color attributes, offering insights into the sensory leverage of visual saliency in the competition among products on online shopping websites. These sensory leverages differ from the familiar influence factors based on consumer behavior data.

Last, we examine the impact of neighboring products on the target product, particularly highlighting the role of visual grouping based on similarities in visual features. We propose methods to promote visual saliency based on color features and neighbor-product relationships.

In the subsequent sections, we review relevant literature, and propose hypotheses regarding the influence of vertical and horizontal positions, three color attributes, and the similarity of color attributes on a target product's visual saliency. We present evidence from an eye-tracking experiment and conclude with a discussion of our findings and their implications for marketing practitioners.

3.2 Literature Review

3.2.1 Visual saliency

Feature integration theory suggests that the human visual system integrates complex sensory stimuli to create perceptual representations of features [19]. In just a single fixation, humans can extract semantic category, spatial layout, and object identities from a natural scene [20]. However, visual objects compete for visual attention – the limited capacity in visual processing [69]. A visual object that possesses specific attributes and occupies a particular spatial location is more likely to stand out from its surroundings and gain visual conspicuity over other objects [24]. This perceptual quality, characterized

Figure 3.2 : Visualized fixation duration on the webpage

by the ability to immediately grab attention and maintain gaze for a longer duration, is referred to as visual saliency [19, 23, 24]. Visual saliency can be quantified by measuring the total fixation duration allocated to a specific area or object [26] (see Figure 1 for an example of visual saliency visualization of products displayed on an online shopping website).

Existing research explores saliency detection through both bottom-up and top-down models. The bottom-up model focuses on the distinctive subjective perceptual quality that causes certain visual items to stand out from their surroundings, including factors such as color and luminance contrast, compactness, and texture [19]. Researchers have developed and optimized saliency models based primarily on natural scenes, as well as examining the visual saliency of advertisements [19,24–27,80]. In the context of online shopping, the bottom-up model captures the initial stage of visual processing when individuals browse aimlessly. A product that captures attention may trigger clicking-through and subsequent actions that lead to a purchase. In contrast, the top-down model emphasizes task-driven attributes, such as goal-oriented visual search, in the processing of visual stimuli [23, 26]. For instance, when searching for a product with specific visual features, individuals engage in a typical top-down process.

3.2.2 Color attributes and saliency

Visual features play a significant role in determining the saliency of an image and its downstream consequences. For instance, the novelty of a visual object, its aesthetic quality, and areas of high contrast, saturation, intensity, lightness and variations in spatial color patterns have a strong ability to capture attention [29]. Individuals exhibit different sensitivities in processing the features [29]. When considering the three attributes of color in the HSV color space - hue, saturation, and brightness - the influence of hue on consumer behavior is emphasized [79]. For instance, Mehta and Zhu (2009) suggest that the color red can evoke associations with danger and mistakes, making people more vigilant and risk-averse and enhancing their performance on detail-oriented tasks [82]. On the other hand, the color blue suggests openness, peace, and tranquility, activating people's motivation and optimizing their performance on creative tasks. The effects of saturation on arousal have also been explored in previous studies [79, 83, 84]. These experiments manipulated either the hue or saturation of given stimuli while strictly controlling other visual attributes, such as using a pair of texts in blue or red.

In this research, we aim to specifically examine the elementary color visual attributes—color saturation, brightness, and color complexity—found in the highly diverse displayed product images. These attributes collectively capture the overall characteristics of the image, hold significant importance in human vision and are universally applicable in leveraging product promotion [85].

3.2.3 Positions on interface and saliency

The placement of a product can have a significant influence on consumer preference and choice. Previous research has explored two mechanisms, namely attention-driven and position cue inference-based, to explain this influence. The attention-driven mechanism suggests that individuals are more likely to notice products placed in the center of a display [86]. In order to minimize mental effort in processing visual information, people tend to allocate more attention to and choose items in the center position rather than those at the extremities [87]. While attention on a product may not improve information recall or increase choice or purchase, the advantage of attracting attention through center positioning helps address the "unseen therefore unsold" problem.

The inference-based mechanism posits that individuals have formed meta-cognitive associations with positions and attribute specific meanings to them. For instance, products listed in the middle of an array are seen as the most popular [88], and those placed at the end of an aisle are often perceived to be on discount [89]. These findings stem from analyses of horizontally positioned products on store shelves or point of purchase (POP) advertisements. In the context of an e-commerce interface, the center position can be defined as both horizontally and vertically in the middle. Therefore, it is crucial to investigate how the influences differ when considering the vertical and horizontal center positions.

3.2.4 Visual saliency competition

Products displayed on the same page compete for consumers' limited attention. This competition arises from the mechanism of human visual perception. In the early 1990s, researchers explored how a target item captures attention and how this capture is influenced by its relevance to non-target objects (also referred to as singleton detection) [90]. The attentional engagement theory explains how a visual item can be easily distinguished from distractors. The dissimilarity in shape and size between the target and non-target objects collectively determines the extent to which the target item can capture attention [91,92]. Building on the attentional engagement theory, Pieters et al. (2007) focused on marketing practices and proposed the impact of competitive clutter in retailers' advertisement design. They adopted a bottom-up approach to visual information processing and revealed how the size of design elements, such as brand, text, pictorial, price, and promotion information, influences visual saliency. They also explored how the distinctiveness of the target products and the heterogeneity of the distractors affect the trade-off in determining visual saliency [26].

It is worth noting that their research was conducted based on advertisements printed in newspapers, brochures, leaflets, or door-to-door direct mail. In these manually designed product displays, the size of the trademark, logo, promotion, product image, and text information of each product can be deliberately adjusted. In contrast, on an online shopping product page, diversified product images are displayed in slots of the same size according to pre-defined templates. The products shown in each slot have highly dissimilar sizes and layouts. When multiple products are displayed on one interface, all other products form the background against which a target product stands out. The background exhibits high heterogeneity within each slot but little variance within the grid system of the page design. Thus, considering all other products on the interface as the background of the target item may be less effective. Consequently, we narrow our focus, examining the role of adjacent neighbors and how local information about the target product enhances visual grouping and determines the saliency of the target product.

By testing the impacts of adjacent neighbors' color attributes, we can distinguish the orientation effect of the color attributes of neighboring products. Moreover, in practice, optimization based on given neighbor information could be more efficient than optimization based on holistic background information for a given target product.

3.2.5 Saliency enhanced by neighbors

Target and non-target discrimination establish the foundation for the discussion about the visual saliency of a target. Duncan and Humphrey [91, 92] indicated that the dissimilarity between target and non-target benefits the target, and the dissimilarity between non-targets harm the target. The difficulty slope of searching for a target becomes steeper when non-targets become heterogeneous. The displayed products for online shopping generally look heterogeneous, making the dissimilarity between the target and the non-target a vital issue in determining visual saliency. When the visual objects have limited features (e.g., size, color, and verticality exclusively), it is sufficient to consider all non-targets as the target's background. By contrast, complex product images are hardly perceived as an entity holistically against a target product. Consumers would tend to consider the local visual information of the target, i.e., exclusively the neighbor proximate to the target. If the target and its neighbor share sensory similarities, human vision tends to organize visual items into groups. Gestalt psychology indicates the rule of proximity and similarity, suggesting that visual objects close to each other or sharing similar attributes tend to be grouped [93].

The visual grouping of a target and its similar neighbor may generate two types of influences on the target's visual saliency. On the one hand, the similarity makes it more difficult to distinguish the target from its neighbor and attenuates the attention assignment. On the other hand, the grouped images occupy a large surface size and attract more attention. It is possible that both the target and the non-target gain advantage from visual grouping that suppresses the attention on the ungrouped images. Overall, the target's visual saliency can benefit from its neighbors exclusively when the advantage it gains more from visual grouping is more than the disadvantage caused by the difficulties in discrimination. The trade-off caused by two types of conflicting power determines visual saliency and motivates our exploration.

Further, the similarity between a target and its neighbor can be measured in different dimensions, such as saturation, lightness, and color complexity. Prior research manipulated the similarity of a selected attribute based on the assumption that the features have an equal capability of attention attraction. Our research highlights that features are different in capturing attention, and their dissimilarity to their neighbors may either attenuate or strengthen the effect of the target's feature in attention attraction.

In the following section, we propose hypotheses on the following understandings, including (1) how color attributes (i.e., saturation, lightness, and color complexity) influence the visual saliency of the product profile images on an online shopping page, (2) how location influences visual saliency, (3) the interactive effect of location and color attribute on visual saliency, and (4) how the color attributes of the neighbors at eight positions around the target influences the visual saliency gained by three color attributes.

3.3 Hypotheses

3.3.1 The influences of color attributes on visual saliency

Saturation refers to the intensity or amount of pigment in color [83]. Existing literature indicates that advertisement with high saturation induces a high level of arousal and raises the feeling of excitement [83]. High saturation can raise the level of arousal [84, 94], and arousal would lead to a high likelihood of visual processing. Therefore, a product image of high saturation would arouse consumers to pay more attention to the product. We propose that

H1a: High saturation of product images increases fixation duration.

Brightness refers to perceived luminance [95]. Physically, a high intensity of light reflected from a visual object in the direction of one's eyes causes perceived brightness (i.e., luminance). The gray or black component of colors on an image is captured by the eyes and perceived as brightness changes from dim to bright or white to black. Theoretically, perceived brightness is a complex perception issue. The perceived luminance, brightness contrast, and object reflectance as three dimensions collectively determine the brightness perception in a natural scene. The perceived brightness of the product image can be simplified, assuming that designers and marketing professionals have optimized the image to match the real product to reduce the losses from product return due to the failure to meet the expectation. The image brightness reflects the product reflectance and the luminance condition when the image was taken. The product images that contain more black components illustrate a high contrast against the white background of the webpage and therefore are more likely to attract attention.

Prior research on the dark and light colors based on the Munsell color system (Hagtvedt and Brasel, 2016) reported consumers' attention to light (vs. dark) color under the condition of high (vs. low) frequency sound but did not report the main effect of brightness. In line with Hagtvedt et al.'s research, the impact of brightness is explored regarding its semantic association with weight [96], size [79], and affective reaction [83]. Our research considers the impact of pixelated image attributes on the sensation but not semantic meaning.

H1b: Low lightness of product images increases the fixation duration.

Color complexity refers to the color intricacy of an image. An image of high color complexity contains more detailed information about the shapes, textures, and shades of visual scenes and objects. Consistent with prior research that addresses feature complexity hurts attention assigned to advertisement [97], we argue that when a product image competes for attention against other products, more details and high intricacy hinders the key feature that attracts attention. Consumers are more likely to process visually simple and well-ordered images.

H1c: Low color complexity of product images increases fixation duration.

3.3.2 The influences of horizontal and vertical position on visual saliency

High-priority information on the webpage conforms to the conventions of the layout. For example, the plotting priority area on a webpage of news is identified as the top left corner where people usually start to read [98], on an abstract painting for a novice viewer was revealed at the center [99], and the left navigation options when performing a product seeking task on online shopping website [98]. In a free browsing setting where product images are listed in rows and columns, consumers without a clear target for information searching would start from the center, which brings the advantage to the location at the center. Therefore, we propose that

H2: the image at the center gains an advantage in attracting consumers' attention.

Specifically, considering horizontal and vertical respectively, we propose that

H2a: Horizontally, the image in the middle attracts more attention than the left or right columns.

H2b: Vertically, the image in the middle attracts more attention than in the bottom or top rows.

3.3.3 The interactive effect of location and color attribute on visual saliency

We analyze the layout of the product-display webpage. First, to fit the monitor size, such as 4:3 or 16:9, designers list multiple products in a line and limited lines on a page. In other words, the number of columns is more than that of the lines. Second, the product image is arranged above the texts about price, utilitarian information, and promotions. The text area separates the lines of images, shaping a stronger grouping effect between images in rows than in columns. Reading from left to right has strengthened the inclination of horizontal comparison. A product image at the left or right column can attract a consumer's attention by using high saturation and low complexity image and reduce the disadvantage caused by location. However, the adoption of low brightness when the image is located at the left or right columns can lift the visual attraction limitedly. Consumers may expect the item horizontally at the center to be important and should be highlighted by high contrast, while the less important ones at the side match more with the low lightness and the role as a minor role with low contrast. Based on the perceptual ties between the center and high contrast, the impact of low lightness would be strengthened by the location of the center.

Therefore, we propose that

H3a: Horizontally, positions at the center (vs. at the left and right column) attenuate the advantage caused by high saturation.

H3b: Horizontally, positions at the center (vs. at the left and right column) attenuate the advantage caused by low color complexity.

H3c: Horizontally, positions at the center (vs. at the left and right column) aggravate the disadvantage caused by high brightness.

As the texts and blank areas separate the rows of product images, the likelihood that an image at the top or bottom rows uses color attributes to gain an advantage reduces. The image at the center can strengthen its advantage more than the images at the top or bottom row by adopting high saturation and low complexity. The separation also causes comparison difficulties between rows which attenuates the advantage of brightness for images at the center. We propose that

H3d: Vertically, positions in the middle (vs. at the top or bottom rows) enhance the advantage caused by high saturation.

H3e: Vertically, positions in the middle (vs. at the top or bottom rows) enhance the advantage caused by low color complexity.

H3f: Vertically, positions in the middle (vs. at the top or bottom rows) diminish the advantage of low lightness.

3.3.4 The effect of visual grouping influenced by the similarity in each color attribute

The grouping principles of gestalt state that elements near each other are grouped with high strength. The relationship between proximity and the strength of grouping was described as a power model [100,101]. The principle of similarity state that visual objects sharing similar attributes are more likely to be grouped than those different in attributes [85]. It remains unknown whether a target product benefits or hurts by the similarity to its neighbors and whether the similarity in different dimensions plays the same role for the target product. Therefore, in our research context, we address the similarity in three-dimensional color attributes between adjacent product images in different directions and attempt to provide empirical evidence on how the grouping principles of gestalt states work on featured similarities and directions.

The neighbors' position relative to that of the target product image can be differentiated following the compass in cardinal direction (i.e., north, east, south, and west in a clockwise direction, with W, E, N, and S for short) and intercardinal directions including northeast (NE), southeast (SE), southwest (SW), and northwest (NW). Images are located closer horizontally than vertically, which causes a higher likelihood at which a target image is grouped with its left and right neighbors and influenced by their similarity. People read with eye-movement orientation from top to bottom and from left to right [102], leading to a higher likelihood that consumers compare the target product with its underneath neighbor. Therefore, the impact of neighbor's similarity is likely to be observed from the left, right, and underneath neighbors (i.e., in W, E, and S directions). The orientation of visual search is dominated by orthogonal filters oriented horizontally and vertically [83]. Trained by the direction of the reading and writing system (mostly from left to right), human eyes are inclined to track a visual object from left to right, but not the opposite [103, 104]. The asymmetry in visual orientation may also increase the likelihood at which a target product is influenced by its neighbors on the diagonal from top-left to right-down. Above all, we propose that

H4a: A target product is influenced by its neighbors in eight directions to different extents. Particularly, the neighbors in W, E, S, NW, and SE directions may generate a significant impact.

A neighbor's influence on the target can be considered in two folders. First, we should consider whether the neighbor's saliency can spill over on or compete against the target. The attribute enhances the visual saliency of the target one (e.g., saturation) and may benefit its neighbor due to the proximity. People look at a salient product image, and neighbors of the image gain a better chance of being noticed. In contrast, it is also possible that the salient neighbor gains an advantage in attention attraction and shapes contrast against the target. Consumers would process the neighbor product image at a higher concentration level and tend to ignore the target [81, 105]. Therefore, the neighbor's influence on the target depends on the two influences' strengths.

H4b: The neighbor attributes may enhance or attenuate the target's saliency.

Then we consider the group effect of neighbors. When adjacent product images share high similarity in color attributes, they may be visually grouped and perceived as an area of the shared attributes. Notably, the similarity in attention-grabbing attributes may gain an advantage over the surroundings and attract attention more than the sum of the products when they are processed independently. By contrast, the dissimilarity hinders the effect of the visual grouping and attenuates the overall attention assigned to both products. Generally, we propose that a target product's attribute may benefit from its dissimilarity to the target one. The high contrast of saturation breaks the sense of unity, generates a variance for processing, and attracts attention. Therefore, we propose that

H4c: The neighbor attributes may enhance or attenuate the impact of target image attributes on its saliency.

3.4 Experiment Procedure

We selected twenty-three web pages of two types of products (i.e., laptop and necklace) on Amazon and Taobao. A laptop is a typically utilitarian product with a high need for information search when consumers make a purchase decision, while the necklace is a hedonic product with rich sensory information directly supporting a purchase decision. We collected the product default recommendation page and the display page based on keywords search results. Each webpage contains 9 to 16 products of the same category and all sample web pages contain 208 products. The two well-known online shopping websites are selected since they cover the majority of global consumers.

We recruited 91 college students from a northern university in China. The participants consist of undergraduate and graduate students, aged between 21 and 27. The majority of students have pursued engineering majors, such as software, chemical engineering, and biological engineering, among others. Additionally, 12% of participants have focused on literature, linguistics, and pedagogy. Among the participants, there are 50 males and 49 females. It is worth noting that all participants have successfully passed the color-blindness test.

Each participant was invited to a lab to view the web pages in random order. Each webpage was displayed for 5 seconds. Participants were told to view the products in the same way as they surf and shop online. They are not required to seek particular information or make a purchase decision instantly.

We collected eye-tracking data using a high frequency (60 Hz) eye tracker (Tobii T60) on a monitor with two infrared image sensors. When participants observed the webpages on the monitor, the eye tracker non-intrusively recorded their eye movements, including gaze durations and times on each item, visit durations and times, saccades, and inflations of pupils on the webpage. All the participants were required to complete a calibration procedure to ensure that the device recorded their eye movements accurately. The lab's light condition was strictly controlled to reduce the influences of sunlight or artificial light on the monitor display.

We separated each webpage into images of individual products. Then we compute the total fixation duration and number of visits to each product by each participant. We use each participant's fixation duration on each product image to measure visual saliency [97].

3.5 Measurement of variables

Based on existing methods and literature [28], we measure the sensory attributes of each product image. The attributes include average saturation, the amount of sensory input, the difference in saturation, visual intricacy, average hue, color complexity, and edge density. Among the sensory attributes, in the following regression model, we consider the first three attributes as independent variables and the rest as control variables.

3.5.1 Saturation

First, we convert every image from the RGB color scheme to an HSV color scheme that defines a color hue, saturation, and lightness. Saturation represents the intensity of the image [106]. We use the average saturation of the entire image, ranging from .047 to .478, with a mean .186 and a standard deviation .079.

3.5.2 Lightness

Lightness refers to the average of the lightness values in the HSV color space of all pixels in an image. Existing literature indicates that lightness influences the perceptual fluency of visual information processing and weight perception, and facilitates visual search [107].

3.5.3 Color Complexity

We measure the intricacy of color based on color complexity measurement (CCM) [28]. CCM calculates the color variation of each pixel within the local mask of the CCM value of the pixel and then uses the average CCM value to represent the color complexity of the entire image. A high CCM value means that the image has high color variation, while a small one means that its color composition is homogeneous.

3.5.4 Horizontal location

Let *D* indicate a displayed image, sssume that an e-commerce interface contains $i \times j$ product matrix ($i \leqslant m$, and$j \leqslant n$), where *i* indicates the number of the columns and *j* the number of the rows, with $i \leqslant 8$ and $2 \leqslant j \leqslant 3$ in our empirical data. We code the image in the first column (i.e., when *i*=1) as the left, the image in the last column (i.e., when *i*=m) as the right, and the rest in the middle between the left and right as the center. The center columns are coded as 0, the baseline, and the left and right columns are coded as 1 and 2, respectively.

We also tried to differentiate the image at the center from those at the side by coding a variable *CenterDummy*. *CenterDummy* equals 1 if the image is at the center and equals 0 when the images are shown in the first or last column.

3.5.5 Vertical location

Vertically, products are displayed at the top if *j*=1, at the bottom if *j*=*n*, and in the middle otherwise. We code the image at the top, middle, and bottom as 1,2, and 3, respectively. When *j*=2, the images contain images at the top and bottom exclusively.

3.5.6 Neighbor's color attribute

The saturation, lightness and complexity of neighbors in each direction are computed, respectively. Taking saturation as the example, for a target product D_{ij}, we calculate its neighbor's attributes as follows. Similar rules apply to lightness and complexity.

$W_{saturation\_ij} = Saturation_{D_{(i+1)j}}$

$E_{saturation\_ij} = Saturation_{D_{i-1,j}}$

$N_{saturation\_ij} = Saturation_{D_{ij-1}}$

$S_{saturation\_ij} = Saturation_{D_{ij+1}}$

$NW_{saturation\_ij} = Saturation_{D_{(i-1)}j-1}$

$NE_{saturation\_ij} = Saturation_{D_{(i-1)j+1}}$

$SE_{saturation\_ij} = Saturation_{D_{(i+1)j+1}}$

$SW_{saturation\_ij} = Saturation_{D_{(i+1)j-1}}$

3.5.7 Difference between neighbors' color attributes

We compute the difference in color attributes between two adjacent images using the value of the neighbor minus that of the target. A large value indicates the neighbor has a higher level of the attributes than the target product image. The neighbors may locate in one of eight directions relative to the target image. We use cardinal and intercardinal directions to indicate the relative position. Specifically, for an image D_{ij}, taken saturation of the neighbor at its right as an example as the following.

$W\_Dif\_SaturationD_{ij} = W_{Saturation_{i,j}} - SaturationD_{ij}$

Similarly, the rules are applicable to complexity and lightness for neighbor images in other directions. For example,

$NW\_Dif\_ComplexityD_{ij} = W_{Complexity_{i-1,j-1}} - ComplexityD_{ij}$

3.5.8 Measurement of control variables

The Amount of Sensory Input reflects the complexity of sensory features [97]. As Berlnyn's theory on the optimal arousal level indicates, complex stimulus attracts more attention in experiment aesthetics [78, 108, 109]. Namely, an image of a large amount of sensory input may evoke more visual processing than an image of little sensory input [97]. As a result, viewers' fixation duration on a product image of a large amount of sensory input would increase.

We measure the amount of sensory input of each product image using its JPEG file size [97]. The JPEG algorithm follows a standard method for image compression [110]. For an image of 280×467 pixels, the coding of the image with 16.7 million possible colors (24 bits) in raw form requires 392 KB. The JPEG compression technique reduces information redundancy and saves the image as a file of 17.5 KB. We then use 17.5 KB as the measurement of the total sensory input. Having captured the webpages on the same resolution and saved them as JPEG files, we separate individual product images as new lossless JEPG files. The product images on the same web page fit into their slots of the same size, which guarantees the comparability of the amounts of sensory input between products. The average amount of sensory input ranges from 5.27 to 41.04, with 20.80 as its mean and 6.01 as the standard deviation.

Visual Intricacy refers to the number of details in an image. For images of the same pixels in width and length, a large file size reveals the image's good quality in representation and high ability to depict details. We measure the compression rate of each image using the JEPG file size divided by the overall number of pixels of the image [97]. A low compression rate means the image contains less intricate details and is perceived with few variations.

Price refers to the product price shown on the page. Price directs the visual search [111]. A high price product involves consumers more to process its information than a low-price product [112]. When the product price is shown as a range, we use the median as its price. For example, if a price ranges from 50 to 200, we adopt 125 to indicate its price. A log-transformed price is used in the regression model as the control variable.

The discount Rate is measured by the discounted price divided by the original price. Discount information is the key factor in consumers' attention and elaboration [113–115].

Edge Density depicts a visual object's boundary. We adopt the Sobel Edge detection technique to detect the edge in the image [116] and to find the boundaries of objects in an image. Then we compute the ratio of the number of pixels in the extracted edges divided by the overall pixels of the image.

3.6 Data Description and Model Free Evidence

We compute the variables' mean and standard deviation and perform a bivariate correlation analysis (see Table 3.1).

3.6.1 Advantage of Locations

The basic ANOVA analysis provide basic evidence to the impact of locations. We compare the average fixation durations on the product images at different locations. Horizontally, a one way ANOVA analysis shows that the three groups are significantly different (F(2, 10830)=9.283, p=.000). M_{left}=7.75, SD_{left}=11.49; M_{mid}=8.00, SD_{mid}=10.94; M_{right}=6.86, SD_{right}=10.38. The images on the right attract significantly less attention than other images (with p¡.01). The images on the right and in the middle do not show any statistical difference.

Vertically, a one-way ANOVA analysis shows that the three groups are significantly different (F(2, 10830)=20.80, p=.000). M_{up}=7.78, SD_{up}=10.80; M_{mid}=9.78, SD_{mid}=13.08; M_{bottom}=7.19, SD_{bottom}=10.70. The posthoc test reveals that the three groups are significantly different (all with $p<.01$).

The results confirm the priority of the center position in both horizontal and vertical directions (see Figure 3.3). Meanwhile, the left position has an advantage over the right, and the top position has an advantage over the bottom. Our conclusion is consistent with the existing arguments on the blind corner, i.e., the lower right-hand corner of a 2D layout, that attracts the least attention and fails to facilitate memory of the information displayed [117]. Due to the interdependency of each observation, further evidence about the effect of locations is provided by the following specified models.

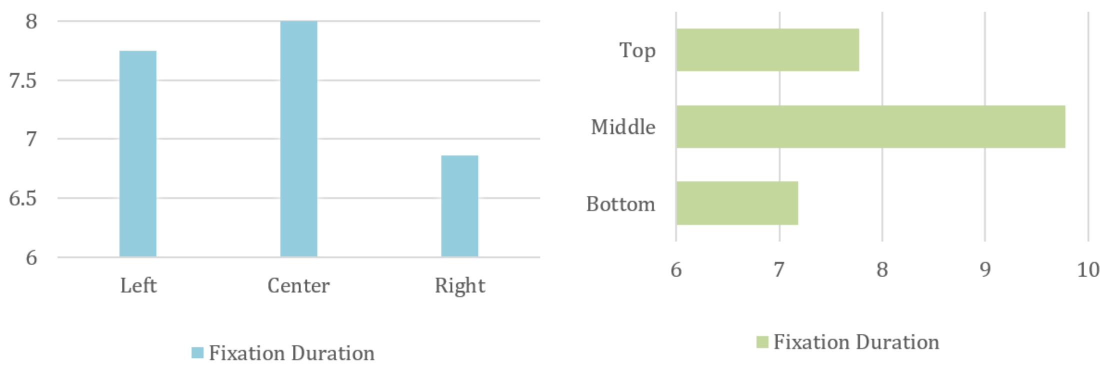


Figure 3.3 : The average fixation duration on products at vertical and horizontal locations

Table 3.1 : Descriptive statistics and bivariate correlations

	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10
1. Fixation	7719	11006	66	190283										
2.Size	20.97	5.9	8.958	41.08	0.04***									
3.CompressRate	0.24	0.06	0.127	0.49	0.01	0.61***								
4.SobelEdge	0.08	0.02	0.046	0.12	0.02	0.42***	0.73***							
5.Price	1085	2883	1.700	31500	0.03**	0.13***	0.18***	0.31***						
6.Discount	0.92	0.18	0.228	1.29	-0.01	-0.10***	0.08***	0.19***	0.13***					
7.Saturation	0.19	0.08	0.057	0.48	0.04***	0.13***	0.50***	0.46***	0.18***	0.12***				
8.Lightness	0.11	0.09	0.008	0.41	0.03**	0.36***	0.67***	0.63***	0.28***	0.17***	0.71***			
9.CCM	0.73	0.15	0.417	0.95	-0.03**	-0.28***	-0.61***	-0.62***	-0.25***	-0.23***	-0.63***	-0.82***		
10.Center	0.51	0.50	0	1	0.03***	-0.02*	0.01	0.00	0.08***	-0.02	-0.01	0.01	0.03**	
11.Middle	0.08	0.27	0	1	0.06***	0.01	0.07***	-0.08***	-0.08***	-0.17***	-0.01	-0.00	-0.01	-0.07***

Note: Values in the table show means, standard deviation, the minimum and the maximum values of each variable, and the Pearson Correlation between variables. The number of observations is 10624.
**. Correlation is significant at the 0.01 level, and *. significant at the 0.05 level (2-tailed).

3.6.2 Identification Models

We examine the main effect of color attributes and locations on the web page and specify multiple level mixed-effects generalized linear models.

$$ln(FixationDuration)_{iws} = a_0 + a_1 ColorAttributes_{ws} + a_2 Location_{ws} + a_3 Product_{ws} + a_4 Participant_i + a_5 Webpage_w + \varepsilon_{iws} \qquad (a)$$

where $lnFixationDuration_{itc}$ is the logarithmic fixation duration of participant *i* spent on the *w* web-page's product. $ColorAttributes_{ws}$ is a matrix consisting of saturation, lightness, and complexity. $Location_{ws}$ is a matrix consistent vertical location and horizontal location. $Product_{ws}$ as a matrix denotes the variables that represent the product appearance (i.e., The amount of sensory input, visual intricacy, edge density) and promotion-related information (e.g., price and discount rate). $Participant_i$ is individual fixed effect, and it captures individual heterogeneity. $Webpage_w$ is the fixed effect of each webpage, and it captures the effect of layout and displayed products. ε is a stochastic disturbance term. Such model specification helps us avoid endogeneity and yield the causal effect of exogenous visual attributes on an individual's information processing.

We examine the interactive effect of color attribute and location by adding the interactive term of color attributes and location into the model (a) by creating

$$ln(FixationDuration)_{iws} = a_0 + a_1 ColorAttributes_{ws} + a_2 Location_{ws} + a_3 Product_{ws} + a_4 Participant_i + a_5 Webpage_w + a_6 ColorAttributes_{ws} \times Location_{ws} + \varepsilon_{iws} \qquad (b)$$

To explore the effect of neighbor's color attribute in different directions, we add the Neighbor's color attributes by creating

$$ln(FixationDuration)_{iws} = a_0 + a_1 ColorAttributes_{ws} + a_2 Location_{ws} + a_3 Product_{ws} + a_4 Participant_i + a_5 Webpage_w + a_6 NeighborAttributes_{iws} + \varepsilon_{iws} \qquad (c)$$

We also analyze the interactive effect of the target's color attributes and its difference from its neighbor's.

$$ln(FixationDuration)_{iws} = a_0 + a_1 ColorAttributes_{ws} + a_2 Location_{ws} + a_3 Product_{ws} + a_4 Participant_i + a_5 Webpage_w + a_6 Neighbor\_Difference_{iws} + a_7 Neighbor\_Difference_{iws} \times ColorAttributesColorAttributes_{ws} + \varepsilon_{iws} \qquad (d)$$

3.7 Results

3.7.1 The effect of color attributes and location

Table 3.2 shows the results based on Model (a) and Model (b). Particularly in Table 3.2, Model 1 includes product and webpage attribute-related control variables exclusively. Model 2 include three color attributes and location attributes, testing the impact of Horizontal location using two types of coding method. Model 3-10 test each interactive effect of color attributes and horizontal or vertical locations.

Table 3.2 : Regression models of the influence of color attributes and position on product display saliency

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Size	0.0184***	0.0234***	0.0233***	0.0236***	0.0236***	0.0236***	0.0233***	0.0233***	0.0233***	0.0233***
	(0.00302)	(0.00309)	(0.00309)	(0.00309)	(0.00309)	(0.00310)	(0.00309)	(0.00309)	(0.00309)	(0.00309)
CompressRate	-1.653***	-2.505***	-2.513***	-2.571***	-2.557***	-2.565***	-2.427***	-2.534***	-2.506***	-2.357***
	(0.332)	(0.358)	(0.358)	(0.360)	(0.359)	(0.361)	(0.358)	(0.358)	(0.358)	(0.361)
SobelEdge	4.712***	5.471***	5.595***	5.480***	5.448***	5.467***	4.917***	5.256***	5.254***	4.908***
	(1.181)	(1.227)	(1.230)	(1.227)	(1.227)	(1.233)	(1.233)	(1.231)	(1.234)	(1.236)
Log_Price	0.0118*	0.00727	0.00705	0.00767	0.00794	0.00786	0.0105	0.00885	0.00850	0.0100
	(0.00618)	(0.00632)	(0.00632)	(0.00633)	(0.00633)	(0.00635)	(0.00636)	(0.00637)	(0.00637)	(0.00638)
DiscouRate	-0.0636	0.00738	0.00549	0.0108	0.0159	0.0144	0.0391	0.0204	0.0136	0.0353
	(0.0632)	(0.0645)	(0.0646)	(0.0646)	(0.0647)	(0.0649)	(0.0649)	(0.0649)	(0.0647)	(0.0650)
Saturation		0.929***	1.146***	0.971***	0.943***	0.969***	3.885***	0.912***	0.924***	4.991***
		(0.209)	(0.257)	(0.211)	(0.209)	(0.288)	(0.737)	(0.210)	(0.209)	(1.040)
Lightness		-0.849***	-0.805***	-0.574*	-0.817***	-0.728**	-0.879***	0.540	-0.854***	-2.897*
		(0.269)	(0.271)	(0.307)	(0.270)	(0.367)	(0.269)	(0.764)	(0.269)	(1.508)
CCM		-0.383***	-0.370***	-0.383***	-0.528***	-0.484**	-0.409***	-0.396***	-1.172**	-0.826
		(0.138)	(0.138)	(0.138)	(0.156)	(0.189)	(0.138)	(0.138)	(0.512)	(0.845)
Center (vs. Left&Right)		0.0974***	0.176***	0.150***	-0.113	-0.0260	0.0855***	0.0970***	0.0972***	0.0816***
		(0.0220)	(0.0582)	(0.0358)	(0.108)	(0.237)	(0.0221)	(0.0220)	(0.0220)	(0.0223)
Middle (vs.Top&Bottom)		0.325***	0.331***	0.327***	0.327***	0.328***	-0.254*	0.173*	0.903**	0.0663
		(0.0430)	(0.0432)	(0.0430)	(0.0430)	(0.0433)	(0.145)	(0.0893)	(0.364)	(0.728)
Center×Saturation			-0.421			-0.0316				
			(0.289)			(0.421)				
Center×Lightness				-0.484*		-0.168				
				(0.262)		(0.503)				
Center×CCM					0.287**	0.202				
					(0.145)	(0.251)				
Middle×Saturation							3.116***			4.258***
							(0.745)			(1.063)
Middle×Lightness								1.429*		-2.060
								(0.735)		(1.516)
Middle×CCM									-0.799	-0.432
									(0.499)	(0.853)
Constant	7.696***	7.816***	7.758***	7.785***	7.914***	7.870***	7.855***	8.838***	7.816***	7.838***
	(0.115)	(0.192)	(0.195)	(0.192)	(0.198)	(0.226)	(0.231)	(0.203)	(0.409)	(0.736)
Participants fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Web-page fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,624	10,624	10,624	10,624	10,624	10,624	10,624	10,624	10,624	10,624
Number of groups	88	88	88	88	88	88	88	88	88	88

Note: The dependent variable is each participant's log-transformed total fixation duration on each product image. Values in the table are unstandardized regression coefficients. Standard errors are in parentheses. *<.1; **<.05; and ***<.01. The rules are applicable to following tables of regression models in this chapter.

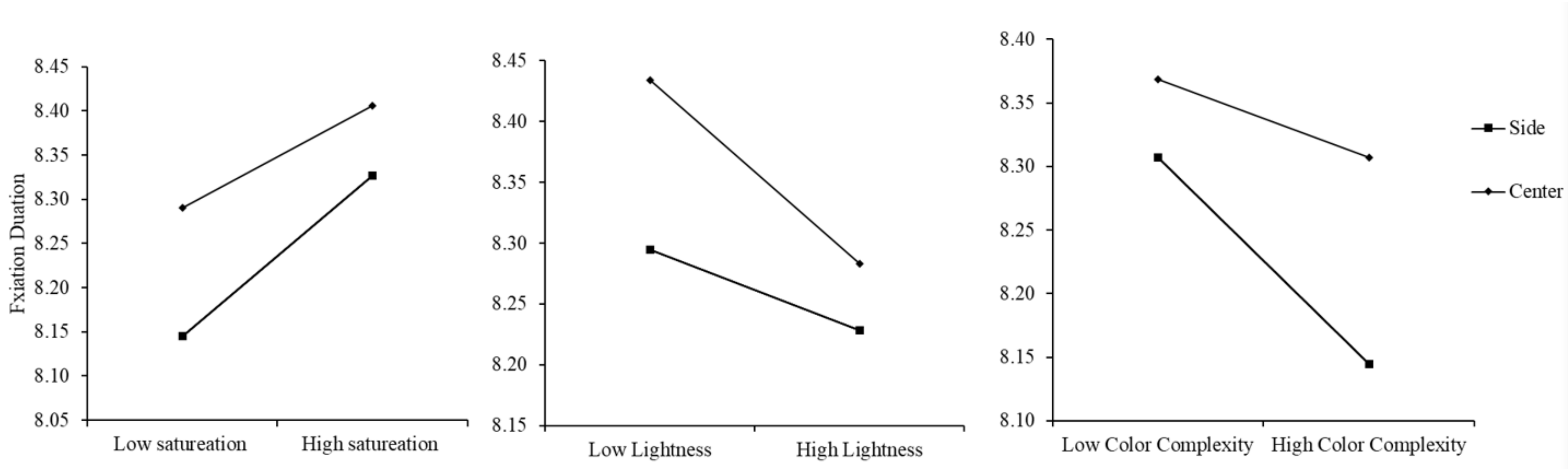


Figure 3.4 : The interactive effect of center and color attributes

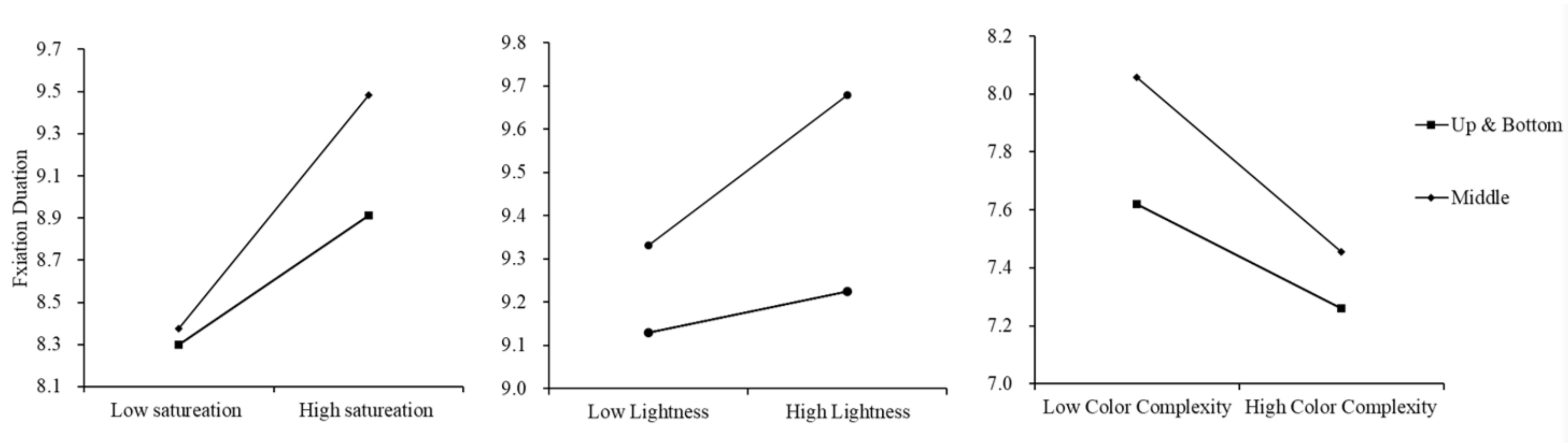


Figure 3.5 : The interactive effect of middle position and color attributes

Table 3.3 : Robustness check using regression models to test the influence of color attributes and position on product image saliency

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Size	0.0225***	0.0219***	0.0227***	0.0227***	0.0214***	0.0223***	0.0223***	0.0225***	0.0223***	0.0212***
	(0.00311)	(0.00312)	(0.00311)	(0.00311)	(0.00314)	(0.00311)	(0.00311)	(0.00311)	(0.00311)	(0.00315)
CompressRate	-2.425***	-2.441***	-2.495***	-2.493***	-2.477***	-2.347***	-2.461***	-2.424***	-2.220***	-2.280***
	(0.359)	(0.359)	(0.360)	(0.360)	(0.364)	(0.359)	(0.359)	(0.358)	(0.363)	(0.367)
SobelEdge	4.870***	5.051***	4.905***	4.833***	5.099***	4.275***	4.449***	4.278***	4.329***	4.159***
	(1.237)	(1.240)	(1.238)	(1.237)	(1.247)	(1.244)	(1.244)	(1.271)	(1.312)	(1.329)
Log_Price	0.00526	0.00427	0.00515	0.00577	0.00292	0.00853	0.00665	0.00660	0.00797	0.00625
	(0.00637)	(0.00639)	(0.00638)	(0.00638)	(0.00648)	(0.00641)	(0.00641)	(0.00641)	(0.00645)	(0.00654)
DiscouRate	0.0329	0.0260	0.0452	0.0457	0.0410	0.0667	0.0561	0.0429	0.0705	0.0778
	(0.0648)	(0.0650)	(0.0650)	(0.0651)	(0.0653)	(0.0653)	(0.0653)	(0.0650)	(0.0654)	(0.0660)
Saturation	0.842***	0.564**	0.910***	0.870***	0.927***	3.860***	0.819***	0.832***	4.932***	5.741***
	(0.210)	(0.256)	(0.211)	(0.213)	(0.309)	(0.737)	(0.210)	(0.210)	(1.038)	(1.102)
Lightness	-0.570**	-0.417	-0.895***	-0.553*	-0.764**	-0.593**	0.955	-0.606**	-2.360	-2.757*
	(0.276)	(0.290)	(0.298)	(0.283)	(0.373)	(0.277)	(0.767)	(0.277)	(1.514)	(1.576)
Complexity	-0.307**	-0.263*	-0.326**	-0.150	-0.244	-0.332**	-0.292**	-1.113**	-0.522	-0.416
	(0.139)	(0.141)	(0.140)	(0.159)	(0.185)	(0.139)	(0.140)	(0.513)	(0.848)	(0.874)
Left	-0.0527**	-0.192***	-0.0803*	0.152	0.111	-0.0383	-0.0561**	-0.0551**	-0.0383	0.0289
	(0.0265)	(0.0723)	(0.0462)	(0.135)	(0.298)	(0.0268)	(0.0266)	(0.0265)	(0.0269)	(0.329)
Right	-0.153***	-0.192***	-0.258***	0.133	-0.299	-0.144***	-0.160***	-0.154***	-0.151***	-0.204
	(0.0279)	(0.0743)	(0.0446)	(0.137)	(0.305)	(0.0280)	(0.0280)	(0.0280)	(0.0283)	(0.326)
Top	-0.298***	-0.305***	-0.301***	-0.301***	-0.299***	0.296**	-0.105	-0.941**	0.171	0.256
	(0.0441)	(0.0443)	(0.0442)	(0.0442)	(0.0446)	(0.147)	(0.0908)	(0.369)	(0.735)	(0.743)
Bottom	-0.367***	-0.380***	-0.374***	-0.373***	-0.380***	0.221	-0.247***	-0.846**	-0.0846	0.220
	(0.0449)	(0.0453)	(0.0450)	(0.0450)	(0.0455)	(0.148)	(0.0914)	(0.366)	(0.753)	(0.762)
Left×Saturation		0.750**			0.583					0.467
		(0.362)			(0.493)					(0.499)

Right×Saturation		0.204			-1.227**					-1.805***
		(0.369)			(0.547)					(0.557)
Left×Lightness			0.234		-0.663					-0.193
			(0.388)		(0.685)					(0.749)
Right×Lightness			0.893***		1.847***					2.025***
			(0.299)		(0.630)					(0.692)
Left×CCM				-0.278	-0.293					-0.188
				(0.179)	(0.305)					(0.333)
Right×CCM				-0.395**	0.218					0.217
				(0.185)	(0.335)					(0.355)
Top×Saturation						-3.206***			-3.822***	-4.348***
						(0.758)			(1.076)	(1.087)
Bottom×Saturation						-3.164***			-4.787***	-5.462***
						(0.760)			(1.088)	(1.121)
Top×Lightness							-1.831**		1.111	1.381
							(0.747)		(1.529)	(1.550)
Bottom×Lightness							-1.167		2.763*	2.579
							(0.744)		(1.561)	(1.602)
Top×Complexity								0.890*	0.165	0.149
								(0.507)	(0.862)	(0.871)
Bottom×Complexity								0.666	0.421	0.193
								(0.502)	(0.876)	(0.885)
Constant	8.205***	8.229***	8.244***	8.085***	8.191***	7.641***	8.053***	8.821***	7.736***	7.602***
	(0.192)	(0.193)	(0.193)	(0.201)	(0.225)	(0.233)	(0.203)	(0.412)	(0.739)	(0.765)
Participant fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Webpage fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,624	10,624	10,624	10,624	10,624	10,624	10,624	10,624	10,624	10,624
Number of groups	88	88	88	88	88	88	88	88	88	88

Note: To distinguish the difference in the roles of left and right and the roles of top and bottom in the interactive effect of three color attributes and locations, we re-coded the horizontal location and vertical location each into two dummy variables and conducted a robustness check using regression models. The horizontal position is coded as the left, center, and right. Among the three categories, the center is taken as the baseline. The vertical position is coded as top, middle, and bottom. Among them, the middle is taken as the baseline.

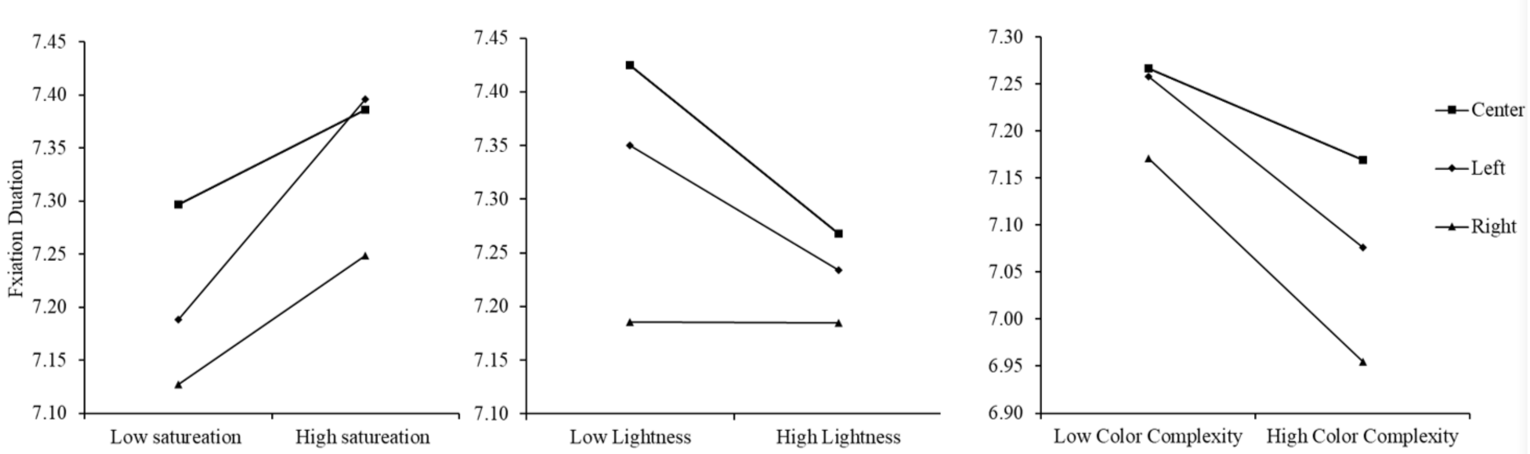


Figure 3.6 : The interactive effect of location and color attributes horizontally

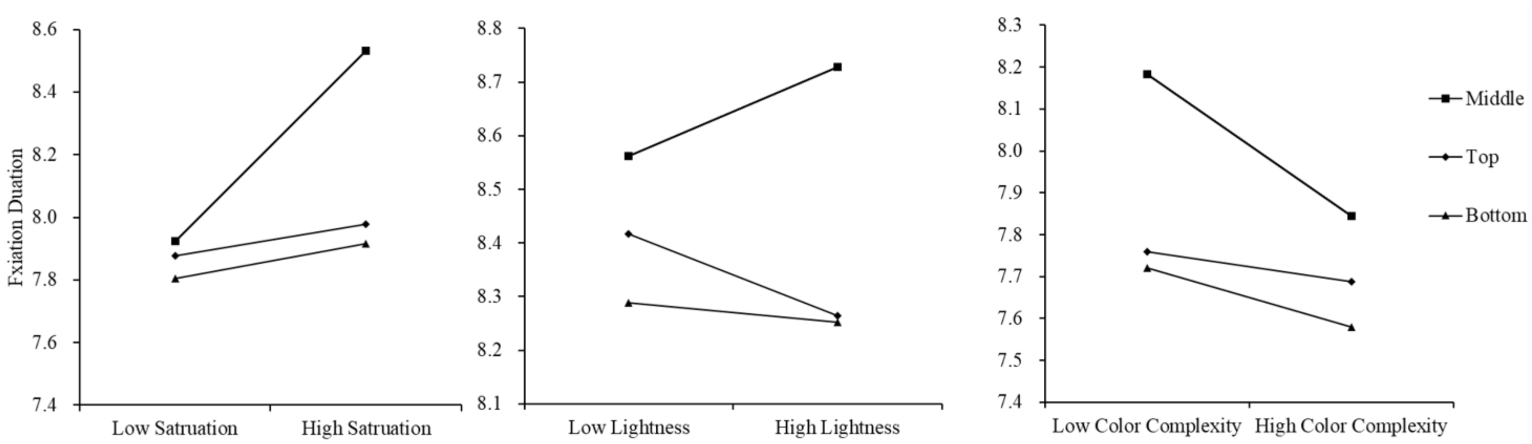


Figure 3.7 : The interactive effect of location and color attributes vertically

Specifically, Model 2 shows that saturation increases the fixation duration on the displayed product (H1a), while lightness and complexity reduce the fixation duration (H1b and H1c). One percent change in saturation, lightness, and color complexity leads to 0.93%, 0.85% and 0.38% changes in fixation duration, respectively. Horizontally, the location at the center (vs. at the left or right column) has a statistically significant negative impact on fixation duration with the coefficient 0.0974, showing the advantage of the center location in gaining fixation duration (H2a). Vertically, the location in the middle row has a statistically significant and positive impact on fixation duration with a coefficient 0.325, indicating the advantage of the middle row (H2b). In general, the center (vs. left and right) effect is smaller than the middle (vs. the top and bottom) effect.

Note, in Table 3.2, we code the center and middle location as two dummy variables for a brief and clear presentation. To further discriminate the difference between the left and right and the top and the bottom location when taking the center and middle location as the baseline, we code the horizontal and vertical locations each as two dummy variables to reveal how the left is different from the right location and how the top is different from the bottom location. The main effects of locations are shown as Model 1 in Table 3.3. The results are consistent with the regression analysis and the ANOVA analysis in Figure 3.3.

In Table 3.2, Model 4-6 test the moderation effects of horizontal location and color attributes, as shown in Figure 3.4. As a result, the interactive effect of center and saturation is not statistically significant. The location of the center has a statistically marginal significant interactive effect on the negative effect of lightness and a negative interactive effect on the negative effect of complexity. As shown in Figure 3.4, low lightness has the advantage of attracting attention, and such an advantage is strengthened by the location of the center (H3b). High lightness attracts less attention, and its disadvantage in gaining fixation duration is aggravated by the center position (H3c). Model 7 includes all interactive effects of center location and color attributes, and the significant moderation effect becomes not statistically significant any longer, suggesting that there may exist high-level interactions between horizontal neighbors. When we further examine the moderation effect by differentiating the role of left and right (Table 3.3, model 2-4), left (vs. center) and saturation has a positive moderation effect (Model 2), right (vs. center), and lightness has a positive moderation effect (Model 3), and right (vs. center) and color complexity has a negative moderation effect (Model 4), see Figure 3.6. When Model 5 includes all interactive effects of center location and color attributes, we could observe the interactive effect of right (vs. center), and lightness remains.

In Table 3.2, Model 8-10 test the moderation effects of vertical location and color attributes, and the effects are visualized in Figure 3.4. Model 8 shows that there exists a statistically significant interactive effect of saturation and middle (vs. top and bottom) location and middle (vs. top and bottom) location. The advantage of high saturation in raising fixation duration is strengthened by the location in the middle (vs. at the top and bottom). Model 9 shows a marginal significant interactive effect of lightness and the middle position. When the interactive effect is included in the model, the influence of lightness becomes not statistically significant. The interactive effect of color complexity and the middle position is not statistically significant as shown in Model 10. Model 11 includes interactive effects of vertical location and the three color variables and reveals a stable interactive effect of saturation and middle position. We further examine the moderation effect by differentiating the role of top and bottom (Table 3.3, model 6-8. Top (vs. middle) and bottom (vs. middle) each positively moderate the effect of saturation (Model 6). Top (vs. middle) positively moderates the effect of lightness (Model 7) and negatively moderates the effect of color complexity (Model 8), see Figure 3.7. Model 9 includes the interactive effects of vertical positions and three color attributes and shows that the moderation effect of saturation remains stable, and Model 10 includes all interactive effects mentioned above. Overall, the interactive effect of horizontal location and lightness (H3c) and that of vertical location and saturation (H3d) are robust. The models

Table 3.4 : An example of saliency position layout

D	D	C	G	G
B	A	A	A	I
F	F	E	H	H

show a statistically positive effect of the amount of sensory input and a negative effect of visual intricacy, suggesting rich sensory information increases viewers' fixation duration, but high visual intricacy does not. Price and discount, the most important variables in purchase decision-making were not elaborated on when participants were told to look at the product display without a clear target.

On average, product display with high saturation, low lightness, and low complexity gains more attention from consumers. Consumers are more likely to pay attention to the product displayed at the center (vs. at the left or right column) and in the middle rows, suggesting that the priority of recommendation should be displayed in order following the perceived saliency. Given a 5×3 slots pages, the most typical layout setting of our research, the premium of the positions can be visualized as the following. Position A is the most salient, position B follows, and the position of decreasing saliency follows the alphabetic order.

The display of products by default follows the order that one reads texts, from left to right by lines from top to bottom, which create the inconsistency between recommendation priority and visual saliency. Such that the fittest product may fail to get sufficient attention. Our research indicates a perception-centered priority assignment method to improve the consistency between perceived saliency and recommended priority.

Our exploration of the interactive effect between color attributes and location reveals that product displays assigned in the middle or center location can be optimized. Specifically, if a product is displayed horizontally at the center, it can enhance the saliency by using low lightness. If vertically in the middle, it can enhance saliency by using high saturation color.

3.7.2 The influences of neighbors

Products can optimize their saliency by collaborating with their neighbors. Therefore, our research attempts to discriminate how the neighbors of the target products influence the target products' saliency. The neighbors are categorized as adjacent ones and those on the diagonal. According to equation (c), we test the effect of the neighbors' color attributes on the target products.

Table 3.5 shows the effect of adjacent neighbors' color attributes on the target product's saliency. As a result, the target's left, right, and beneath neighbors' saturation (Model 1-3) and lightness (Model 4-6) reduces the saliency of the target product, while their color complexity (Model 7-9) increases the saliency of the target product. Among the neighbors, the beneath neighbors' color attributes have a stronger effect on the target product than the horizontal neighbors. The north neighbor influences the target product's saliency exclusively through its complexity. In model 5, the same effect occurs to lightness. In Table 3.6, we conducted a robustness check using different coding of the location variables, and the results remain robust.

Table 3.5 : Regression models testing the influence of neighbors' color attributes on the saliency of the target product

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Size	0.0297***	0.0179***	0.0284***	0.0345***	0.0196***	0.0304***	0.0133***	0.0321***	0.0186***	0.0288***
	(0.00506)	(0.00382)	(0.00381)	(0.00492)	(0.00378)	(0.00381)	(0.00482)	(0.00496)	(0.00379)	(0.00382)
CompressRate	-3.213***	-2.092***	-3.056***	-3.509***	-2.076***	-3.234***	-1.574***	-3.331***	-2.085***	-3.093***
	(0.538)	(0.451)	(0.447)	(0.525)	(0.451)	(0.444)	(0.565)	(0.531)	(0.451)	(0.449)
SobelEdge	7.771***	5.204***	5.858***	9.025***	5.778***	6.355***	6.375***	8.981***	6.004***	5.962***
	(1.833)	(1.533)	(1.483)	(1.828)	(1.510)	(1.497)	(1.996)	(1.835)	(1.509)	(1.490)
Log_Price	0.0224**	0.0117	0.0208***	0.0387***	0.0129*	0.0217***	-0.0208**	0.0292***	0.00784	0.0157**
	(0.00895)	(0.00766)	(0.00791)	(0.00938)	(0.00767)	(0.00798)	(0.00957)	(0.00913)	(0.00753)	(0.00769)
DiscoutRate	-0.00756	-0.0386	0.107	-0.00585	0.000486	0.123	0.194**	0.00774	-0.00776	0.131*
	(0.0911)	(0.0801)	(0.0775)	(0.0909)	(0.0809)	(0.0776)	(0.0977)	(0.0912)	(0.0807)	(0.0780)
Saturation	1.359***	0.453	1.381***	1.081***	0.451	1.428***	0.392	1.441***	0.418	1.346***
	(0.313)	(0.277)	(0.264)	(0.315)	(0.276)	(0.266)	(0.328)	(0.313)	(0.276)	(0.264)
Lightness	-0.851**	-0.0913	-1.134***	-0.773*	-0.171	-1.185***	0.681	-1.335***	-0.305	-1.276***
	(0.404)	(0.345)	(0.342)	(0.394)	(0.344)	(0.344)	(0.488)	(0.382)	(0.346)	(0.352)
CCM	-0.479***	-0.253	-0.453***	-0.749***	-0.240	-0.495***	-0.0485	-0.853***	-0.410**	-0.604***
	(0.173)	(0.171)	(0.164)	(0.177)	(0.170)	(0.165)	(0.310)	(0.189)	(0.183)	(0.178)
HorizCenter	-0.0723*	-0.437	-0.0574*	-0.0802**	-0.487	-0.0620**	-0.122***	-0.0726*	-0.484	-0.0551*
	(0.0393)	(0.375)	(0.0293)	(0.0390)	(0.375)	(0.0294)	(0.0412)	(0.0392)	(0.375)	(0.0293)
HorizCenter	-0.268***	-0.142***	0.0244	-0.215***	-0.143***	-0.00885	-0.113**	-0.240***	-0.152***	-0.0248
	(0.0406)	(0.0301)	(0.178)	(0.0412)	(0.0301)	(0.178)	(0.0441)	(0.0408)	(0.0302)	(0.178)
VerticalMiddle	-0.426***	-0.416***	-0.297***	-0.383***	-0.420***	-0.303***		-0.381***	-0.429***	-0.297***
	(0.0519)	(0.0567)	(0.0574)	(0.0516)	(0.0567)	(0.0574)		(0.0518)	(0.0567)	(0.0574)
VerticalMiddle	-0.347***	-0.465***	-0.403***	-0.252**	-0.462***	-0.396***	-0.369***	-0.287***	-0.478***	-0.402***
	(0.106)	(0.0575)	(0.0586)	(0.106)	(0.0575)	(0.0586)	(0.0514)	(0.106)	(0.0575)	(0.0586)

S_Saturation	-1.080***									
	(0.261)									
W_Saturation		-0.617***								
		(0.211)								
E_Saturation			-0.788***							
			(0.206)							
S_Lightness				-1.628***						
				(0.267)						
W_Lightness					-0.698***					
					(0.196)					
E_Lightness						-0.704***				
						(0.183)				
N_CCM							0.383**			
							(0.163)			
S_CCM								0.751***		
								(0.166)		
W_CCM									0.379***	
									(0.115)	
E_CCM										0.341***
										(0.120)
Participant Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Webpage fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	8.416***	8.493***	8.365***	8.381***	8.327***	8.272***	7.611***	7.765***	8.173***	8.096***
	(0.235)	(0.240)	(0.215)	(0.232)	(0.233)	(0.215)	(0.355)	(0.258)	(0.237)	(0.225)
Observations	4,568	6,483	6,460	4,568	6,483	6,460	4,413	4,568	6,483	6,460
Number of groups	87	86	86	87	86	86	87	87	86	86

Table 3.6 : Robustness check by regression models testing the influence of neighbors' color attributes on the saliency of the target product

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Size	0.0281***	0.0183***	0.0292***	0.0314***	0.0199***	0.0313***	0.0132***	0.0297***	0.0191***	0.0299***
	(0.00459)	(0.00379)	(0.00371)	(0.00446)	(0.00375)	(0.00370)	(0.00482)	(0.00450)	(0.00376)	(0.00371)
CompressRate	-3.246***	-2.084***	-3.073***	-3.342***	-2.062***	-3.251***	-1.572***	-3.265***	-2.078***	-3.131***
	(0.501)	(0.452)	(0.439)	(0.492)	(0.451)	(0.435)	(0.565)	(0.497)	(0.451)	(0.439)
SobelEdge	8.870***	5.136***	5.959***	9.740***	5.700***	6.519***	6.360***	9.873***	5.926***	6.069***
	(1.814)	(1.532)	(1.484)	(1.809)	(1.509)	(1.498)	(1.994)	(1.818)	(1.508)	(1.492)
Log_Price	0.0208**	0.0127*	0.0238***	0.0373***	0.0138*	0.0253***	-0.0207**	0.0276***	0.00885	0.0191**
	(0.00885)	(0.00763)	(0.00782)	(0.00925)	(0.00763)	(0.00786)	(0.00956)	(0.00903)	(0.00749)	(0.00761)
DiscoutRate	-0.0959	-0.0309	0.0835	-0.0731	0.00695	0.104	0.194**	-0.0708	-0.000758	0.109
	(0.0887)	(0.0798)	(0.0772)	(0.0885)	(0.0805)	(0.0774)	(0.0976)	(0.0887)	(0.0804)	(0.0777)
Saturation	**1.371*** **	**0.489***	**1.378*** **	1.098***	0.481*	1.441***	0.382	1.458***	0.454*	1.348***
	(0.313)	**(0.275)**	**(0.264)**	(0.314)	(0.275)	(0.266)	(0.323)	(0.313)	(0.275)	(0.264)
Lightness	-1.087***	-0.172	-1.285***	**-0.869*** **	**-0.235**	**-1.333*** **	**0.698**	**-1.481*** **	**-0.383**	**-1.432*** **
	(0.401)	(0.340)	(0.339)	**(0.394)**	**(0.339)**	**(0.340)**	**(0.478)**	**(0.380)**	**(0.341)**	**(0.349)**
CCM	-0.552***	-0.283*	-0.522***	-0.799***	-0.267	-0.564***	-0.0448	-0.911***	-0.437**	-0.676***
	(0.172)	(0.171)	(0.163)	(0.175)	(0.169)	(0.163)	(0.309)	(0.188)	(0.183)	(0.177)
CenterDummy	0.166***	0.145***	0.0504*	0.143***	0.146***	0.0571*	0.118***	0.152***	0.156***	0.0493*
	(0.0321)	(0.0301)	(0.0291)	(0.0323)	(0.0300)	(0.0292)	(0.0344)	(0.0324)	(0.0301)	(0.0291)
VertiMidDummy	0.409***	0.438***	0.340***	0.368***	0.439***	0.341***	0.369***	0.367***	0.451***	0.341***
	(0.0515)	(0.0552)	(0.0560)	(0.0511)	(0.0551)	(0.0560)	(0.0514)	(0.0514)	(0.0551)	(0.0560)

S_Saturation	-0.935***									
	(0.259)									
W_Saturation		-0.613***								
		(0.211)								
E_Saturation			-0.770***							
			(0.206)							
S_Lightness				-1.693***						
				(0.266)						
W_Lightness					-0.709***					
					(0.195)					
E_Lightness						-0.758***				
						(0.183)				
N_CCM							0.383**			
							(0.163)			
S_CCM								0.750***		
								(0.166)		
W_CCM									0.372***	
									(0.115)	
E_CCM										0.340***
										(0.120)
Constant	7.931***	7.915***	8.017***	7.956***	7.751***	7.911***	7.122***	7.343***	7.577***	7.753***
	(0.234)	(0.237)	(0.217)	(0.232)	(0.229)	(0.217)	(0.365)	(0.253)	(0.234)	(0.227)
Participants fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Web-page fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,568	6,483	6,460	4,568	6,483	6,460	4,413	4,568	6,483	6,460
Number of groups	87	86	86	87	86	86	87	87	86	86

To further reveal whether the influences of neighbors on the target are caused by the contrast between the neighbor and the target, we code the differences in color attributes. Particularly, in models illustrated in Table 3.7, *Dif* refers to the difference of the target product and its neighbor, i.e., the value of the neighbor's color minus that of the target. We specify the direction of the neighbor and the color attributes for the variables depicting the difference. Model 1-3 show that the neighbor's saturation reduces the target saliency due to the neighbor's competition for attention against the target. Model 4-6 show that the neighbor's high lightness also reduces the target saliency, probably because high lightness neither shapes contrast to highlight the target nor draws attention to the target through the spillover effect. Model 7-9 show that the neighbor's complexity increases the target saliency due to its contrast.

Table 3.7 : Influences of adjacent product images' difference in average saturation on fixation duration

VARIABLES	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model
Size	0.0147***	0.0297***	0.0179***	0.0284***	0.0145***	0.0345***	0.0196***	0.0304***	0.0133***	0.0321***	0.0186***	0.0288***
	(0.00480)	(0.00506)	(0.00382)	(0.00381)	(0.00480)	(0.00492)	(0.00378)	(0.00381)	(0.00482)	(0.00496)	(0.00379)	(0.00382)
CompressRate	-1.728***	-3.213***	-2.092***	-3.056***	-1.736***	-3.509***	-2.076***	-3.234***	-1.574***	-3.331***	-2.085***	-3.093***
	(0.561)	(0.538)	(0.451)	(0.447)	(0.562)	(0.525)	(0.451)	(0.444)	(0.565)	(0.531)	(0.451)	(0.449)
SobelEdge	5.752***	7.771***	5.204***	5.858***	6.088***	9.025***	5.778***	6.355***	6.375***	8.981***	6.004***	5.962***
	(2.016)	(1.833)	(1.533)	(1.483)	(1.994)	(1.828)	(1.510)	(1.497)	(1.996)	(1.835)	(1.509)	(1.490)
Log_Price	-0.0196**	0.0224**	0.0117	0.0208***	-0.0185*	0.0387***	0.0129*	0.0217***	-0.0208**	0.0292***	0.00784	0.0157**
	(0.00958)	(0.00895)	(0.00766)	(0.00791)	(0.00957)	(0.00938)	(0.00767)	(0.00798)	(0.00957)	(0.00913)	(0.00753)	(0.00769)
DiscoutRate	0.186*	-0.00756	-0.0386	0.107	0.177*	-0.00585	0.000486	0.123	0.194**	0.00774	-0.00776	0.131*
	(0.0979)	(0.0911)	(0.0801)	(0.0775)	(0.0978)	(0.0909)	(0.0809)	(0.0776)	(0.0977)	(0.0912)	(0.0807)	(0.0780)
1.horizCenter	-0.109***	-0.0723*	-0.437	-0.0574*	-0.116***	-0.0802**	-0.487	-0.0620**	-0.122***	-0.0726*	-0.484	-0.0551*
	(0.0414)	(0.0393)	(0.375)	(0.0293)	(0.0419)	(0.0390)	(0.375)	(0.0294)	(0.0412)	(0.0392)	(0.375)	(0.0293)
2.horizCenter	-0.102**	-0.268***	-0.142***	0.0244	-0.105**	-0.215***	-0.143***	-0.00885	-0.113**	-0.240***	-0.152***	-0.0248
	(0.0440)	(0.0406)	(0.0301)	(0.178)	(0.0443)	(0.0412)	(0.0301)	(0.178)	(0.0441)	(0.0408)	(0.0302)	(0.178)
1.VerticalMiddle		-0.426***	-0.416***	-0.297***		-0.383***	-0.420***	-0.303***		-0.381***	-0.429***	-0.297***
		(0.0519)	(0.0567)	(0.0574)		(0.0516)	(0.0567)	(0.0574)		(0.0518)	(0.0567)	(0.0574)
2.VerticalMiddle	-0.363***	-0.347***	-0.465***	-0.403***	-0.366***	-0.252**	-0.462***	-0.396***	-0.369***	-0.287***	-0.478***	-0.402***
	(0.0515)	(0.106)	(0.0575)	(0.0586)	(0.0514)	(0.106)	(0.0575)	(0.0586)	(0.0514)	(0.106)	(0.0575)	(0.0586)
Saturation	**0.664***	**0.279**	**-0.165**	**0.593***	0.441	1.081***	0.451	1.428***	0.392	1.441***	0.418	1.346***
	(0.391)	**(0.407)**	**(0.339)**	**(0.316)**	(0.339)	(0.315)	(0.276)	(0.266)	(0.328)	(0.313)	(0.276)	(0.264)
Lightness	0.752	-0.851**	-0.0913	-1.134***	**0.642**	**-2.401*** **	**-0.869*** **	**-1.889*** **	0.681	-1.335***	-0.305	-1.276***
	(0.492)	(0.404)	(0.345)	(0.342)	**(0.549)**	**(0.415)**	**(0.395)**	**(0.407)**	(0.488)	(0.382)	(0.346)	(0.352)
CCM	0.256	-0.479***	-0.253	-0.453***	0.181	-0.749***	-0.240	-0.495***	**0.334**	**-0.102**	**-0.0306**	**-0.263**
	(0.300)	(0.173)	(0.171)	(0.164)	(0.296)	(0.177)	(0.170)	(0.165)	**(0.300)**	**(0.195)**	**(0.175)**	**(0.172)**
ColorAttribute		**Saturation**				**Lightness**				**Complexity**		
Direction	**N**	**S**	**W**	**E**	**N**	**S**	**W**	**E**	**N**	**S**	**W**	**E**
Neighbor	**0.302**	**-1.080*** **	**-0.617*** **	**-0.788*** **	**-0.0423**	**-1.628*** **	**-0.698*** **	**-0.704*** **	**0.383** **	**0.751*** **	**0.379*** **	**0.341*** **
	(0.274)	**(0.261)**	**(0.211)**	**(0.206)**	**(0.283)**	**(0.267)**	**(0.196)**	**(0.183)**	**(0.163)**	**(0.166)**	**(0.115)**	**(0.120)**
Constant	7.643***	8.416***	8.493***	8.365***	7.745***	8.381***	8.327***	8.272***	7.611***	7.765***	8.173***	8.096***
	(0.363)	(0.235)	(0.240)	(0.215)	(0.352)	(0.232)	(0.233)	(0.215)	(0.355)	(0.258)	(0.237)	(0.225)
Participant Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Webpage fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,413	4,568	6,483	6,460	4,413	4,568	6,483	6,460	4,413	4,568	6,483	6,460
Number of groups	87	87	86	86	87	87	86	86	87	87	86	86

Table 3.8 shows how the color attributes of the neighbors on the left-up and right-down of the target influence the targets' saliency. As the results, saturation, lightness, and color complexity of the neighbors on the diagonal have a consistent impact on the targets' saliency with the effect between horizontal neighbors and the effect between the target product and its neighbor underneath.

Given the neighbor's impact, we further test whether the difference in color attributes between the target product and its neighbor moderates the influence of the target's attributes on its saliency (Table 3.9). Model 3 and model 4 reveal the moderation effects ($p<.05$) between the target and its left and right neighbors regarding the color attributes of saturation. We did not find other statistically significant moderation effects ($p<.05$). The moderation effects are shown in Figure 3.8. A horizontal neighbor of higher saturation reduces the effect of the target's saturation on saliency, suggesting the neighbor and the target's saturation compete against each other in attention attraction. Meanwhile, when the horizontal neighbor's saturation is lower, the effect of the target's saturation on saliency is suppressed, implying the disappeared spillover effect from a neighbor of higher saturation. Overall, the competition effect is stronger than the spillover effect.

A neighboring product with a higher saturation level than the target may be more advantageous in competing for attention. The dissimilarity of the average saturations of adjacent product images may benefit the one with higher average saturation in attention attraction.

This section explores the competition of a target product for visual saliency against neighbor products and reveals how a neighbor product's color attributions in each direction influence the target's visual saliency.

3.7.3 Influences of neighbor directions and their color attributes

Prior research highlights the visual saliency of a target item against all other distractors as a background. Our research moves forward and provides evidence on the influences

Table 3.8 : Regression models testing how color attributes of the neighbors on the diagnal directions influences the saliency of the target product

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Size	0.0135**	0.0382***	0.0158***	0.0403***	0.0142***	0.0389***
	(0.00528)	(0.00481)	(0.00523)	(0.00479)	(0.00523)	(0.00480)
CompressRate	-1.523**	-4.045***	-1.498**	-4.346***	-1.261*	-4.170***
	(0.660)	(0.585)	(0.661)	(0.564)	(0.666)	(0.579)
SobelEdge	3.811*	7.606***	2.922	8.871***	3.444	9.465***
	(2.314)	(2.275)	(2.341)	(2.222)	(2.314)	(2.230)
Log_Price	-0.0164	0.0325***	-0.0156	0.0278***	-0.0209**	0.0280***
	(0.0100)	(0.0108)	(0.0100)	(0.0104)	(0.0101)	(0.0104)
DiscoutRate	0.179*	-0.0231	0.195*	0.00767	0.199*	0.0108
	(0.107)	(0.0962)	(0.108)	(0.0965)	(0.108)	(0.0966)
Saturation	0.272	2.116***	0.408	2.283***	0.116	2.141***
	(0.410)	(0.371)	(0.418)	(0.391)	(0.406)	(0.375)
Lightness	1.688***	-1.514***	1.341**	-1.674***	0.814	-1.848***
	(0.589)	(0.433)	(0.581)	(0.427)	(0.598)	(0.429)
CCM	0.371	-0.367*	0.240	-0.418**	-0.171	-0.539***
	(0.373)	(0.190)	(0.377)	(0.188)	(0.402)	(0.192)
CenterDummy	0.112***	0.107***	0.102**	0.109***	0.120***	0.110***
	(0.0419)	(0.0386)	(0.0421)	(0.0385)	(0.0419)	(0.0385)
VertiMidDummy	0.560***	0.441***	0.533***	0.447***	0.541***	0.446***
	(0.0579)	(0.0632)	(0.0581)	(0.0631)	(0.0578)	(0.0631)
NW_Saturation	-1.079***					
	(0.334)					
SE_Saturation		-0.912***				
		(0.323)				
NW_Lightness			-0.862***			
			(0.284)			
SE_Lightness				-0.663**		
				(0.272)		
NW_CCM					0.615***	
					(0.158)	
SE_CCM						0.431**
						(0.178)
Constant	7.329***	7.705***	7.328***	7.565***	7.157***	7.241***
	(0.459)	(0.245)	(0.459)	(0.249)	(0.455)	(0.303)
Participants fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Web-page fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,456	3,555	3,456	3,555	3,456	3,555
Number of groups	87	87	87	87	87	87

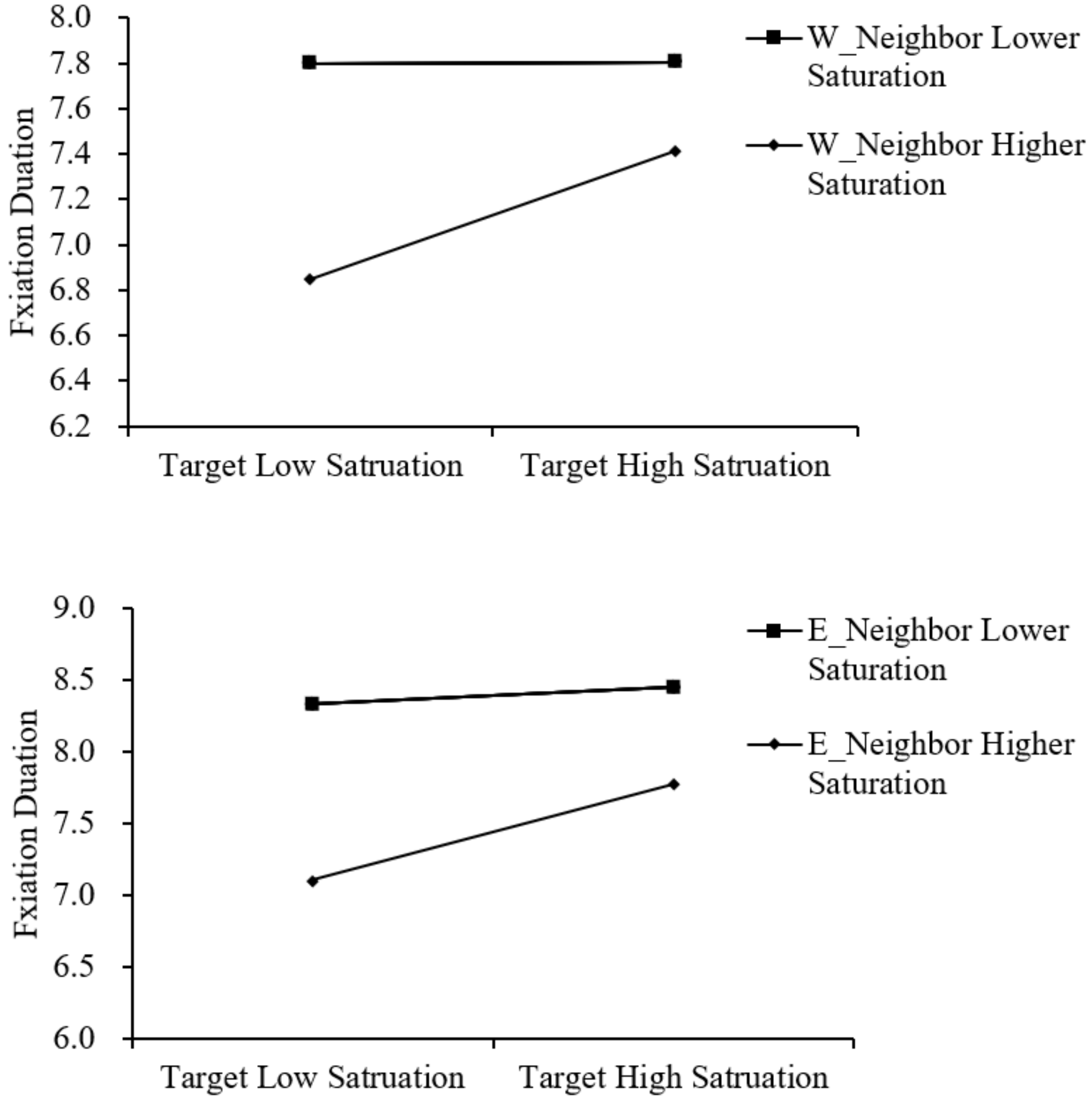


Figure 3.8 : The moderation effect of west and east neighbor's saturation difference on the target saliency

of each neighbor's attributes, confirms the influences from the left, right, and underneath neighbor's influences, and highlights the heterogeneity of directions in visual processing.

Among the three directions, the neighbor's high saturation and high lightness reduce the target's saliency, and the neighbor's high complexity increases the target's saliency. We consider the influences of the neighbors as the consequences of two opposite powers, i.e., the attention competition against the target and attention spillover to the target. When located adjacent to a salient neighbor, the target may lose in the competition for attention, with less attention reserved. The target may gain the chance of attention shifting from the nearby salient visual focus. Both effects could change, and their combination leads to the variation of the neighbor's impact.

Regarding the color attributes, we infer that the neighbor's high saturation reduces the target's saliency due to its advantage in attention competition and dominates its impact on the target. The neighbor's high complexity reduces its saliency but increases the target's saliency. Neighbor's high lightness reduces the target's saliency mainly by suppressing the attention spillover effect. The reduction in spillover effect overwhelms the earned attention from the neighbor of high lightness.

When two neighbors are similar in a color dimension, they are likely to be grouped and perceived as tightly connected. Considering that two products of high saturation shape a local area of high saturation, the area may gain an advantage in attention-grabbing over the surroundings. Such advantages are more than what can be achieved by each product independently. The gained advantage may compensate for the loss in attention competition for the product image of lower saturation and enhance the attention-attraction for the product of high saturation.

Table 3.9 : Regression models testing how the target image's difference from its neighbor influences its saliency

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Size	0.0151***	0.0301***	0.0185***	0.0290***	0.0144***	0.0343***	0.0196***	0.0309***	0.0139***	0.0303***	0.0188***	0.0289***
	(0.00491)	(0.00506)	(0.00383)	(0.00383)	(0.00481)	(0.00493)	(0.00379)	(0.00383)	(0.00484)	(0.00505)	(0.00379)	(0.00385)
CompressRate	-1.747***	-3.268***	-2.180***	-3.168***	-1.717***	-3.507***	-2.103***	-3.226***	-1.618***	-3.226***	-2.164***	-3.091***
	(0.564)	(0.538)	(0.453)	(0.450)	(0.563)	(0.525)	(0.454)	(0.444)	(0.566)	(0.534)	(0.453)	(0.449)
SobelEdge	5.624***	7.119***	4.535***	5.312***	6.085***	8.685***	5.636***	6.498***	6.006***	8.264***	6.012***	5.955***
	(2.053)	(1.865)	(1.568)	(1.505)	(1.994)	(1.944)	(1.534)	(1.502)	(2.009)	(1.876)	(1.509)	(1.491)
Log_Price	-0.0187*	0.0232***	0.0130*	0.0221***	-0.0180*	0.0383***	0.0130*	0.0227***	-0.0202**	0.0278***	0.00891	0.0159**
	(0.00995)	(0.00895)	(0.00768)	(0.00793)	(0.00962)	(0.00941)	(0.00768)	(0.00802)	(0.00958)	(0.00916)	(0.00755)	(0.00782)
DiscoutRate	0.189*	-0.0116	-0.0332	0.120	0.176*	-0.00280	0.00366	0.119	0.187*	0.00565	-0.00132	0.131*
	(0.0982)	(0.0911)	(0.0801)	(0.0777)	(0.0978)	(0.0911)	(0.0811)	(0.0776)	(0.0978)	(0.0911)	(0.0807)	(0.0780)
1.horizCenter	-0.106**	-0.0736*	-0.438	-0.0552*	-0.118***	-0.0821**	-0.486	-0.0641**	-0.125***	-0.0909**	-0.505	-0.0560*
	(0.0425)	(0.0393)	(0.375)	(0.0293)	(0.0420)	(0.0391)	(0.375)	(0.0295)	(0.0412)	(0.0405)	(0.375)	(0.0298)
2.horizCenter	-0.100**	-0.266***	-0.148***	0.0205	-0.110**	-0.219***	-0.145***	-0.00255	-0.113**	-0.258***	-0.164***	-0.0237
	(0.0442)	(0.0406)	(0.0302)	(0.178)	(0.0454)	(0.0422)	(0.0304)	(0.178)	(0.0441)	(0.0420)	(0.0308)	(0.178)
1.VerticalMiddle		-0.432***	-0.422***	-0.300***		-0.382***	-0.421***	-0.299***		-0.372***	-0.438***	-0.297***
		(0.0520)	(0.0568)	(0.0574)		(0.0516)	(0.0567)	(0.0574)		(0.0520)	(0.0569)	(0.0575)
2.VerticalMiddle	-0.360***	-0.369***	-0.474***	-0.405***	-0.366***	-0.254**	-0.463***	-0.389***	-0.367***	-0.304***	-0.483***	-0.402***
	(0.0522)	(0.107)	(0.0577)	(0.0586)	(0.0514)	(0.106)	(0.0576)	(0.0589)	(0.0514)	(0.106)	(0.0575)	(0.0587)
Saturation	**0.697***	**0.535**	**0.0168**	**0.761****	0.436	1.111***	0.446	1.406***	0.353	1.403***	0.359	1.349***
	(0.404)	**(0.429)**	**(0.351)**	**(0.326)**	(0.339)	(0.320)	(0.277)	(0.267)	(0.329)	(0.314)	(0.278)	(0.265)
Lightness	0.760	-0.865**	-0.0750	-1.062***	**0.580**	**-2.347*****	**-0.798***	**-2.025*****	0.747	-1.380***	-0.212	-1.287***
	(0.493)	(0.404)	(0.345)	(0.344)	**(0.566)**	**(0.428)**	**(0.418)**	**(0.423)**	(0.489)	(0.382)	(0.350)	(0.358)
CCM	0.256	-0.531***	-0.299*	-0.463***	0.169	-0.753***	-0.242	-0.519***	**0.300**	**-0.232**	**-0.0456**	**-0.260**
	(0.300)	(0.175)	(0.173)	(0.164)	(0.297)	(0.177)	(0.170)	(0.167)	**(0.301)**	**(0.207)**	**(0.176)**	**(0.173)**
ColorAttribute		**Saturation**				**Lightness**				**Complexity**		
Direction	**N**	**S**	**W**	**E**	**N**	**S**	**W**	**E**	**N**	**S**	**W**	**E**
Dif	**0.123**	**-2.076*****	**-1.326*****	**-1.597*****	**0.133**	**-1.816*****	**-0.801*****	**-0.442**	**-0.961**	**-0.473**	**-0.469**	**0.431**
	(0.603)	**(0.590)**	**(0.410)**	**(0.436)**	**(0.475)**	**(0.452)**	**(0.278)**	**(0.287)**	**(0.859)**	**(0.685)**	**(0.495)**	**(0.560)**
Dif ×Target	**0.804**	**4.706***	**3.536****	**3.484****	**-1.262**	**1.135**	**0.734**	**-1.926**	**1.919**	**1.825***	**1.271***	**-0.126**
	(2.422)	**(2.502)**	**(1.754)**	**(1.657)**	**(2.738)**	**(2.202)**	**(1.407)**	**(1.621)**	**(1.204)**	**(0.992)**	**(0.721)**	**(0.766)**
Constant	7.636***	8.480***	8.561***	8.384***	7.756***	8.404***	8.339***	8.271***	7.676***	7.958***	8.210***	8.091***
	(0.363)	(0.237)	(0.242)	(0.216)	(0.353)	(0.236)	(0.234)	(0.215)	(0.358)	(0.278)	(0.238)	(0.228)
Participant Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Webpage fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,413	4,568	6,483	6,460	4,413	4,568	6,483	6,460	4,413	4,568	6,483	6,460
Number of groups	87	87	86	86	87	87	86	86	87	87	86	86

The interactive effect of the neighbor's color difference and the target color are shown in Figure 3.8 and Table 3.9. The interactive effect is statistically significant regarding saturation. When the neighbor's saturation is lower than the target, the target gains more attention than the neighbor. We observed that the influences of the target's saturation are attenuated, suggesting the low saturation neighbor failed to be grouped with the target as a salient area and, therefore, able to gain more attention in a synergetic way. When the neighbor's saturation is higher than the target, although the target loses attention due to its disadvantage in attention competition, it benefits from the synergy with the high saturation neighbor. The evidence shows the applicability of gestalt rules and sheds light on how the neighbors influence the target.

3.8 Conclusion and General Discussion

Our research adopts a bottom-up and stimuli-driven method to explore the influences of sensory features of product images and locations on visual saliency. First, our research examined the influences of color attributes, including saturation, lightness, and color complexity, on product display salience. Second, we explored the saliency caused by the positions of the webpage layout and showed that horizontally at the center and vertically in the middle lines are premium in attracting attention. Our findings shed light on the display sequences of recommended products, highlight the difference between the probability of perceived saliency and the display by default following the approach as people read text (i.e., from the left to right by lines), and indicate the approach of optimization. Third, our research attempts to find out how a product can improve its saliency when assigned a given location by testing the interactive effect of location and color attributes. According to the analysis that discriminates the horizontal locations into the left, center, and right, we observed that the display at the left could adopt high saturation to improve its saliency level to compensate for the disadvantage caused by the left (vs. center position). The display at the right should adopt low lightness to enhance its saliency effectively. Fourth,

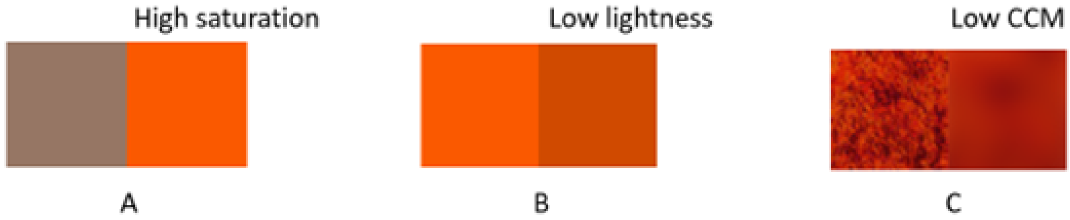


Figure 3.9 : Images with high saturation, low lightness, and low complexity are salient

Note: for each pair in this figure, using red as the example, the right block has a higher saturation, lower lightness, and lower complexity value than their adjacent neighbors on the left are perceived as more salient.

we focused on each pair of a target product and its neighbor in a certain direction and explored how the neighbors influence the target's saliency. Particularly, the interactive effect of target saturation and its similarity to its neighbors provide evidence to understand the underpinning mechanism through which visual patterns are formed and causes saliency of given areas.

The findings can be summarized and visualized as follows.

(1). Images with high saturation, low lightness, and low complexity attract more attention and are perceived as more salient (see Figure 3.9).

(2). The middle (vs. top and bottom) and center (vs. side) positions have the advantage of attracting attention (see Figure 3.10).

(3). The advantage of the middle position is strengthened by high saturation, indicating that using high saturation colors for products in middle lines can enhance attention attraction (see Figure 3.9-A)

(4). Neighbors along the up-right and bottom-right diagonal have an influence on the target product, with specific attributes such as low saturation, low lightness, and high complexity affecting the target product positively (see Figure 3.11).

Figure 3.10 : Area saliency map

Note: a highly salient area is represented by a high saturation color. Contrary to the saliency area of text reading (shown as the left figure), our findings indicate the priority position of product display in the right figure and recommend visually salient positions for optimizing product display.

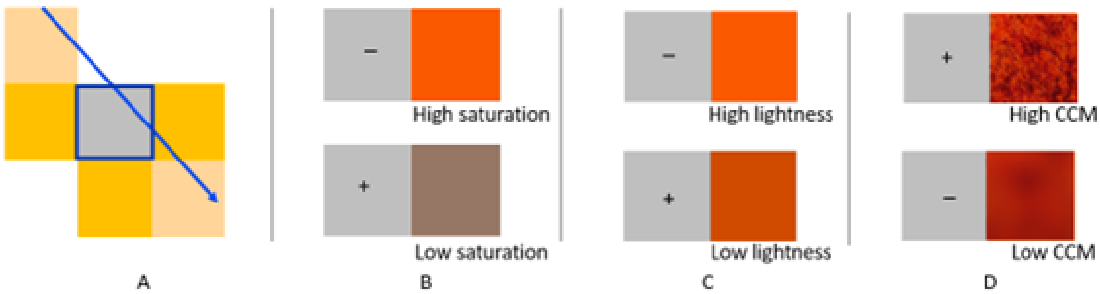


Figure 3.11 : The impact of neighbor's attributes

Note: in Figure A, given the target product was assigned at the center, among eight surrounding neighbors, the five from right up to the right bottom colored yellow may generate influence. Specifically, a target product colored grey (shown as the left side grey blocks in Figures B, C, and D) may benefit (marked as plus) from a neighbor of low saturation, low lightness, and high complexity.

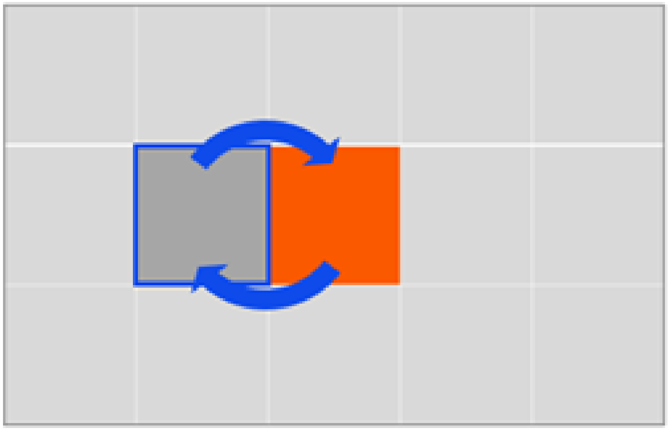


Figure 3.12 : The mechanism of neighbor's impact

(5). The impact of a salient neighbor on the target product (the grey block with blue borders in Figure 3.12 is a combination of the shadow effect and spotlight effect, as indicated by the direction of attention attraction (shown as the blue arrows).

Overall, our research contributes to the literature as follows. First, our research indicates how the most fundamental image attributes and the basic position variables influence consumers' attention assignment and contributes to the foundation for a human-machine empath and recommendation optimization. Among design and display elements [26], our research focuses on pictorials' most generally applicable attributes. We address that sensory information in parallel with the customer behavior data can influence consumers' choices by enhancing the visual saliency of certain products in a bottom-up approach, especially at the early stage of information processing. Consumers become increasingly sensitive to recommendation algorithms and concerned about their privacy, which may nullify the effort in obtrusive manipulation [73]. The undetectable manipulation based on sensory attributes may effectively influence the consumers' choice.

Second, our findings on the influences of sensory features, locations, and their interaction shed light on the saliency map of multimedia interfaces composed of artificial images (vs. natural scenes). The competitions among products on web pages are different from the well-documented visual saliency model of natural scenes [19] and the phenomenon described by co-saliency computation [110, 118, 119]. Our research selected the online shopping product profile images and carefully set the experiment in which the products are the same category on each web page and visually structured by clear rules. The products compete for consumers' attention relying on the features of saturation, lightness, color complexity, and locations. Such that, we advance the understanding of individual product's saliency in a scenario of online shopping.

Third, prior research on saliency tends to consider a visual object as a target and all others as its background. Considering the recommended products are shown in slots of a uniform size, we focus on the local space surroundings of the target rather than the holistic webpage as the background. Our research constructs pairs of interactive relationships between a target product and its neighbor, analyzes the effects of color attributes of neighbors in each direction, and explains the underpinning mechanism of visual saliency competition. Classical research in marketing has explored how the comparison between products influences consumers' choices. Consumers incline to make a change in their preference between two initially equally good options when a third option is presented [120] and induces the comparison in terms of utilitarian function and price. The attraction effect or asymmetric dominance effect by the third option is nominated as the decoy effect. Our research extends the attributes used for comparison from the utilitarian functions and price and includes visual attributes as effective attributes that influence at the perceptual level.

3.9 Marketing Applications

The research findings support their applicability to various webpage design contexts. This research uses necklaces and laptops as samples to study the impact of visual attributes. Laptops, being utilitarian products, are not affected significantly by visual design, making them suitable for testing the rules and representative of products in general.

In addition, the discussion on saliency focuses on comparing fixation durations within a webpage of the same product type, allowing for examining saliency independent of semantics. Lastly, the presentation slots on online shopping are based on classical grid systems, making the findings applicable to other graphic designs that rely on grid systems.

Our findings can be used to optimize marketing practices. The positive effect of center and middle on saliency reveals the gap between the recommendation sequences and perceived saliency and suggests the display order consistent with perceived saliency may boost consumers' click-through rate and satisfaction. The findings on location also contribute to a new path of pricing for advertisement. Search engine companies charge for recommendations to gain profit [121]. A space on the web page generally has a robust click-through rate and conversion rate [122], which prepares the foundation to influence consumers' visual search. The spaces on the top of a page are believed to be promising for click-through rate [106]. Our research addresses that when consumers surf online, the position at the center could be a better place for attraction. The bottom right corner of a precedent page is not better than the center on the subsequent page.

Second, the findings on the influences of saturation, lightness, and color complexity and their interactivities with location shed light on how the product display should set the constraints in saliency optimization. Websites managers can apply our findings to maximize the total fixation duration on the webpage overall or to maximize the saliency of a selected target product. The global view of maximization aims to elongate consumers' information processing on a given webpage and improve visual saliency subtly. The local view of maximization attempts to improve the visual saliency of selected targets by assigning them to optimized locations and arranging neighbors of specific attributes. The local view-based saliency optimization can potentially be developed as a new premium service.

Third, our findings on the neighbors' influence indicate how product images assigned in a given location can be adjusted according to location and its neighbors. If a product display is assigned to the left column, it is effective to improve saliency by choosing images of high saturation. If a product is located vertically in the middle rows, the adoption of high saturation and low color complexity images can enhance visual saliency. Considering color complexity as the factor that reduces both the target and its neighbor's saliency, the online shopping platform may suggest a simple color style to retailers.

3.10 Future Research and Limitation

To apply our findings in practice, we will test the rules of visual saliency based on the actual experience of visual surfing, clicking through rates, and purchasing data on a real online shopping website. Future research may estimate the influences and indicate the optimization method under the constraints of image changeability, the goal of optimization, and the sufficiency of neighbor information. Further understanding of human visual processing can contribute to AI-aided design and improve human and computer interaction.

The effects we observed are based on used product images from online websites. The images' saturation, lightness, and color complexity have not been universally used as leverages of purchase yet. When most product displays manipulate the given visual features, it remains unknown to what extent our findings are applicable. For example, although high saturation increases fixation duration. To an extreme, a black-and-white image among high saturation others may look different and attractive. The optimization method based on existing product displays should be applied prudently since the evolution in competition might generate more challenges.

In a separate pagination mode, consumers must click the "next page" button to load more products, which is the typical setting of our research. An increasing number of consumers adopt mobile phones to shop, which boosts the widespread adoption of the scrolling-down webpage design. An infinite scrolling setting eliminates the pre-defined boundary of pages and loads content continuously as consumers scroll down the page. Consumers switch between scrolling and staying. Scrolling inhibits fixations and information extraction, and each brief staying allows the product's information to be processed. If we treat each displayed content during a user's stay as a page, the visual processing in infinite scrolling mode is comparable to separate pagination mode, and our research findings can still be applied. However, the constraints of the application in the scrolling down pages need further examination.

Future research should aim to test the robustness of the findings by utilizing data from different product types and online shopping platforms. Additionally, it is important to control for other visual-related factors, such as the angle of product display, product details presentations, and product usage context, to address any potential missing variable concerns.

Chapter 4

The perceived speed of visualized time elapsing

In the fast-paced world of business, every second counts. For instance, reducing the delivery time of customer orders can boost customers' willingness to pay a premium price. Expedited services for road rescue requests can also command higher charges. Accurately estimating and fulfilling time-sensitive demands provide opportunities to unlock significant value. As a result, temporal information plays a fundamental role in business decision-making, encompassing tasks such as evaluating scheduling efficiency, planning for timely product delivery, and estimating preparation time for potential risks. Visualizing temporal information using spatial distance and directions in two-dimensional space through digital interfaces aids this work. Time is typically visualized as moving either rightwards or leftwards. It has not been systematically examined whether the visualized temporal information in a business context is perceived accurately, particularly when a desired or undesired event is described as moving toward the future or stationary at a future time. This chapter reports empirical studies that examine the influences of horizontal movement on the perceived distance and speed of visual items. Additionally, it analyses how physiological and cultural factors influence biases in time perception and provides insights for interface designers to mitigate these biases in interpreting temporal information based on event and time information schemas.

Although horizontal lines are commonly used in visualization and have been extensively studied in the field of perception, there is a lack of sufficient research on how they influence consumers' perception and decision-making when processing speed information. The business setting provides the opportunity to explore how the basic rules of

Figure 4.1 : Progress Bar

horizontal lines are applied. Specifically, when individuals judge speed rely on visualized spatial information, whether they perceive themselves or the object/event as the moving entity, and whether the approaching of an event or object is desirable influences how they choose a baseline for speed comparison and judgment. Understanding these conditions can provide valuable insights for applying visual rules effectively and sheds light on business condition-based strategies of visualization design.

4.1 Introduction

Orientation refers to the relative position or direction of a visual object. Horizontally, it can be distinguished between left and right. It is a crucial visual element that represents the movement of an object on a static image and indicates potential or upcoming changes in relative position. Orientation is commonly used to convey temporal information. For instance, in interface design, the progress bar for page loading or file downloading typically moves from left to right, indicating the distance from the current state to task completion at the right end. Orientation information can be creatively combined with animation or glyphs of agents. For example, a progress bar can represent the loading speed for unpaid users as a snail slowly crawling toward the right destination 4.1. The page loading rate can be visualized as an astronaut walking toward the right.

Another typical case is trajectory data visualization [123]. With the increasing gener-

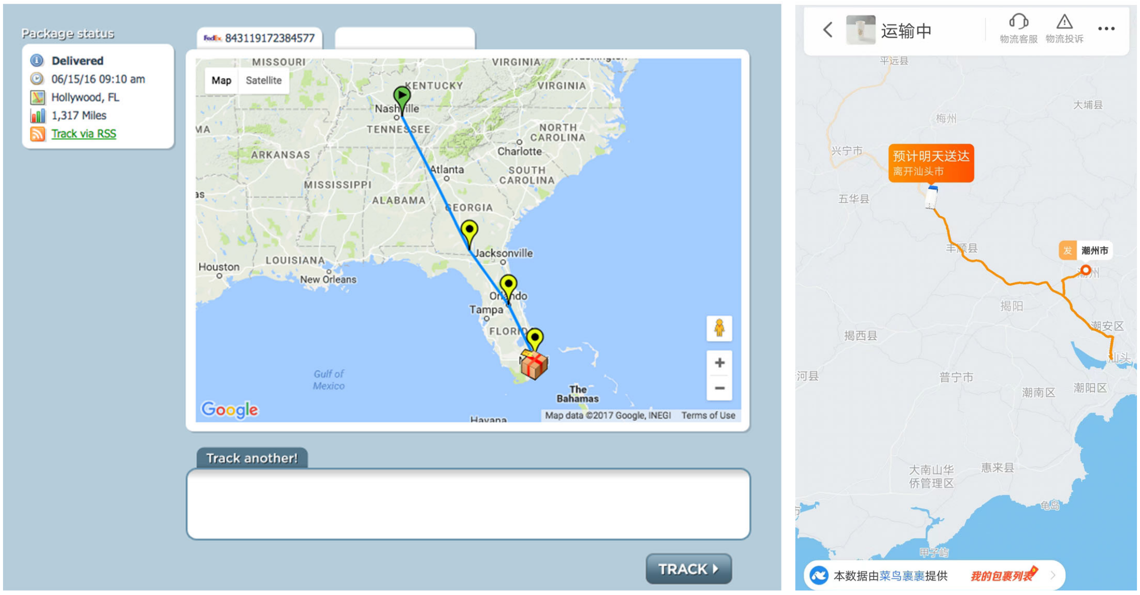


Figure 4.2 : Shipment tracking interface

ation of spatiotemporal data through mobile devices and sensors, the movement patterns of sampling entities (such as people, vehicles, and natural phenomena) and their spatial properties over time are represented as routes on a map. These routes highlight the locations over time both horizontally and vertically. One practical implementation of route visualization on consumer mobile devices is in online shopping platforms, where users can see their package's current location relative to the destination and observe its delivery progress along a simplified map. Visual techniques for package tracking have become widely adopted. In Figure 4.2, the left side depicts the Boxoh interface, which visualizes package locations using Google Maps. On the right, we see the shipment tracking interface of Cainiao, a major Chinese logistics company under the Alibaba Group, where an engaging animation simulates the movement of the package.

Imagine that on a similar shipment tracking interface, a package delivered from Perth to Sydney (left to right) in Australia shows the same distance as that delivered in the opposite direction. Consumers should be equally satisfied with the delivery if packages are delivered within a similar time limit, assuming the same fee is charged. However, the movement orientation may shape asymmetry in the perception of moving speed and cause a difference in satisfaction.

The examples above share a common foundation, using spatial information to indicate temporal information. The left-to-right orientation is a visual convention seen in timelines, Cartesian axes, musical pentagrams, and flow charts. However, the interpretation and accuracy of temporal information conveyed by this convention have not been thoroughly examined.

In this research, we conducted experiments to explore how the horizontal orientation of a visual object influences the viewer's interpretation of temporal information and decision-making. Our findings contribute to the literature in several ways. Firstly, we demonstrate how visualized temporal moving orientation affects temporal perception, providing insights into the creation of meaning and accurate temporal information. The reliance on spatial information to interpret temporal information allows us to examine the influence of physiological constraints (such as hemispheric processing in the brain and right-eye dominance) and cultural factors (such as reading and writing systems) on visual conventions. Secondly, we analyze the schemas through which agents, temporal intervals, and events are visually defined and interpreted, revealing how individuals mentally simulate the passage of time to make judgments. Finally, we differentiate between the processing of temporal information for desired and undesired future events and distinguish decision-making contexts focused on gains and losses.

4.2 Literature and Hypothesis

4.2.1 The distinction between left and right

Left and right locations are perceived differently in a two-dimensional space. Gestalt theorists proposed "right heavines" as human perceptual forces [124]. They indicated that the object on the right side would be assigned a higher visual weight than on the left [124,125]. This distinction is attributed to the dominance of the right eye in the population and the brain's hemispheric processing. Studies have shown that approximately 65% of people are right-eye dominant, 32% are left-eye dominant, and the remaining 3% are ambi-ocular [125, 126]. The dominant eye tends to provide information for direction computation at a more intensified level, leading to an overestimation of heaviness on the right side [127,128]. The research on hemispheric processing has revealed that the brain's left hemisphere directs spatial attention from left to right when processing information [129].

In addition to physiological factors, the direction of a reading and writing system also plays a role in determining environmental regulations of horizontality. A study comparing Dutch (written from left to right) and Israeli (written from right to left) participants found that the Dutch associated faster with the left side of a page, while Israeli individuals held the opposite view [130]. Subsequent research examined the phenomenon of "inhibition of return" (IOR) during reading [103, 104]. IOR suggests that our eyes track visual objects along an expected movement trajectory, and once attention shifts from a location, its return to that location becomes less likely. This effect impedes human responses when a target reappears in the same location, but enhances responses when the target moves to a new location. To investigate the influence of reading direction on the IOR effect, participants who were native English speakers (left-to-right reading) and Arabic speakers (right-to-left reading) were recruited. It was observed that English speakers responded slower when the initial target appeared on the left, compared to when it appeared on the right. In contrast, Arabic speakers demonstrated the opposite pattern of response when the initial target appeared on the left (vs. right). These findings highlight the cultural influence of the reading system on visual momentum and contribute to our understanding of visual processing.

4.2.2 Spatial-temporal association

Spatial concepts are closely linked to the processing of temporal information. Sentences such as "we are looking forward to a happy future," "falling behind schedule," and "running ahead of time" illustrate how spatial-related terms like forward, behind, and ahead are used to describe an individual's position on a timeline. Linguistic research suggests that this association between time and space reflects a metaphorical connection between spatial and temporal concepts [131]. Furthermore, studies have confirmed that people conceptualize time using spatial representations [131–133]. In these representations, the passage of time relies on an internal spatial reference frame, with a mental timeline running from left to right [134, 135]. The past is associated with the left side of the timeline, while the future is associated with the right side. Experimental studies have demonstrated that when people think about the past, the sequence of events is mentally represented from left to right [107]. Additionally, research has shown that individuals tend to view time-related products, like self-improvement items or antiques, more favorably when the future is depicted as on the right side, compared to the left side. However, this effect is reversed for participants whose reading and writing direction is from right to left [136].

Physiological and eye-behavior evidence has revealed mental simulation during the processing of a specific segment of the timeline, either rightwards or leftwards, as a temporal interval. People mentally envision time passing along the timeline. The rightward direction of the timeline aligns with the convention of right-to-left reading and writing systems, and it is processed with a momentum that requires less effort and time compared to processing in the leftward direction.

4.2.3 Metaphorical schemata underpinning the temporal-spatial association

Viewers' perception of temporal information serves as a benchmark for interpreting future time in two ways. Two metaphorical schemata, namely ego-moving schemas and time-moving schemas, are used to understand time in the future [137, 138]. The first schema conceptualizes time as the ego progressing along the timeline towards the future (e.g., approaching the deadline). The second schema likens the timeline to a river or conveyor belt moving from the future to the present (e.g., the deadline is approaching) [131, 139, 140]. These two schemata clearly define the distance between the present and the future, and can be extended to describe how people perceive an event (Figure 4.3).

An event has its own timeline. When this timeline is synchronized with an individual's timeline (e.g., when making plans for a future event), the ego-moving schema is likely to be adopted. In this schema, individuals perceive themselves as moving forward and estimate when they will approach the end of the event in the future. In this condition,

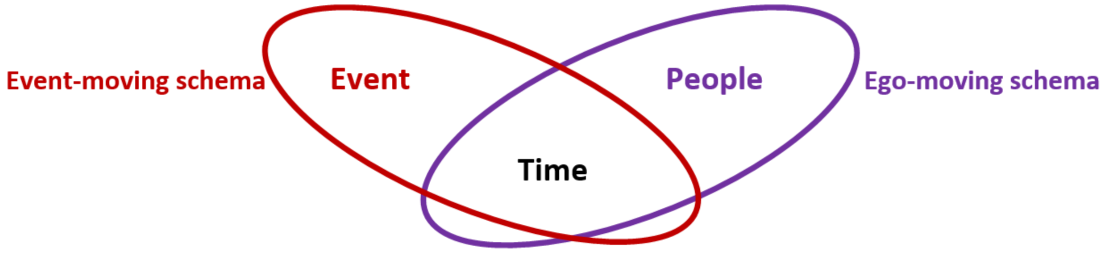


Figure 4.3 : Two schemata when people think about the time of a coming event

a rightwards (vs. leftwards) timeline prompts the viewers to mentally rehearse moving quickly towards the event's conclusion based on their perception of the image. As a result, their perceived time elapsing is used to directly estimate the event's progress, and they perceive the future to be close and time to be passing quickly. Based on this, we propose the following hypothesis:

H1a: The present would be perceived to elapse faster when visualized rightwards (vs. leftwards) moving to the future, such that the individual's future is perceived near.

Alternatively, the timeline of an event may be determined by external factors such as committee decisions or natural disasters, regardless of an individual's will or participation. However, in reality, this objective timeline is coupled with the subjective perception of time. In such cases, people tend to perceive themselves in a fixed position and assume that the event progresses as time passes and approaches them. We refer to this schema as the "event-moving schema," emphasizing the coupling of the event timeline with the objective timeline. Viewers adopt this schema when assessing the progress of an event or the efficiency of a time interval.

Given that the event is independent of the viewer's timeline, viewers first estimate the time required to complete the entire event at a hypothetical speed and then compare this with the given progress or duration. This transition from the viewer's timeline to the event timeline occurs during two stages of processing information. Viewers use their perceived progress as a scale to evaluate the event's progress. A larger scale underestimates the actual progress and speed of the event.

Specifically, when viewers observe a rightwards (versus leftwards) timeline, they perceive a rapid completion of the event. Consequently, they believe that each unit of time allows for more event progress. This perception leads to the belief that the given time interval elapses slowly and lasts longer. The consequences of this timeline switch can be likened to an individual getting off a fast time-traveling shuttle and perceiving time to pass slowly. This slow passage of time makes people impatient while waiting for desired events and confident in dealing with undesired events.

One could argue that the effect of the rightwards timeline has alternative explanations other than the perceived slower time passage. The Space-Number-association of Response Codes (SNARC effect) might provide one such explanation. The SNARC effect explains the mental representation of mathematical properties in a horizontal space. It suggests that larger numbers lead to rightward responses, while smaller numbers lead to leftward responses. This effect is automatically activated when processing Arabic numbers [141]. Applying the duration perception, people respond faster to short intervals with the left than the right hand and faster to a long interval with the right hand than the right hand [134]. The effect suggests that rightward is associated with longer duration, which could explain the same consequences in the perceived adequate time interval. We argue that the SNARC effect addresses the right position consistent with a large number.

By contrast, our research focuses on the same time interval visualized by rightwards and leftwards timelines. Viewers judge the given time interval by mentally simulating the passage of time according to the visualized movement orientations, which differs from the mechanism of the SNARC effect. Overall, we propose that:

H1b: An event in the future visualized by the rightwards timeline is perceived as slower elapsing than that visualized by the leftwards timeline.

4.2.4 The interaction of the coming event desirability and ego (vs. event) moving schema

The upcoming events can be categorized as either desired or undesired. The time intervals between the present moment and a future desired event are perceived as beneficial, allowing individuals to savor the anticipation of fulfillment [142]. People expect to have an adequate amount of time to fully enjoy and optimize the utility of the desired event. On the other hand, the time interval between the present and an undesired event is seen as an opportunity to prepare for the impending threat. People anticipate delaying the event in order to have more time for preparation and to minimize potential losses. As a result, people tend to extend the time interval before both desired and undesired events.

Individuals selectively process visually presented temporal information related to the desired or undesired events. Previous research has shown that experiences of positive emotions, such as happiness, tend to induce an ego-moving schema and a greater sense of control [138, 143]. Conversely, experiences of negative emotions, such as anxiety and depression, are more likely to lead to a passive perception of time. The ego-moving schema assumes that the individual is a more capable actor than the event-moving schema. When individuals mentally simulate being in control of the situation (compared to a passive position where time moves), their ego is triggered, resulting in a heightened sense of control. These individuals may lack the motivation to carefully consider the visual information and optimize their decision-making by actively adjusting their schedules. Therefore, the ego-moving schema weakens the influence of the timeline direction of a desired coming event. In contrast, viewers in the event-moving condition adopt a passive position and are motivated to enhance their sense of control by closely attending to visual information about the desired event. Based on these observations, we hypothesize:

H2a: The ego-moving schema weakens the impact of the timeline direction of a desired coming event.

When confronted with an impending threat or undesired event, individuals assess their ability to mitigate potential losses. The ego-moving schema implies that individuals see themselves as capable agents capable of taking effective actions, leading them to pay extra attention to information about the direction of the timeline. On the other hand, the event-moving condition places individuals in a passive state, reducing their perception of agency and leading to decreased engagement with temporal information. Based on these observations, we propose the following hypothesis:

H2b: The event-moving schema weakens the impact of the timeline direction of an undesired event.

In the subsequent section, we conducted three studies consisting of five experiments to provide empirical support for the hypotheses.

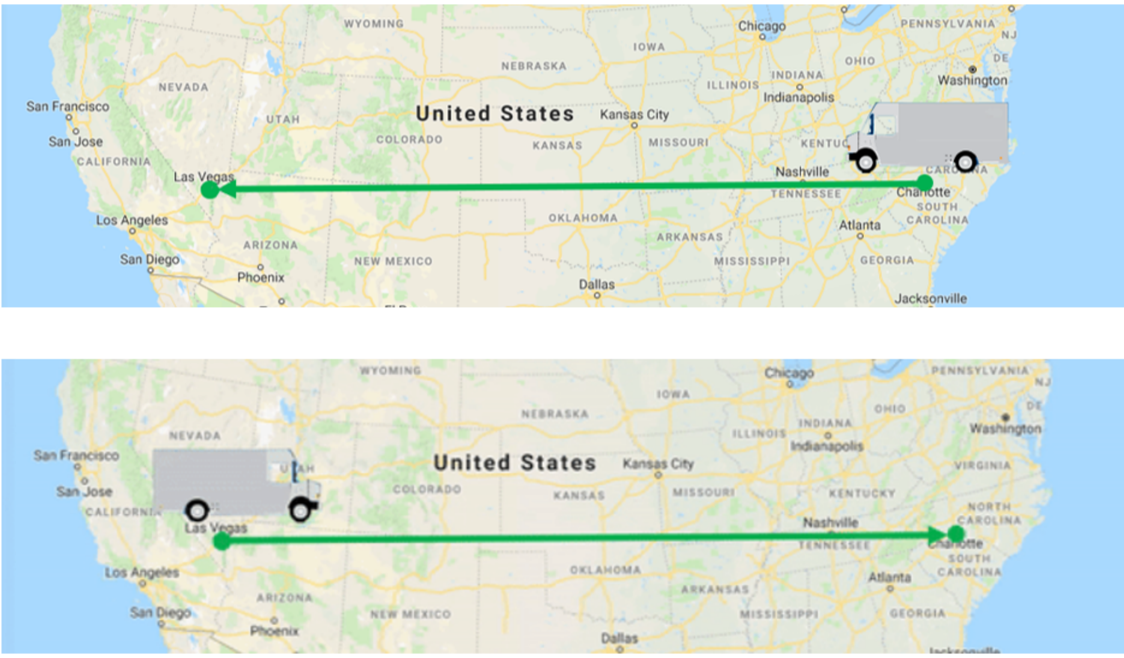


Figure 4.4 : The stimuli design for two groups in Study 1

4.3 Study 1 Perceived Speed of Leftwards and Rightwards Movement

4.3.1 Study 1a Lorry animation

Study 1 was designed to test the main effect of the rightwards and leftward movement on the perceived speed when a given visual object moves the same distance within the same duration.

Stimuli. We created two versions of the animations. The first frames of the animations were shown in Figure 4.4, in which a lorry starts from a departure city. The animations show a lorry moving from the departure city to the destination city at a given speed. It takes 7 seconds to complete a round of simulation. The animation repeatedly plays before the participants click to end the play. In one animation, the lorry moves from left to right (east to west), delivering the package from Las Vegas, NV, to Charlotte, NC, United

States. In the second animation, the lorry moves the opposite direction (west to east), from Charlotte to Las Vegas. The only difference between the two versions of the animation is the moving direction of the lorry.

Participants were randomly assigned to two groups. We asked participants to look at one of the animation versions and imagine that they would have to mail a one-pound package to the destination in 2200 miles, and their image would be delivered by the lorry. The participants were assumed to interpret the animation in the event-moving schema. The delivery of the products as an event approaches the destination where they were.

Procedure. We recruited 217 participants from Amazon Mechanical Turk (mTurk), a crowdsourcing marketplace that allows individuals to complete surveys. The participants registered their permanent residential locations as the United States, with English as their native language. The participants were asked to answer two simple questions after exposure to visual stimuli. Among the participants, 109 were assigned to the rightward delivery condition, and 108 were assigned to the leftward condition. First, they were told to estimate how many days it would take to complete the delivery. Then they were told to estimate the delivery fee between the two cities. To help them estimate, they were told the mail price between Kansas City, Missouri, and Minneapolis, Minnesota (440 miles) is around 17 dollars. Their delivery fee should range from 20-45 dollars. We choose Kansas and Minneapolis as examples to avoid the influences of horizontality when processing the price baseline information. The two cities share similar longitudinal positions, and the delivery route can be visualized as a vertical line.

Results. A one-way ANOVA shows that the rightwards delivery was estimated to be delivered in 8.11 days on average, and the leftwards delivery in 7.31 days (M_{right}=8.11,

SD_{right}=2.96, M_{left}=7.31, SD_{left}=2.91, F(1, 215)=3.98, *p*=.047). The results show that the rightwards lorry is perceived to move slower than the leftwards lorry. Therefore, it takes more days to complete the delivery. The results of one-way ANOVA did not find a statistical difference between the estimated price in the two conditions (M_{right}=32.37, SD_{right}=7.85, M_{left}=31.31, SD_{left}=8.31, F(1, 215)=0.92, *p*=.339). The results suggest that the participants estimated duration of the delivery is not caused by the estimated service payment.

Discussion. Study 1a manipulates the participants' mental simulations of the rightwards and leftwards movement and shows that the rightward momentum of eye-movement behavior causes the perceived low speed of the rightwards moving object and estimated longer duration to complete the given distance. The similar estimated service rate suggests that the service quality or price in the two cities cannot explain the difference in the delivery time. The experiment provides evidence to support H1b.

One may challenge the results of Study 1a for the following issues. First, animation strengthens the manipulation of mental stimulation. The effect of leftwards and rightwards movement may not be replicable when using static images for manipulation. Second, the reputation of Las Vegas and Charlotte may raise associations as the confounder of the results. Third, the main effect of rightwards movement when given time or distance was requested for judgment in the event-moving schema when the visualized event does have a clear interpretation tendency between the two schemata. Therefore, we conducted Study 1b using static images to show the robustness of our findings.

Figure 4.5 : The visual stimuli design for Study 1b

4.3.2 Study 1b: Static Image

Stimuli Design. We visualize how a consumer comes to get their online ordered products colored green (Figure 4.5). Grey blocks separate the consumer and the product, suggesting the time interval used for delivery. The participants were told that they had paid for the service that promised delivery within three days and that "they were approaching the product reception." Then they are asked to look at an image carefully. The image is randomly selected from the pair of visual stimuli in Figure 4.5. Then, participants were required to report how long they believed the product would be delivered and how much they needed to accelerate the delivery. The two questions request participants first to rehearse the delivery process and establish the baseline of time elapsing speed, then use the baseline speed to judge the delivery that is out of their control.

Procedures. Eighty-three second-year undergraduate students (44 in the group of rightwards timeline and 34 male) were recruited from a major university in the United States. They participated in the experiment for credits. They were randomly assigned visual stimuli on a computer screen and then instructed to imagine that they purchased 150 dollars of organic food online and paid 10 dollars for delivery services. Then look at the figure for at least 10 seconds. They were told, "you are getting your delicious organic food in 72 hours." Then they were asked how many hours the package would take before it was received by selecting a number on a scale ranging from 1 to 100 hours. They then asked to report to what extent they needed the package delivered faster (1=Completely not, and 7= Extremely need).

Results and Discussion. A one-way ANOVA showed that the rightwards direction led to a marginally significant longer estimated duration to deliver the product (M_{right}=71.98, SD_{right}=8.36, M_{left}=67.15, SD_{left}=14.19, F(1, 81)=3.59, *p*=.062) and a marginally significant higher need for faster delivery (M_{right}=4.32, SD_{right}=1.29, M_{left}=3.67, SD_{left}=1.92, F(1, 81)=3.35, *p*=.071) than the leftwards one. The result replicates the findings using animation for manipulation and provides evidence that participants perceived the fast rightwards (vs. rightwards) movement in their mental timeline causes the described event to be perceived slower. The findings are consistent with H1b and provide an indirect understanding of H1a.

Both experiments in Study 1 tested the package delivery as the desired event, and consumers were not in charge of the delivery. When participants gain high control over their desired event or when participants are requested to process temporal information of the undesired event, the impact of horizontal movement direction needs further exploration.

4.4 Study 2 The Impact of Rightward Timeline on Time Elapsing Perception

Study 2 contains two experiments, each testing the viewers' perceived time elapsing when processing the temporal information of undesired and desired coming events.

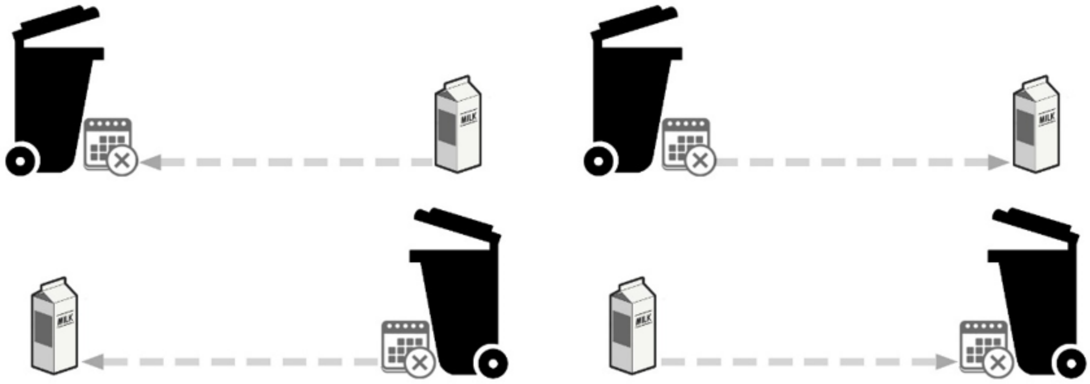


Figure 4.6 : The stimuli design for Study 2a

4.4.1 Study 2a Undesired coming expiration

Stimuli Design. We created visual stimuli for a 2 (rightwards vs. leftwards moving) by 2 (ego vs. event moving) experiment design as shown in Figure 4.6. Participants were reminded that they purchased a box of milk that had to "be used before the expiration." We created the icons of milk, trashcan, and calendar. The trashcan and calendar are positioned together to refer to the expiration date. In the ego-moving schema, the milk moves to the trashcan. Here, the milk consumption is under individuals' control, and the milk expiration timeline is coupled with the individual's consumption timeline. Therefore, the ego-moving schema is applicable. In the event-moving schema, the trashcan moves toward the milk. The moving direction was set either rightwards or leftwards. Viewers were randomly assigned to one of the four images in Figure 4.6 and told to imagine the event of milk expiration.

Procedures. We recruited two hundred and two participants from a Chinese online panel, www.wjx.com, a leading online survey platform in China, with over 10 million registered users and more than 500,000 surveys conducted every day. The participants were randomly assigned to view one of the four visual stimuli in their own space on a computer. Among the participants, 55, 48, 51, and 48 were assigned to the rightwards-ego-moving, rightwards-event-moving, leftwards-ego-moving, and leftwards-event-moving conditions, respectively. Participants were told that they had bought 1500 milliliters of milk. Before they put it in their refrigerator, they saw the image that remained to drink before expiration in seven days. Then they were asked how likely they believed they would finish drinking the milk before the expiration date (1= completely impossible, and 7= definitely will). If participants perceived a high moving speed, they would report being unlikely to finish drinking the milk; otherwise, they would be confident to drink all before expiration.

Results and Discussion. First, a one-way ANOVA showed that the direction to the right led to significantly higher confidence in finishing drinking before the expiration date than the left (M_{right}=5.55, SD_{right}=1.22, M_{left}=5.15, SD_{left}=1.30, F (1, 200)=5.16, p=.024). The results show that the rightwards movement was perceived more slowly than the leftwards movement and caused a higher confidence level to avoid an undesired consequence.

The interactive effect of the moving schema and moving direction is significant F(3, 198)=4.74, p=.031. When the box of milk is assigned moving (i.e., the ego-moving schema), rightwards movement leads to significantly higher perceived confidence in consumption before expiration (M_{right}=5.73, SD_{right}=1.27, M_{left}=4.96, SD_{left}=1.41, F(1, 104)=8.65, p=.004). When the trashcan is assigned moving (i.e., the event-moving schema), rightwards movement does not cause a significant difference in viewer perceived confidence (M_{right}=5.35, SD_{right}=1.14, M_{left}=5.35, SD_{left}=1.14, F(1, 94)$<$1). The results

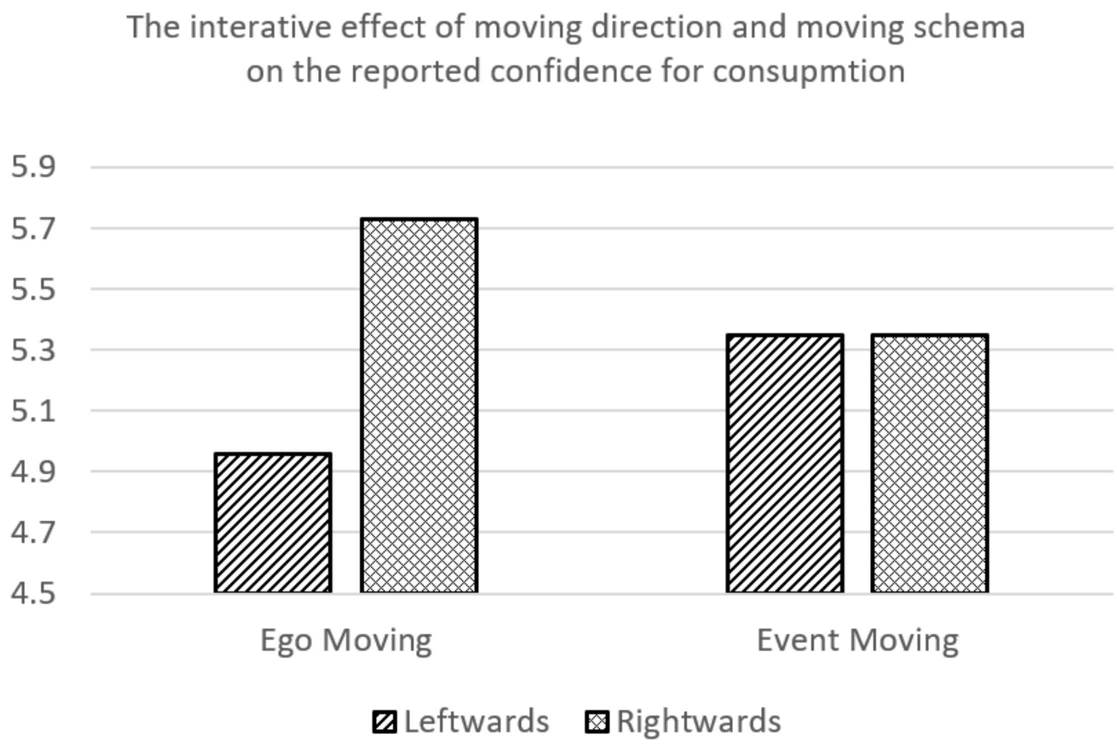


Figure 4.7 : The interaction of moving direction and moving schema on time perception for Study 2a

(Figure 4.7) show that rightwards movement makes a difference exclusively when people acknowledge the possibility of coping with undesired consequences. When such a possibility is withheld by the event-moving schema, the impact of the rightwards movement disappears. The results support H2b.

4.4.2 Study 2b Approaching vacation as a desired event

Stimuli Design. We created four illustrations as visual stimuli for a 2 (rightwards vs. leftwards moving) by 2 (ego vs. event moving schema) design following the same way in Study 1a. The group of ego-moving schema was shown as "I am going to have a vacation." While the group of event-moving schema was shown as "the vacation is

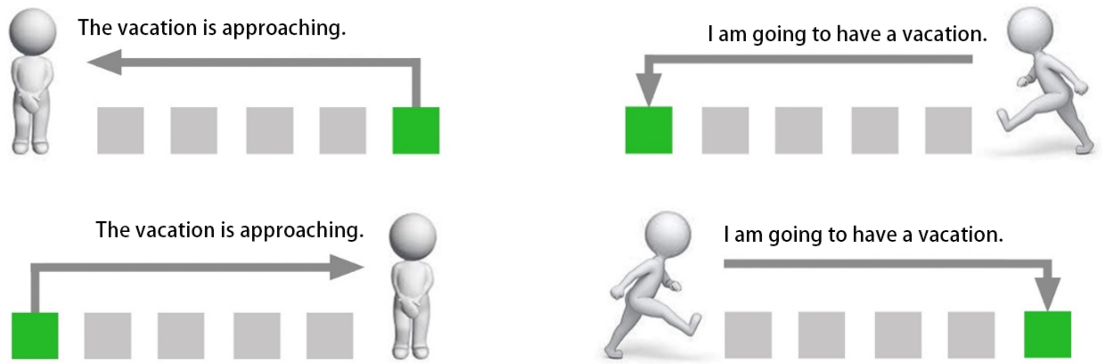


Figure 4.8 : The stimuli design for four groups in Study 2b

approaching." A timeline was manipulated rightwards or leftward, indicating the interval between the present and the time when the vacation starts (Figure 4.8).

Procedures. One hundred and thirty-eight participants from a Chinese online panel (www.wjx.com) were randomly assigned to one of the four visual stimuli on a computer. Among the participants, 33, 35, 38, and 32 were assigned to the group of rightwards ego-moving schema, rightwards event-moving schema, leftwards ego-moving schema, and leftwards event-moving schema, respectively. Participants were told to look at the given visual stimuli and imagine the following scenario.

You worked hard and performed excellently last year. Your organization awards you a paid vacation to Jeju Island, Korea, which is right your dream destination. You are excited. Your boss asked you to register the date when you would like to take the vacation on a given webpage. You can choose any date in the following 30 days. In how many days would you like to leave for the vacation?

Vacation is desired. The interval between the present and a dream vacation trip allows people to savor and anticipate the coming happiness. The interval extension provides extra benefits. The rightward momentum would cause perceived fast time elapses, which motivates the participants to elongate the interval for sufficient savoring time.

Note, Study 1a and 1b and Study 2a asked participants to report their perception about a given time interval in the future based on their perceived time elapsing from mentally simulating the timeline. The lorry in Study 1a and the delivery speed in Study 2a are behind the mentally rehearsed movement and were perceived as slow. In Study 2a, the milk expiration simulation completes faster when primed by the rightwards (vs. leftwards) timeline, and therefore the given duration of seven days seems sufficiently long for milk consumption. Differently, Study 2b adopts a fixed distance in the image to represent a customizable interval. The perceived time moving speed is the mentally simulated timeline moving speed and is directly used in choosing the favorite date for vacation.

Results and Discussion. The ANOVA analysis showed that rightwards movement led to significantly more waiting days before a vacation than leftwards movement (M_{right}=14.41, SD_{right}=7.08, M_{left}=11.70, SD_{left}=6.54, F(1, 136)=5.47, *p*=.021). The results suggest that people rehearse the time elapsing faster by looking at the rightward timeline than the leftward timeline. To savor more, they elongate the waiting duration by registering at a later date. The interactive effect of the subject of movement and moving direction is significant F(3, 134)=3.24, *p*=.065. In the event-moving schema, the rightwards timeline causes significantly more days before vacation than the leftwards timeline (M_{right}=15.37, SD_{right}=6.81, M_{left}=10.44, SD_{left}=6.04, F(1, 65)=9.77, *p*=.003). In the ego-moving schema, timeline direction does not cause a significant difference in waiting days (M_{right}=13.39, SD_{right}=7.31, M_{left}=12.76, SD_{left}=6.84, F(1, 69)$<$1, *p*=.71). The results (Figure 4.9) indicate that when people perceived a sense of control to make a

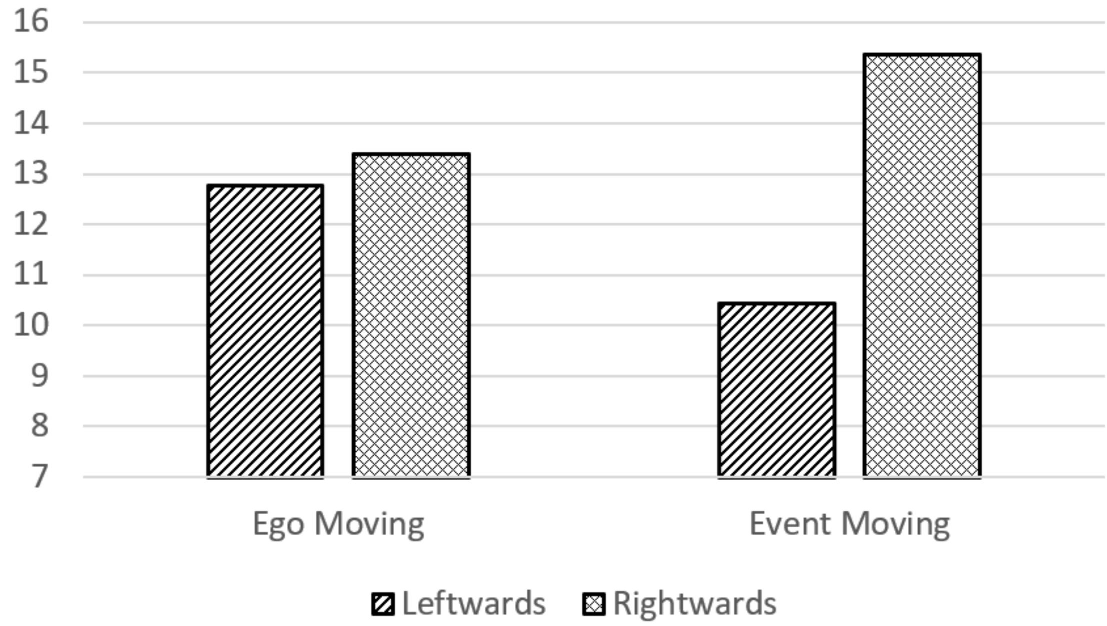


Figure 4.9 : The interaction of moving direction and schema on time perception for Study 2b

time-related decision, they react insensitively to the timeline direction. When they are positioned in a passive position, they would be motivated to adjust the waiting time duration based on the perceived time elapses. The results support H2a.

4.5 Study 3 The Efficiency of The Premium Express Delivery

We conducted Study 3 to explore the mechanism by which the direction of the timeline influences the perceived delivery speed.

Stimuli Design. We follow the scenario of delivery service in Study 1b and created four pairs of illustrations for a 2 (moving schema: ego vs. event moving) by 2 (moving direction: rightwards vs. leftwards) experiment design (Figure 4.10). Each pair of illustrations contains an image at the left depicting the default delivery service within 72

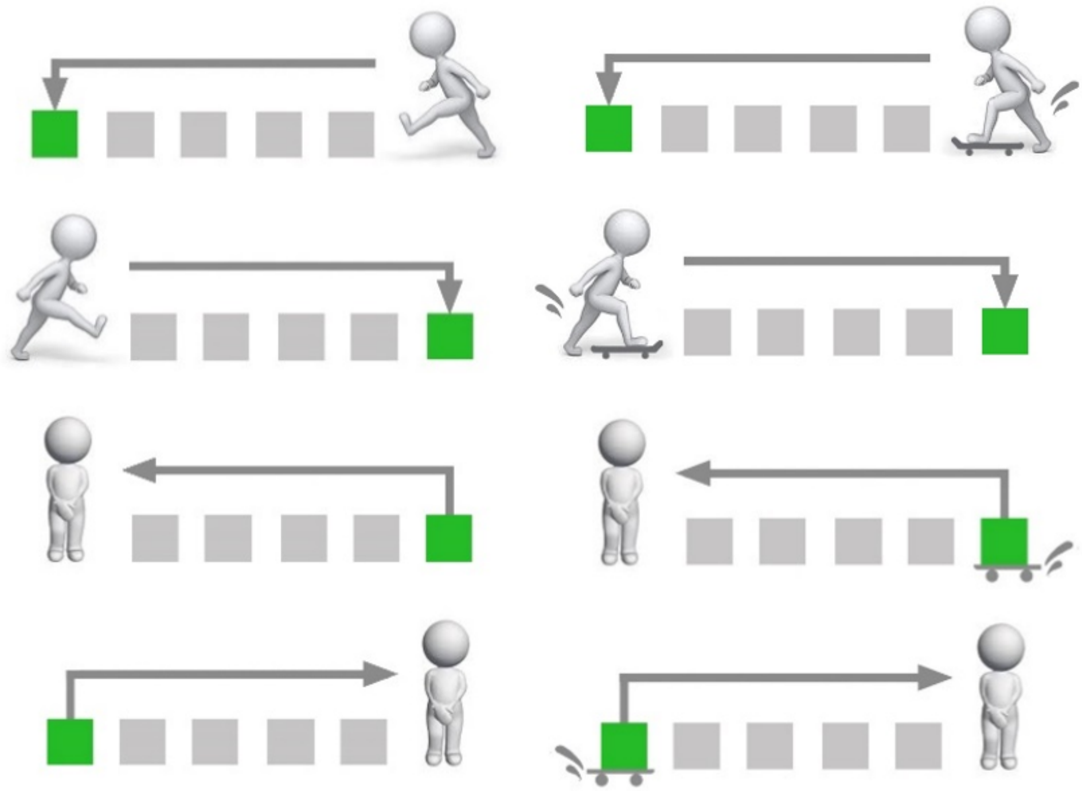


Figure 4.10 : The four pairs of experimental stimuli for Study 3

hours and an image at the right indicating the premium delivery service. The second image contains a skateboard, suggesting delivery speed acceleration.

Procedures. We recruited one-hundred and sixty-seven participants from a major university in northern China. The participants were third- and fourth-year students, mostly majoring in engineering and aged from 20-24. Among them, 71 were female. They were randomly assigned a pair of visual stimuli on a computer among the four pairs in Figure 4.10. As a result, 72 were in the ego-moving group and 68 were in the rightwards-moving group).

First, participants were shown the image of the default service (shown as the left image in each pair) and instructed that the image describe the delivery services of an online shopping package. They were told that “You ordered a box of peaches from a well-known place of the original for 150 yuan. The default delivery will take three days, at the price of 10 yuan”. The participants in the event-moving group were told that“your delicious fruit will reach you in 72 hours”; by contrast, the participants in the ego-moving group were told that “you are getting your fruit in 72 hours”. Participants were asked to evaluate how fast the fruit is delivered (1= very slow, 5= very fast), their perceived sense of control (“I am completely in control of the delivery time,” 1=strongly disagree, and 7= strongly agree), and their perceived efficacy of the delivery (“The delivery is extremely efficient,” 1=strongly disagree, and 7=strongly agree).

Then, they were shown the paired image of the premium service (shown as the right part in each pair) and told that premium services could accelerate the delivery. “Now premium delivery services are available.” The participants in the event-moving-moving group were shown that “The fruit Package can reach you in 24 hours. Less time. Better taste.” Those in the ego-moving group were shown that “You are getting your Fruit package in 24 hours. Less time. Better taste.” Again, participants were asked to report their perceived efficacy of the premium delivery service.

Results and Discussion. ANOVA analysis shows a significant interactive effect of moving direction and moving schema on the perceived speed of the delivery ($F(3, 163)=6.34$, $p=.013$). The main effects of moving schema and moving direction are not statistically significant. In the ego-moving schema, the rightwards movement is perceived as not significantly different from the leftwards movement (M_{right}=2.50, SD_{right}=.77, M_{left}=2.26, SD_{left}=.73, $F(3, 163)=1.78$, $p=.153$). We can infer that as the package reception is desired, viewers in the condition of ego-moving had been primed with an active image in

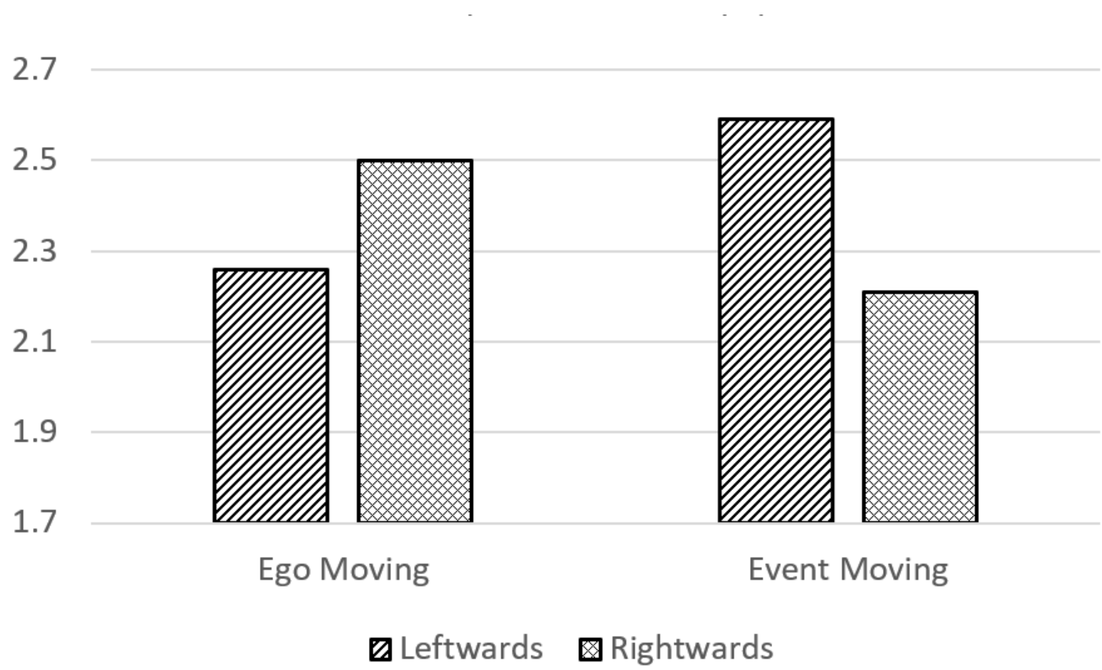


Figure 4.11 : The interaction of moving direction and schema on perceived delivery speed.

acquiring the package. They perceived an adequate sense of control and were less sensitive to the given visual stimuli.

However, in the event-moving schema, the rightwards movement is perceived as slower than the leftwards movement (M_{right}=2.21, SD_{right}=.78, M_{left}=2.59, SD_{left}=.84, F(3, 163)=2.76, *p*=.044). The results (Figure 4.11) show that in the event-moving schema, viewers imagine that the event of product reception at a future time point is approaching. The rightwards momentum of eye movement causes a quick simulation. The participants perceived the fast speed of the package delivery, such that the rightwards moving package is assumed to complete sooner than the leftwards one (H2a).

A repeated measure ANOVA was performed to compare the effect of moving direction on the perceived delivery efficacy improvement. The leftwards premium delivery service was perceived as more efficient than the rightwards one (F(1, 165)=5.32, *p*=.022). We

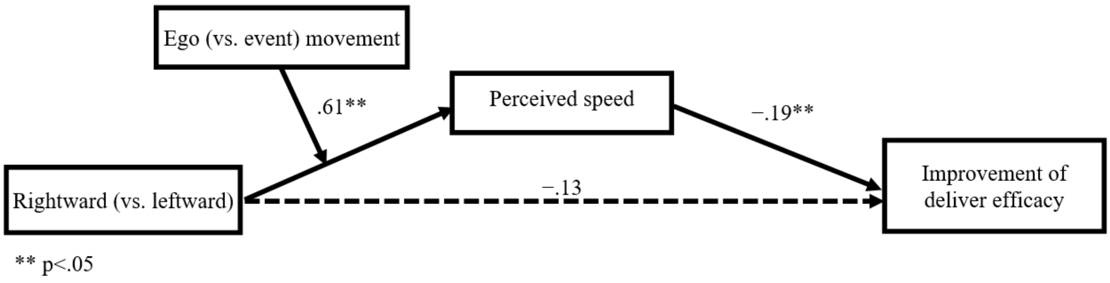


Figure 10: The moderated mediation effect of perceived speed

Figure 4.12 : The moderated mediation effect of perceived speed.

did not find a significant interactive effect of the moving direction and schema on the perceived improvement of the delivery speed.

We further tested the moderated mediation effect of perceived delivery speed on the improvement of delivery speed (PROCESS Model 7, bootstrapping samples=5,000; see Figure 4.12). The moderated mediation effect is significant (95% CI= -.296 -.002). The direct effect was insignificant ($p \geq .10$). The moderated mediation model shows that in the event-moving schema, the rightwards moving direction causes perceived high delivery speed but a low possibility of improvement by premium service. The results suggest that visualized rightwards movement may improve consumers' satisfaction with the default delivery, and visualized leftwards movement provides the opportunity for premium service recommendations and extra charges.

4.6 General Discussion

Overall, this research conducted five experiments in three studies to provide empirical evidence on the influence of the direction of time elapsing (rightwards vs. leftwards) on viewers' time perception. We demonstrate that physiological constraints, such as the inhibition of return, as well as cultural influences from reading and writing direction, shape an individual's rightwards momentum when mentally simulating a future event. A future event can be visualized using two schemas: an ego-moving schema, where individuals move along their timeline towards the event, or an event-moving schema, where the event approaches the individuals. The direction of movement, whether leftwards or rightwards, and the distances in a two-dimensional space refer to the time interval between the present and the occurrence of the event. The rightwards momentum in visual processing leads to contrasting perceptions of time between the two schemas. The ego-moving schema primes individuals to use perceived temporal moving speed to infer the progress of the event, resulting in subjective bias when estimating objective time due to the perceived scale. Specifically, rightwards movement causes a perception of faster movement and underestimation of the duration between the present and the future event (H1a, supported by evidence from Study 2b). In contrast, the event-moving schema requires viewers to differentiate their current timeline from the timeline of the given event. Viewers use their perceived movement speed as an estimate of the progress speed to judge durations or the time when the event will occur in reality. The rightwards direction primes a fast-moving timeline in their minds, creating an impression that the described event should have occurred sooner (H1b, supported by findings from Study 1a, 1b, and Study 2a). As a result, they perceive the progress of the described event to be slower, leading to an inflated interval.

This research also provides evidence on time perception in relation to desired or undesired events. Individuals in the ego-moving schema, with a sufficient sense of efficacy, are insensitive to the direction of movement of the desired future event (H2a). In contrast, individuals in the event-moving schema, who occupy a passive position to make a difference, lack the motivation to elaborate on temporal information and are insensitive to undesired future events (H2b).

First, this research addresses the potential of temporal information visualization in changing viewers' decision-making and advances the understanding of temporal-spatial association. Prior research has identified the right-future and right-large numerical magnitude association and applied the associations to multiple scenarios of information processing. For example, products suggesting a desirable feature in the future (e.g., modern style product or weight control product) located at the right (vs. left) are easy to process and generate consumers' favorable attitude [136]. Product profile images facing inward (vs. outward) toward the center (vs. edge) benefit the information processing [144]. Product orientation and consumers' swiping behavior when using applications on mobile devices impact consumers' product evaluation [102]. The research enriches the horizontal orientation literature by analyzing visualized rightwards and leftwards time elapsing direction. We highlighted how the interval between the present and the future when an event happens would be judged by the scale primed by given leftwards or rightwards movement information.

Second, this research contributes to the understanding of temporal perception by highlighting how visual information processing sets the foundation for judgment in event-moving and ego-moving schemas. While the association of the future with the right has become convention in revealing temporal information on interfaces, events can be conceptualized using either the event-moving or ego-moving schema, visually offering two options for horizontal arrangement. Individuals can be positioned on the left, approaching the future event, or the event can be positioned on the left, coming toward individuals who are waiting at a future time point. This arbitrary choice leads to inevitable bias in perception of time intervals. By examining temporal perception primed by horizontal movement direction, our research reveals the influence of physiological and cultural factors on the accurate delivery of semantic meaning. In doing so, we shed light on the importance of creating and updating visual rules according to context to ensure accuracy in expression.

Third, this research examines intertemporal decision-making for desired (vs. undesired) events and reveals how visual information about time is elaborated on and used in information processing. Drawing on classical literature that distinguishes time as either a cost or a benefit [142], our research identifies the boundary conditions under which visually represented temporal information is elaborated on, advancing our understanding of customers' impatience and savoring effects. We find that individuals are motivated to enhance their sense of control over desired events in the event-moving schema and to mitigate losses from undesired events in the ego-moving schema. This finding enriches the literature on loss aversion in the domain of temporal information processing.

4.7 Managerial implication

As an increasing number of timing decisions now require support from visualization, our findings have wide applicability in optimizing interface design and enhancing accurate communication for diverse tasks. The direction of movement, which may appear to be an arbitrary choice in visual communication, in fact plays a critical role in manipulating viewers' temporal perception. Interface designers should consider whether users anticipate an event as desired or undesired, as well as whether individuals are inclined to

Table 4.1 : Finding summaries and their application

	Event-moving schema		Ego-moving schema	
Event	Desired event	Undesired event	Desired event	Undesired event
Moving direction	Leftwards moving is perceived faster	No difference	No difference	Rightwards moving is perceived faster

think about the time interval in terms of the event-moving or ego-moving schema. Based on a thorough analysis, designers should select the appropriate orientation that is adaptive to these conditions in order to optimize users' experiences or service providers' performance. We have summarized the optimization approach according to our findings in Table 4.1. According to the table, using a progress bar that moves rightwards by default is a sub-optimal choice when consumers or customers are required to judge a given waiting duration (i.e., event-moving schema). Opportunities to enhance the visual impact arise when viewers are seeking improvement for undesired events in the event-moving schema or when they aim to avoid a reduction in gain from desired events in the ego-moving schema.

Compared to prior text-based communication, our research highlights the potential of using visualized information in collaboration with text to enhance users' experiences. Adapting visualized temporal information to users' needs offers operational flexibility for service providers. For instance, an automatic queueing system can depict the long waiting time as moving rightwards in an ego-moving schema, showing the queuer what they can expect and reducing abandonment rates immediately after booking. Similarly, a delivery system can visualize the product's movement as leftwards when asking consumers to rate their delivery time, while also providing customized pricing options. In an interface for a self-control task, illustrating progress as moving rightwards in the early stages can boost users' confidence in goal setting and task completion, while moving leftwards can indicate that they have reached a plateau and are facing challenges in maintaining their achievement. The visual element can effectively modulate users' temporal perception and cater to the served population for improved scheduling.

4.8 Limitations and Future Research

This research highlights the influence of visualized temporal information in the stage of information processing and judgment. However, time perception is a dynamic process, and it is unclear whether the visual influences on bias in the perception of time elapsing speed would be adjusted or corrected in subsequent stages. This could lead viewers to wait for a longer time, raising their expectations for the service and potentially resulting in disappointment. Future research should utilize first-hand empirical data to examine the sequential consequences of visualized temporal information, providing evidence from field studies to enhance the external validity of laboratory experiment findings.

This research hypothetically selected vacation duration and milk expiration as desired and undesired events, respectively, and tested the effects of moving direction and moving schema in two separate experiments. Future research should carefully design scenarios that are considered either desired or undesired by different individuals and investigate the viewers' processing of temporal information using consistent stimuli. Additionally, considering that people have a tendency to adopt specific metaphorical schemas when processing event information, future research should control the preference for schemas and design scenarios that are adaptable to both schemata.

This research focuses on the prospective outcome of temporal information visualization, but the extent to which the direction of time movement influences retrospective assessment remains unknown. Furthermore, it is unclear how people process temporal information when both the past and the future are involved in visualization and judgment. Future research should explore time perception in scenarios where mixed tenses are used to describe ongoing events.

Chapter 5

Conclusion and Future Directions

5.1 Conclusion

The dissertation investigates the impact of visual elements, such as shape, color, location, and orientation, on the usability of interface views. Understanding the processing of visual elements can fundamentally improve user-centered interface design. However, a mystery surrounds how these visual elements are perceived, organized, and interpreted. Scholars in fine arts (e.g., Sir Ernst H. Gombrich) and semiotics (e.g., Charles Sanders Peirce) have explored these key questions by examining how images convey visual objects in reality. Their work has provided valuable insights into styles, motifs, and the categorization of signs, advancing our understanding of visual information and driving efforts to establish a systematic framework of visual rules, analogous to what linguistics has achieved with languages [34, 145–147]. However, these endeavors have encountered challenges due to the inherent ambiguity and indeterminacy of semantic meanings associated with visual signs. Interpretation heavily relies on contextual constraints and domain-specific definitions. Subsequent research has focused on visual features within specific scenarios and examined their influences on various stages of visual information processing [29, 72, 148].

Given the widespread adoption of e-commerce that caters to a large global population of consumers, the visual design of business interfaces continually evolves and optimizes.

Interfaces, as complete artificially constructed systems of visual signs, adhere to established conventions while also creating new rules. Some rules arbitrarily assign semantic meaning and functions to newly created signs. Understanding how visual elements shape viewers' perception and interpretation within specific application scenarios represents a bottom-up approach to addressing fundamental questions in visual communication. For our studies, we selected network visualization, online product profile display, and temporal information visualization as the contexts in which we examine how shapes (with a particular focus on curves), color, location, and orientation influence users' information processing.

Chapter 2 explores the impact of edge bundling at various tension levels on user performance. It provides empirical evidence to understand the tradeoff between speed and accuracy in visual search, uncovering an inverted U-shaped relationship between tension and accuracy. This relationship is shaped by how bundling tension bends lines to increase complexity and cluster edges to reduce complexity. Moderate tension is advantageous in revealing skeleton information, assuming that the endpoints are discernible. Additionally, the study demonstrates that tension increases fluency and facilitates quick visual search.

Chapter 3 utilizes eye-tracking technology to analyze how color attributes, such as saturation, lightness, and color complexity, of product profile images, as well as their position on the webpage and the color features of neighboring images, influence their visual saliency. The findings confirm that lightness and color complexity decrease fixation duration, while saturation, being positioned at the top (compared to the middle and bottom) vertically, and at the center (compared to the side) horizontally, increase fixation duration. Further evidence highlights the interactive effect of position and color attributes, as well as the impact of neighboring images' color features in discerning the available color features for saliency optimization. These findings also illuminate the effect of adjacent displays and guide saliency optimization based on local information.

Chapter 4 examines the bias of time perception when individuals process visualized temporal information. A series of experiments shows that rightwards (compared to leftwards) time elapsing is perceived as fast and leads to an underestimation of the duration between the present and future events in the ego-moving schema. However, in the event-moving schema, rightwards movement results in an overestimation as viewers differentiate their timeline from the event timeline and utilize their perception of fast movement to judge the event. As a result, the described event is perceived as if it should have occurred sooner and unfolds slowly over time. Notably, viewers are less inclined to consider the direction of movement when the desired event is described in the ego-moving schema and the undesired event in the event-moving schema. Overall, this research sheds light on how physiological constraints and cultural factors contribute to the accurate representation of temporal information.

The dissertation contributes to interface design and visualization by examining the organization of visual elements and their impact on perception. The well-known Gestalt principle suggests that the whole of a design is greater than the sum of its parts, highlighting the importance of the interaction between visual elements. The research on edge bundling explores how varying bundling tension affects visual grouping and emphasizes the role of edge interaction in creating visual complexity. The study on product profile image salience investigates the influence of location and neighboring attributes on the saliency of a focal product, proposing a method for optimizing saliency based on local information. The research on temporal information visualization explores the interactive effect of time elapsing direction and metaphorical schema on time perception, while also examining how event desirability moderates the likelihood of visual information elaboration by viewers. These studies shed light on how visual elements are organized and when changes in visual features can have a significant impact.

The dissertation demonstrates how visual behavior adapts to different visual interfaces. We focused on network data visualization, product profile image presentation, and temporal information visualization, contributing to the domains of user experience and interface usability in business context. While vision research has advanced our understanding of visual behavior, the applicability and impact of these findings on usability require evidence. The use scenarios we examined are complex, requiring designers to consider various tradeoffs. Through in-depth exploration, we uncovered neglected, ambiguous, and counterintuitive facts. For instance, the edge bundling research discusses the tradeoff between speed and accuracy, emphasizing the importance of discernible endpoints when studying the effects of edge bundling. The research on product profile image salience considers the competition between products, highlighting the need for fine-tuned analysis to distinguish the focal product and addressing the difference between webpage visual saliency and recommendation priority. The research on temporal information visualization examines different perception schemata, challenging the intuition that the effect of rightwards (vs. leftwards) time movement is always consistent.

The dissertation illustrates the key stages when users process business data representation interfaces, focusing on recognition, attention, and perception bias. The research on edge bundling and product profile image salience investigates attention allocation from different perspectives. The former treats curves as collaborative visual objects, assuming a fast-processing speed is desired during goal-oriented visual search, while the latter explores the competition between product images for limited attention, emphasizing a longer fixation duration. The research on temporal information visualization emphasizes the accuracy of semantic interpretation as the final stage of visual communication. Visual information processing is a complex process. Our examination of processing speed, duration, and accuracy focuses on specific stages, allowing us to uncover the intricacies of visual communication and identify opportunities for optimizing visual experiences.

5.2 Future Directions

Visual representation involves establishing mapping relationships between visual stimuli and their meanings. These mappings can sometimes be arbitrary and customized, requiring users to learn them from scratch. Users must quickly adapt to the design and interpret visualized business data, which is a challenging task. This dissertation focuses on a specific stage of visual information processing, sets clear business goals, and offers insights to enhance business performance. Through an in-depth exploration within a specific context, this research provides localized knowledge with clear causal relationships. It is essential that future research takes a holistic view to advance the understanding of human-interface interaction as a whole that is greater than the sum of its parts. Future research should aim to provide an overview of how humans are supported by visualized information throughout the various stages of complex decision-making. Specifically, the following issues need to be addressed:

5.2.1 Unseen implicit rules and pre-requisition of visual interface interpretation

"Seeing is believing." Humans have a natural inclination to believe what they see. When users rely on visualized business data to draw conclusions, they often assume that the data has been carefully processed and is sufficiently valid to represent the actual business situation. However, visualized information tends to oversimplify complex realities. Nuances, contextual information, implicit constraints in data selection, prerequisites for causal inference, and contradictory facts are often overlooked or concealed. Without access to this crucial information, users may mistakenly identify false correlations and be led to inappropriate actions. Future research should focus on exploring how the inclusion of in-depth information in visualizations can enhance decision-making processes.

5.2.2 The transition of interface pages during multiple stages of decision-making

Complex decision-making requires robust data support. A successful business decision is highly contingent on the specific context and should take into account its multi-dimensional impact. For instance, while product promotion may boost sales in the short term, it could also lead to a significant number of product returns in subsequent periods due to customer regret. The decision to promote a product hinges on weighing the benefits derived from increased sales against the costs incurred from returns. To adequately consider both short-term gains and long-term losses, users must analyze sales and return data at the very least.

Multiple pages of business data visualization demand users to exert considerable cognitive effort in memorizing visual cues, contextual information, and data selection constraints. They may encounter difficulties in discerning the relationship between new and previously presented information. The sequence of information presentation, as well as the transitions between them, can significantly influence users' interpretation, decision-making, and subsequent actions. Prior research has suggested that the information previously exposed can serve as an anchoring point for evaluating and judging subsequent information [149]. Brief interruptions following exposure to risk information can notably reduce individuals' perception of risk and increase their inclination to take risks [150]. Future research should aim to identify the logical inferences drawn from information across multiple interfaces and explore how matching transitions to such logical patterns can enhance users' sense-making when utilizing business data.

5.2.3 Interpretable impact of humans' heuristic processing using visualization

Machine learning algorithms are extensively utilized for the analysis and identification of patterns within extensive datasets pertaining to human utilization of visualization techniques [151]. The knowledge acquired by artificial intelligence regarding human decision-making through visualization encompasses both rational and irrational responses to stimuli. The occurrence of irrational reactions, stemming from the heuristic processing of visual stimuli, is unavoidable and can significantly accumulate over multiple stages of processing. Subsequent research endeavors could compare decision-making outcomes based on the heuristic processing of visualized information with those derived from rational approaches, thereby establishing a foundation for assessing the influence of human heuristic processing on the quality of decision-making.

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