Encoding with Patterns: A Design Space and Evaluations

Encodage avec des Patterns : Un Espace de Conception et des Évaluations

Thèse de doctorat de l'université Paris-Saclay

École doctorale n°580: Sciences et technologies de l'information et de la communication (STIC)
Spécialité de doctorat: Informatique
Graduate School : Informatique et sciences du numérique.
Référent : Faculté des sciences d'Orsay

Thèse préparée dans l'unité de recherche **Laboratoire interdisciplinaire des sciences du numérique** (Université Paris-Saclay, CNRS, Inria), sous la direction de **Tobias ISENBERG**, Directeur de recherche.

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THESE DE DOCTORAT

NNT : 2024UPASG042

ÉCOLE DOCTORALE
Sciences et technologies de l'information et de la communication (STIC)

Titre: Encodage avec des Patterns : Un Espace de Conception et des Évaluations

Mots clés: *patterns*, variables visuelles, perception, esthétique, développement d'échelle

Résumé: Cette thèse vise à comprendre théoriquement et empiriquement les *patterns* en tant que variable visuelle. Les *patterns* ont été une variable visuelle importante dans la visualisation de données bien avant que l'impression en couleur ne soit devenue courante et abordable, et ils continuent d'offrir des avantages aujourd'hui. Ils sont particulièrement utiles pour les dispositifs à capacités limitées d'affichage en couleur, tels que les écrans *e-ink*, et sont essentiels pour améliorer l'accessibilité pour les personnes daltoniennes, malvoyantes ou aveugles. Les *patterns* possèdent des attributs riches qui peuvent varier pour coder des données. Cependant, s'ils sont utilisés de manière inappropriée, les *patterns* peuvent provoquer des effets visuels négatifs et être esthétiquement peu attrayants. Malgré le potentiel des *patterns*, les recommandations de conception que nous avons sont limitées sur la manière de les utiliser efficacement dans les visualisations. Cette thèse aborde cette problématique à partir de deux perspectives principales : la conception et l'évaluation.

Nous clarifions d'abord les ambiguïtés entourant les termes « texture » et « pattern », un problème provenant de la traduction de la *Sémiologie graphique* de Bertin. Inspirés par les travaux sur les variations de *patterns* et les incohérences dans l'utilisation des variables visuelles, nous les conceptualisons comme une variable composite avec des primitives graphiques. Un espace de conception est développé pour systématiquement décrire ces variations, structuré autour de trois ensembles d'attributs : les relations spatiales entre les primitives, les relations d'apparence entre les primitives et les caractéristiques d'apparence des primitives. De plus, nous relions le concept de *patterns* au processus de lecture de carte et discutons de l'encodage des informations géographiques dans les primitives.

Ensuite, nous étudions empiriquement l'utilisation de *patterns* en noir et blanc pour visualiser des données catégorielles. Nous nous concentrons sur deux types de *patterns* : les *patterns* géométriques (formes abstraites) et les *patterns* iconiques (icônes rappelant les catégories). Nous conduisons trois expérimentations ayant pour but d'étudier les différentes stratégies de conception et de mesurer l'esthétique et l'efficacité. Nos résultats montrent que les préférences esthétiques sont subjectives. En termes d'efficacité, les graphiques remplis de *patterns* ont obtenu des performances similaires à celles des graphiques ne les utilisant pas, avec des variations de performance en fonction du type de graphique. Cela indique que les *patterns* sont une option viable pour l'encodage des données.

Enfin, nous introduisons l'échelle BeauVis pour évaluer l'esthétique des visualisations, validée par des méthodes standards. Composée de cinq items (« enjoyable », « likable », « pleasing », « nice » et « appealing »), cette échelle fournit un instrument standardisé pour comparer l'apparence de diverses visualisations indépendamment du contexte.

En résumé, les principales contributions de cette thèse sont au nombre de trois : théoriquement, nous contribuons à la conceptualisation du *pattern* de variable visuelle et au développement d'un espace de conception pour les variations de *patterns* ; empiriquement, nous fournissons des résultats sur l'utilisation des *patterns* pour la visualisation des données catégorielles ; et, en termes de méthodologie d'évaluation, nous présentons le développement et la validation d'un instrument de mesure pour évaluer l'esthétique des visualisations. Notre travail démontre le potentiel du *pattern* de variable visuelle et établit une base théorique pour de futures recherches et applications des motifs dans la visualisation.

université PARIS-SACLAY

ÉCOLE DOCTORALE
Sciences et technologies
de l'information et de
la communication (STIC)

Title: Encoding with Patterns: A Design Space and Evaluations

Keywords: patterns, visual variables, perception, aesthetics, scale development

Abstract: This thesis aims to theoretically and empirically understand patterns as a visual variable. Patterns have been an important visual variable in data visualization since before color printing became common and affordable, and continue to offer benefits today. They are particularly useful for devices with limited color display capabilities, such as e-ink displays, and are essential for enhancing accessibility for viewers with color vision deficiencies or severe visual impairments. Patterns have rich attributes that can be varied for data encoding. However, if used improperly, patterns can result in negative visual effects and unappealing aesthetics. Despite the potential of patterns, there are limited design guidelines on how to use them effectively in visualization. This thesis addresses this gap from two primary perspectives: design and evaluation.

We first clarify the ambiguities surrounding the terms "texture" and "pattern," an issue that originated from the translation of Bertin's book Semiology of Graphics. Inspired by previous research on pattern variations and inconsistencies in Bertin's use of visual variables, we then conceptualize patterns as a composite visual variable with graphical primitives that can serve as sub-marks. We develop a design space to systematically describe pattern variations that can be used for data encoding. The design space includes three set of attributes: spatial relationships between primitives, appearance relationships between primitives, and individual appearance characteristics of primitives. In addition, we connect the concept of patterns to the map-reading process and discuss encoding geographical information into pattern primitives.

Next, we empirically investigate the use of black-and-white patterns for visualizing categorical data. We focus on two types of pattern: geometric patterns and iconic patterns. Geometric patterns use repeated abstract geometric shapes, while iconic patterns use repeated icons that may stand for data categories. We collect a set of pattern designs from visualization experts and conduct three experiments aimed at studying various design strategies, as well as measuring the aesthetics and effectiveness of these patterns. Our results show that aesthetic preferences are subjective. In terms of effectiveness, charts filled with patterns performed about equally well compared to unicolor charts, with performance variations depending on the chart type. This indicates that patterns are a viable option for data encoding.

Finally, we introduce a rating scale to comparer the aesthetic pleasure of visual data representations, which we call the BeauVis scale. We developed and validated this scale following standard scale development methods. This scale, consisting of five items ("enjoyable," "likable," "pleasing," "nice," and "appealing"), offers a simple and standardized instrument for comparing the visual appearance of different visualizations, independent of data or context.

In summary, the key contributions of this thesis are threefold: theoretically, we contribute to the conceptualization of the visual variable pattern and the development of a design space for pattern variations; empirically, we provide findings on the use of patterns for categorical data visualization; and, in terms of evaluation methodology, we present the development and validation of a measurement instrument for assessing aesthetic pleasure of visualizations. Our work demonstrates the potential of the visual variable pattern and establishes a theoretical foundation for future investigation and application of patterns in visualization.

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Synthèse en français

Cette thèse vise à comprendre théoriquement et empiriquement les *patterns* en tant que variable visuelle. Les *patterns* ont été une variable visuelle importante dans la visualisation de données bien avant que l'impression en couleur ne soit devenue courante et abordable, et ils continuent d'offrir des avantages aujourd'hui. Ils sont particulièrement utiles pour les dispositifs à capacités limitées d'affichage en couleur, tels que les écrans *e-ink*, et sont essentiels pour améliorer l'accessibilité pour les personnes daltoniennes, malvoyantes ou aveugles. Les *patterns* possèdent des attributs riches qui peuvent varier pour coder des données. Cependant, s'ils sont utilisés de manière inappropriée, les *patterns* peuvent entraîner des effets visuels négatifs et être esthétiquement peu attrayants. Malgré le potentiel des *patterns*, les recommandations de conception que nous avons sont limitées sur la manière de les utiliser efficacement dans les visualisations.

Notre question de recherche fondamentale est donc **comment utiliser esthétiquement et efficacement les patterns pour la visualisation de données**. Cette thèse comble cette lacune en s'appuyant sur des considérations larges et contrastées du *pattern* en tant que variable visuelle pour développer une théorie consolidée expliquant, explorant et utilisant les patterns dans la visualisation sous deux perspectives : la conception et l'évaluation. Plus précisément, nous répondons aux quatre questions de recherche suivantes:

RQ1 : Quelle est la variable visuelle « pattern » ?

Pour comprendre l'utilisation des *patterns* dans les visualisations, nous avons d'abord clarifié la terminologie ambiguë et recommandé le terme *pattern* plutôt que *texture* pour désigner la variable visuelle caractérisée par des éléments répétitifs dans les cartes et les graphiques. Le terme texture a des significations plus larges et varie dans son interprétation à travers les domaines de la visualisation et les disciplines connexes, ce qui rend le terme *patterns* plus approprié pour décrire cette variable visuelle. Inspirés par des recherches antérieures sur les variations de *patterns* et les incohérences dans l'utilisation des variables visuelles par Bertin, nous conceptualisons les *patterns* comme une variable visuelle composite avec des primitives graphiques en tant que signes graphiques secondaires.

RQ2 : Quelles variations de patterns pouvons-nous utiliser pour l'encodage des données ?

Nous développons un espace de conception pour décrire systématiquement les variations de *patterns* qui peuvent être utilisées pour encoder des données. L'espace de conception comprend trois ensembles d'attributs : les relations spatiales entre les primitives, les relations d'apparence entre les primitives et les caractéristiques d'apparence des primitives. De plus, nous relions le concept de *patterns* au processus de lecture de carte et discutons de l'encodage des informations géographiques dans les signes graphiques secondaires.

RQ3 : Comment mieux utiliser les patterns en noir et blanc pour les visualisations catégorielles ?

Ensuite, nous étudions empiriquement l'utilisation de *patterns* en noir et blanc pour visualiser des données catégorielles. Nous nous concentrons sur deux types de *patterns* : les *patterns* géométriques et les *patterns* iconiques. Les *patterns* géométriques utilisent des formes géométriques abstraites répétées, tandis que les *patterns* iconiques utilisent des icônes répétées rappelant les catégories de données. Nous conduisons trois expérimentations ayant pour but d'étudier les différentes stratégies de conception et de mesurer l'esthétique et l'efficacité. Nos résultats montrent que les préférences esthétiques sont subjectives. Pour l'efficacité, les graphiques utilisant des *patterns* se sont révélés aussi performants que les graphiques ne les utilisant pas, avec des variations de performance selon le type de graphique. Cela indique que les *patterns* sont une option viable pour l'encodage des données.

RQ4 : Comment comparer l'esthétique des visualisations ?

Enfin, nous introduisons une échelle de notation pour évaluer l'esthétique des représentations visuelles de données, que nous appelons l'échelle BeauVis. Nous développons et validons cette échelle en suivant les méthodes standards de développement d'échelle basées sur la théorie classique des tests. Cette échelle, composée de cinq items (« enjoyable », « likable », « pleasing », « nice » et « appealing »), offre un instrument standardisé et simple pour comparer l'apparence visuelle de différentes visualisations, indépendamment des données ou du contexte.

En résumé, les principales contributions de cette thèse sont au nombre de trois : théoriquement, nous contribuons à la conceptualisation du *pattern* de variable visuelle et au développement d'un espace de conception pour les variations de *patterns* ; empiriquement, nous fournissons des résultats sur l'utilisation des *patterns* pour la visualisation des données catégorielles ; et, en termes de méthodologie d'évaluation, nous présentons le développement et la validation d'un instrument de mesure pour évaluer l'esthétique des visualisations. Notre travail montre le potentiel de la variable visuelle *pattern* et fournit une base théorique pour des futures études et utilisations des *patterns* dans les visualisations.

Publications

Peer-Reviewed Journal Articles

1. Tingying He, Petra Isenberg, Raimund Dachselt, and Tobias Isenberg. BeauVis: A Validated Scale for Measuring the Aesthetic Pleasure of Visual Representations. *IEEE Transactions on Visualization and Computer Graphics*, 29(1):363–373, January 2023. DOI: 10.1109/TVCG.2022.3209390. HAL: hal-03763559

2. Tingying He, Yuanyang Zhong, Petra Isenberg, and Tobias Isenberg. Design Characterization for Black-and-White Textures in Visualization. *IEEE Transactions on Visualization and Computer Graphics*, 30(1):1019–1029, January 2024. DOI: 10.1109/TVCG.2023.3326941. HAL: hal-04167900

3. Anne-Flore Cabouat, Tingying He, Petra Isenberg, and Tobias Isenberg. PREVis: Perceived Readability Evaluation for Visualizations. *IEEE Transactions on Visualization and Computer Graphics*, 31, 2025. To appear. DOI: 10.1109/TVCG.2024.3456318. HAL: hal-04665390

Peer-Reviewed Conference Papers

4. Tanja Blascheck, Lonni Besançon, Anastasia Bezerianos, Bongshin Lee, Alaul Islam, Tingying He, Petra Isenberg. Studies of Part-to-Whole Glanceable Visualizations on Smartwatch Faces. In *Proceedings of the Pacific Symposium on Visualization (PacificVis, April 18-21, Seoul, Korea)*, pages 187-196, IEEE, Los Alamitos, CA, USA, 2023. DOI: 10.1109/PacificVis56936.2023.00028. HAL: hal-04018448

5. Anne-Flore Cabouat, Tingying He, Petra Isenberg, and Tobias Isenberg. Pondering the Reading of Visual Representations. In *Proceedings of the Journée Visu (June 22, Orsay, France)*, 2023. HAL: hal-04240900

Peer-Reviewed Workshop Papers

6. Alaul Islam, Lijie Yao, Anastasia Bezerianos, Tanja Blascheck, Tingying He, Bongshin Lee, Romain Vuillemot, Petra Isenberg. Reflections on Visualization in Motion for Fitness Trackers. In *Proceedings of New Trends in HCI and Sports Workshop (at MobileHCI, September 2022, Vancouver, Canada)*, ACM Press, New York, NY, USA, 2022. HAL: hal-03775633

7. Tingying He, Petra Isenberg, and Tobias Isenberg. Data Embroidery with Black-and-White Textures. In Lonni Besançon, Derya Akbaba, Andrew McNutt, Sara Di Bartolomeo, and Victor Schetinger, editors, *Proceedings of the alt.VIS Workshop (at IEEE VIS, 23 October, Melbourne, Australia)*, article no. 3, 5 pages, 2023. HAL: hal-04197527

8. Anne-Flore Cabouat, Tingying He, Florent Cabric, Tobias Isenberg, and Petra Isenberg. Position Paper: A Case to Study the Relationship between Data Visualization Readability and Visualization Literacy. In *Proceedings of CHI Workshop "Toward a More Comprehensive Understanding of Visualization Literacy"*, article no. 5, 10 pages, 2024. HAL: hal-04523790

In Preparation

9. Tingying He, Jason Dykes, Petra Isenberg, Tobias Isenberg. Toward an Understanding of 'Pattern' as a Visual Variable.

10. Alaul Islam, Tingying He, Anastasia Bezerianos, Bongshin Lee, Tanja Blascheck, Petra Isenberg. Visualizing Information on Smartwatch Faces: A Review and Design Space.

Acknowledgement

The past three years of my Ph.D. studies have been a transformative journey. I sincerely thank everyone who contributed to this experience, even though I cannot acknowledge each person by name here.

First, I would like to thank my advisor, Tobias Isenberg, for his invaluable guidance. I could not have imagined a better advisor. Tobias encouraged me to express my thoughts freely, trusted me to explore various ideas, and provided generous support. His emphasis on transparency and replicability has greatly impacted me. I am also fortunate to have closely collaborated with Petra Isenberg since my Master's program. Three years ago, Petra welcomed me to work on my Master's thesis with her and introduced me to the beautiful world of visualization. When I look back, I am still grateful for that opportunity. Her profound knowledge and great empathy have been incredibly influential throughout my journey. The countless hours spent discussing ideas around the round table with Tobias and Petra are among my most cherished memories.

I would also like to thank my committee members: Sarah Goodwin, Michèle Gouiffès, Theophanis Tsandilas, Wesley Willett, and Jo Wood. Michèle, as the president, skillfully organized my defense. Jo and Theophanis, as my "comité de suivi" (follow-up committee), have been providing feedback on this thesis since the end of my first year, witnessing its completion. Coordinating a suitable meeting time with committee members spread across the globe was extremely challenging, with my defense lasting until 8 p.m. for Sarah in Melbourne, Australia, and 4 a.m. for Wesley in Calgary, Canada. I am truly grateful to them for engaging in this discussion at such unconventional hours, and for their detailed, constructive reports on my thesis. The diverse expertise and thoughtful comments of all committee members have been instrumental in refining this thesis.

My collaboration with Jason Dykes on the pattern design space over the past year has been particularly inspiring. His creativity and thoughtfulness have encouraged me to explore new concepts and embrace the unknown.

I appreciate Raimund Dachselt for his exceptional insights during our work on the BeauVis project. Our discussions throughout the scale development process were crucial to its success.

I am also thankful to all my brilliant collaborators, including Lonni Besançon, Anastasia Bezerianos, Tanja Blascheck, Anne-Flore Cabouat, Florent Cabric, Jean-Daniel Fekete, Alaul Islam, Xinyu Lan, Bongshin Lee, Zihan Lu, Xinhuan Shu, Junxiu Tang, Romain Vuillemot, Yifang Wang, Lijie Yao, Lu Ying, and Yuanyang Zhong. I have learned a lot from each of them in various aspects.

I would like to thank Romain Di Vozzo and Fablab UPSaclay for providing us with equipment, training, and technical support during our exploration of data physicalization.

I am grateful to all my study participants, from visualization experts to anonymous respondents on Prolific. Their engagement laid the foundation for the research findings presented here.

I feel incredibly fortunate to have been part of the Aviz team, an ideal place for research. Thank you to all Avizians for participating in my pilot studies, providing feedback on my manuscripts and presentations, and offering support and inspiration through our daily interactions. I am honored to have shared the workspace at Aviz with Jean-Daniel Fekete, Petra Isenberg, Tobias Isenberg, Frédéric Vernier, Raimund Dachselt, Nivan Ferreira, Catherine Plaisant, Emanuele Santos, Ambre Assor, Florent Cabric, Mickaël Sereno, Gaëlle Richer, Eliane Zambon-Victorelli, Lijie Yao, Natkamon Tovanich, Alexis Pister, Alaul Islam, Jiayi Hong, Katerina Batziakoudi, Yucheng Lu, Sara Di Bartolomeo, Ameya Patil, Junxiu Tang, Lu Ying, Federica Bucchieri, Anne-Flore Cabouat, Nathan van Hille, Zihan Lu, Ebrar A. D. Santos, Lisa Taldir and Katia Evrat. I am especially grateful to Jean-Daniel Fekete, our team leader, for providing constant support to his team members, and to Katia Evrat, our team assistant, for her indispensable help with administrative matters.

I would like to thank all my dear colleagues and friends who have provided feedback on my research on various occasions. Special thanks to those who helped me proofread this thesis at the last minute: Katerina Batziakoudi, Florent Cabric, Yucheng Lu, Zongkai Peng, and Natkamon Tovanich.

I am sincerely grateful to Alexander Lex for the opportunity to join the Visualization Design Lab at the University of Utah as a postdoctoral researcher, which allows me to continue pursuing my passion for visualization research. Our initial conversation at the VIS 2023 conference was a pivotal moment in my career. Alexander's support and encouragement made my relocation to the United States a much smoother process, for which I am truly thankful. I look forward to continuing to grow as a researcher and contributing further to both the visualization community and the broader field of computer science.

My deepest gratitude goes to the most important people in my life. My friends have been precious companions throughout the long journey of existence. I appreciate all those meaningful or seemingly meaningless conversations that anchored me. I am fortunate to have met my partner, Zongkai Peng, who has brought many positive influences into my world. I would like to thank my grandparents. I vividly recall those afternoons from years ago, when we strolled along the riverbank, the path adorned with blooming white rain lilies. I must also mention my parents, whose contributions to my life are beyond what words can describe.

Finally, thank you for taking the time to read my thesis. I wish you the best in your future endeavors.

Declaration of Contribution and the Usage of the Pronouns "We" and "I"

The majority of the work presented in this thesis was carried out in collaboration with others, particularly in Chapter 2, Chapter 3, Chapter 4, and Chapter 5. As the first author of these collaborative works, I took primary responsibility for conducting most of the research, which included (but was not limited to) formulating the initial ideas, reviewing the literature, designing experiments, developing tools, collecting data, performing analyses, and drafting the initial manuscripts. My senior collaborators provided valuable guidance and constructive feedback throughout these projects.

I sincerely appreciate all my collaborators for their efforts and support. Consequently, I have used the pronoun "we" when referring to the collaborative parts and "I" when describing work carried out solely by myself.

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1 - Introduction

Data is everywhere in today's world, and the effective use of abundant and ubiquitous data is thus crucial. Visualization is an important tool that aids in the data analysis process. A commonly accepted definition of visualization is "the use of computer-supported, interactive visual representations of data to amplify cognition [41]."

The information visualization reference model [41, 50] describes how we transform raw data into visual representations and ultimately into insights that we use for sense-making. This model structures the visualization process into multiple steps, with a core step being the visual mapping, i.e., the mapping of data values to visual variables [41].

Visual variables, also referred to as visual channels, are attributes of graphical elements—referred to as "marks"—whose appearance can be manipulated to encode data [132]. The concept of visual variables provides an influential and fundamental framework for visualization design and research [153]. Therefore, it is crucial to identify and articulate the basic visual variables that can be manipulated to encode data effectively [119].

We have quite a few visual variables at our disposal, such as *position*, *hue*, or *size* and their effectiveness ranking has been the subject of much research and discussion in our field [54, 120, 126]. Among the available visual variables is one that researchers call *pattern* [117], which currently lacks a clear definition but typically features repetitive dots or lines . In this thesis, I focus on this visual variable, *pattern*.

1.1 . Pattern as a visual variable

Pattern is a powerful visual variable with broad application potential, and it was already in use for a long time before color printing became affordable and common practice. A century ago, pattern was an important visual variable for data mapping in news graphics [30, 31], often featuring beautifully hand-crafted representations. In Figure 1.1, I present examples from Bertin's book *Semiology of Graphics* [14, 15] and in Figure 1.2, and in Figure 1.2, I include examples from Brinton's book *Graphic Methods for Presenting Facts* [30]. Both of these works have served as sources of inspiration for us.

Patterns continue to offer many benefits in visualization today, particularly by enhancing accessibility in scenarios where the use of color is limited or unavailable [66, 102, 161, **?**]. From a device perspective, black-and-white visuals can improve the expressiveness of visual representations on devices with limited color display capabilities, such as e-ink displays. In addition, visu-

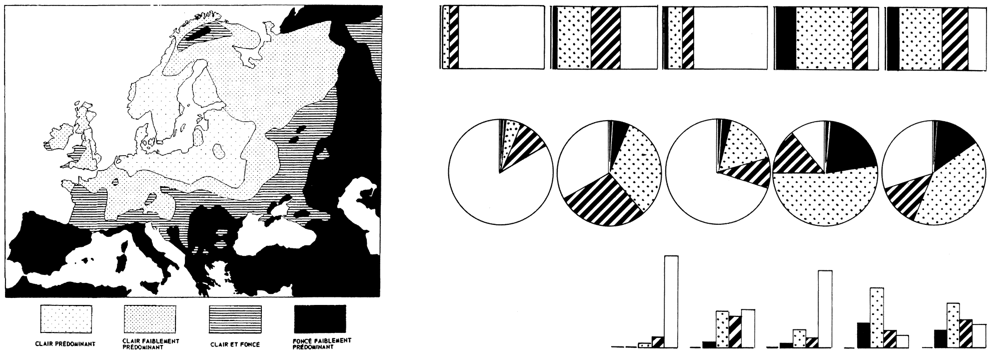


Figure 1.1: Examples of visualizations with black-and-white pattern from Bertin [14, 15]; © EHESS, used with permission.

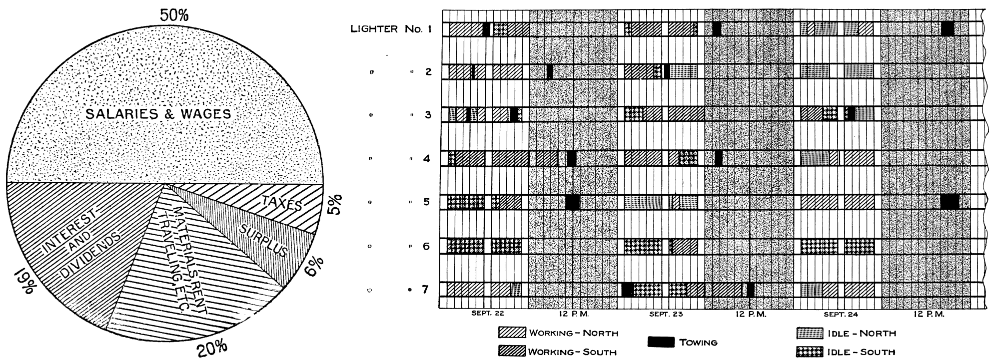


Figure 1.2: Examples of visualizations with black-and-white pattern from Brinton [30]; the images are in the public domain.

alizations with few colors can be applied in physical display contexts such as knitting, embroidery, or 3D printing. From a visualization reader's perspective, using patterns instead of colors can help prevent unintended data-to-color associations and make visualizations more accessible to individuals with color vision deficiencies. Moreover, encoding data in black-and-white enables us to extend visualization techniques to target groups with more severe forms of visual impairments: Black-and-white visualizations can be turned into embossed representations that can be touched and felt.

Despite the historical context and the potential benefits of *pattern* as a visual variable, there have been little design guidelines and empirical research within the visualization community on how to use patterns for visualization. For example, Zeng and Battle [193] reviewed current theories and experiments on graphical perception and categorized them by visual variables. Pattern (the authors call it texture) was the least discussed visual variable, being covered in only 2 out of 59 papers and under different definitions. This inconsistency in the use of terminology—between "texture" and "pattern"—and the varied definitions of this visual variable can be traced back to a mistranslation in the

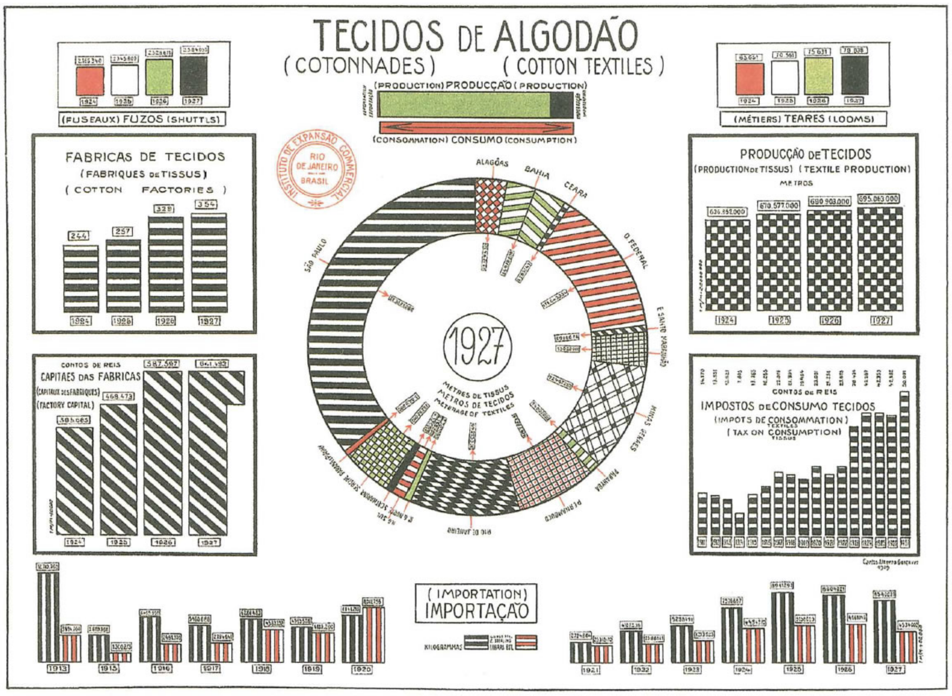


Figure 1.3: An example of a visualization with patterns that are aesthetically unappealing, primarily due to the vibratory effect—an unwanted visual vibration observed in the patterns on these charts [169]. Image from [97]; 🅮 the image is in the public domain.

English edition of Bertin's book, *Semiology of graphics*.

To address this gap, we first clarify the terminology and define the visual variable *pattern* (Chapter 2), then systematically summarize its variations and develop a design space (Chapter 3). Based on this design space, we contribute three empirical studies focused on a specific subset of patterns: black-and-white patterns for categorical visualization (Chapter 4).

1.2 . Aesthetic considerations in visualization with patterns

Patterns have rich attributes that can be varied to create different variations, giving them huge potential to be used in visualization. However, if used improperly, patterns can bring negative effects such as the vibratory effect (an optical illusion making patterns seem unstable, also called the Moiré effect) [14, 15, 169] and visual clutter that may ultimately be distracting, leading not only to ineffective graphics but also to unappealing aesthetic visualizations. Figure 1.3 [97] shows an example of a visualization with patterns that not very beautiful, primarily due to the vibratory effect [169]. Consequently, we should carefully consider and evaluate the visualization's aesthetics when designing patterns for data encoding.

While the discussion here focuses on patterns, aesthetic pleasure is an important aspect of visualization design more broadly. In 2005, Chen [47] listed the study of "pretty or visually appealing" visualization designs under the heading of aesthetics as one of the top ten unsolved problems in information visualization. Research suggests that aesthetics affect the usability and effectiveness of a visualization [45, 89] and has the potential to communicate [28] and engage viewers [5, 166].

To make empirically-grounded statements about the impact of aesthetic pleasure on visualization use, however, we first need a set of research instruments to study this concept. Rating scales are commonly used to capture subjective assessments of aesthetic pleasure, and researchers have developed such scales to study the aesthetic pleasure of websites [109, 131] or design objects [18]. However, there is no validated instrument specifically for measuring the aesthetic pleasure of visualizations. As a result, researchers currently use scales from related fields, or pick their own terms to evaluate aesthetic pleasure, asking participants to rate visualizations according to, for example, how "visually appealing" [3], "elegant" [64], or "aesthetic" [99] they are. Unfortunately, without proper validation, we cannot be certain that these ad-hoc approaches to understanding the aesthetic pleasure of visualizations are reliable and valid.

To address this gap, we developed and validated the BeauVis scale, an instrument specifically designed to measure the aesthetic pleasure of visual data representations (Chapter 5). We used the BeauVis scale in our empirical studies on the aesthetics of patterns (Chapter 4), but it has broader applicability and can also be used to evaluate the aesthetics of more general visualization designs.

1.3 . Thesis statement

Our fundamental research question is **how to aesthetically and effectively use patterns for data visualization**. This thesis addresses this gap by drawing upon broad and contrasting considerations of *pattern* as a visual variable to develop a consolidated theory for explaining, exploring, and using patterns in visualization from two perspectives: design and evaluation.

We initially planned to evaluate the aesthetics of pattern design in visualization, but there is currently no validated scale for measuring visualization aesthetics. Therefore, we first developed a validated instrument that allows researchers and practitioners to compare the aesthetic appeal of different visual data representations before investigating specific patterns. We call this instrument the BeauVis scale. After establishing this scale, we began to explore the design space of patterns. In parallel, we conducted an empirical study focusing on a specific scenario: using black-and-white patterns to encode categorical data. We centered our analysis on two types of patterns: geometric patterns (repeated abstract geometric shapes) and iconic patterns (repeated icons). We collected a set of pattern designs from visualization design experts and conducted controlled experiments to empirically evaluate their aesthetics and effectiveness. Finally, we generalized these findings to develop a comprehensive design space for patterns. We conceptualized the term pattern as a composite visual variable consisting of a group of graphical primitives that can serve as visual marks, and we systematically described the potential variations of patterns.

In this thesis, I present our work in reverse order to establish a more logical flow: I first introduce the general pattern design space, followed by the empirical studies on specific patterns, and finally, the development and validation of the aesthetic scale. To summarize, this thesis addresses the following research questions:

- **RQ1**: What is the visual variable "pattern"?
- **RQ2**: What pattern variations can we use for data encoding?
- **RQ3**: How can we better use black-and-white patterns for categorical visualization?
- **RQ4**: How can we compare the aesthetic pleasure of visual data representations?

Correspondingly, this thesis makes the following contributions:

- Clarification of the terminology "texture" and "pattern," and a conceptualization of *pattern* as a composite variable consisting of a group of primitives that can serve as marks.
- A design space that summarizes the attributes we can vary in a pattern and the application of this model.
- A collection of geometric and iconic pattern designs for categorical visualization from design experts, along with experiments conducted to compare their visual appearance and chart reading effectiveness.
- The development and validation of a scale for measuring the aesthetic pleasure of visual data representations.

1.4 . Thesis overview

After this introduction, the rest of this thesis is structured into the following five chapters. The titles and short descriptions of each chapter are as follows:

- **Chapter 2: Clarification of Terminology and a Discussion of Background on Patterns** clarifies the use of the terms "texture" and "pattern" in the visualization literature and recommends using the term *pattern* over *texture* for the visual variable that consists of a group of primitives used in maps and charts. We also review previous research on pattern variations and discuss inconsistencies in Bertin's use of visual variables.
- **Chapter 3: A Design Space of Pattern as a Visual Variable** describes the design space for pattern variations and summarizes pattern attributes from three aspects: spatial relationships, appearance relationships, and individual characteristics of primitives. We also discuss encoding geographical information into primitives and link *pattern* to the map-reading process.
- **Chapter 4: Empirical Studies on Black-and-White Patterns for Categorical Visualization** presents the results of three experiments that elicited design strategies and measured the aesthetics and effectiveness of using geometric and iconic black-and-white patterns for categorical data.
- **Chapter 5: BeauVis: A Validated Scale for Measuring Aesthetic Pleasures of Visualizations** details the development and validation process of the BeauVis scale.
- **Chapter 6: Discussion and Conclusion** summarizes our work, presents reflections, and discusses potential avenues for future research.

2 - Clarification of Terminology and a Discussion of Background on Patterns

When patterns are described as visual variables, researchers have also referred to them as *texture*. This interchangeability of the terms *pattern* and *texture* may arise from the blended use of these two terms in everyday language and the inclusion of *texture* in Bertin's initial list of visual variables [14, 15]. However, to add to the confusion, the term *texture*, has a diverse set of meanings in the visualization research that goes beyond an understanding of texture as pattern. Researchers working on 3D representations, for example, often use *texture* to mean surface or volume characteristics of 3D objects, represented as realistic images [100, 115]. These textures typically have different visual characteristics and encoding goals from the patterns that are used as a visual variable in abstract data representation. Even in the specific context of discussing the visual variables used for abstract data representations, researchers may interpret the term *texture* as a variation of a specific dimension of a *pattern*, such as "granularity" (Bertin called it "grain" in French), the spacing between the repeated elements, or the shape of these elements. We argue that this melange of terminology hinders the research community in investigating *pattern* as a visual variable or using this encoding effectively because research on patterns and the practice of using them are difficult to compare and situate in the absence of consistent terminology.

Inspired by the literature [42, 117, 132, 180], we therefore suggest to use the term *pattern* to describe a composite visual variable that consists of graphical primitives which can also serve as marks (which we call "sub-marks") for data encoding. In this chapter, we first provide an in-depth discussion and clarification of the terms *texture* and *pattern* in light of existing interpretations around both terms. To better understand the composite nature of patterns, we then review the literature discussing the dimensionality of patterns.

2.1 . *Texture* and *pattern*

Researchers often use the terms *pattern* (e.g., [106, 117, 170]) or *texture* (e.g., [87, 179, 182]) to describe a visual variable characterized by repeated elements. While both terms can make sense and are understandable, Carpendale [42], in her discussion of visual variables, suggest to use the term *texture* for "apparent surface quality of the material like wood or marble" and to use *pattern* for "repetitive use of shape variations." We consider Carpendale's

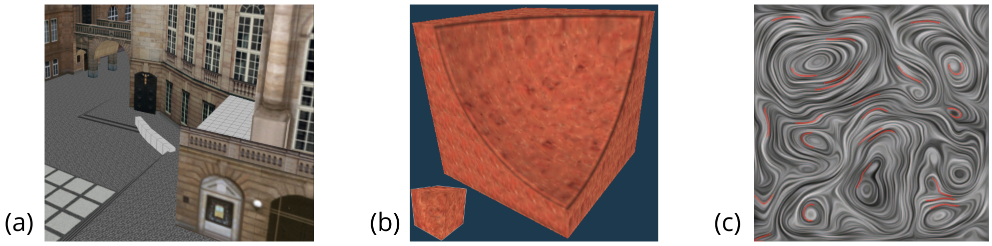


Figure 2.1: Textures in (a) surface rendering [33], (b) volume rendering [115], and (c) flow visualization [125]; all images © IEEE; used with permission.

recommendation reasonable and useful[1] due to two main issues associated with the term *texture*: (1) compared to *pattern*, the term *texture* has a broader meaning in visualization and related fields, can refer to different concepts (as we show in Figure 2.1 and Figure 2.2), making it less precise; and (2), even when *texture* specifically refers to a visual variable, it is subject to different interpretations, as can be observed by comparing various publications that use the term [14, 15, 61, 105, 106, 162, 170]. In this section, we discuss the first of these issues and clarify the use of texture and pattern in the visualization literature, and explain why *pattern* is a more suitable term for this type of visual variable. We discuss the second issue in Section 2.2.

2.1.1 . Texture: Surface characteristics

The term texture is often used to describe an object's "visual or tactile surface characteristics and appearance" [127]. In the computer graphics field, especially in research that relates to rendering, *texture* is a widely used concept. Texture in this context essentially refers to a data structure that stores characteristic (visual or other) information. It is typically represented as a multidimensional array. Through texture sampling, we obtain the necessary data from the texture and map it onto the corresponding location of the object. The visual texture that we ultimately observe on the object is the result of the rendering process [19, 43]. From an appearance standpoint, textures are often closely related to real-world materials, have a sense of depth and realism, and often look continuous.

Leveraging techniques from computer graphics, researchers in 3D visualization use *texture*, for example, to depict materials of a model's surface (e.g., Figure 2.1(a)) or to define a volume's visual characteristics (e.g., Figure 2.1(b)). In flow visualization, researchers also use texture-based techniques, such as Line Integral Convolution (LIC) [38] or spot noise [172], to represent the di-

[1]We agree that *texture* should only be used for materials, but we argue that *pattern* has broader variations beyond only repetitive use of shape variations, as we discuss in Section 2.2.3.

rectionality, magnitude, and other attributes of vectors or tensors (e.g., Figure 2.1(c)).

Texture is also used to refer to surface characteristics in other visualization-related fields beyond computer graphics. In the arts, texture is recognized as one of the seven elements of design, denoting the characteristics of an object's material [74]. In the visual arts, visual textures are called *implied textures* (in contrast to *actual textures*, which are tactile), e.g., to create a simulated appearance of physical materials[74]. In computer vision, researchers investigate *texture analysis* techniques (e.g., *texture segmentation* and *classification*) to enable computers to recognize objects and understand scenes [168]. In the vision sciences, researchers study *texture perception* to understand how humans perceive surface qualities [151].

Importantly, Carpendale [42] brings this work together in her discussion of visual variables for information visualization. Carpendale specifically discusses the possibility of using surface materials (i.e., the computer graphics interpretation of *texture*) as a separate visual variable [42, Table 9]. She illustrates differences in surface quality through the use of photographic images [42, Table 11]. In this case, a (texture) image is applied to elements of a chart, and what we read is both the chart element's value and the information in the texture image. We can thus still call this visual variable *texture* as Carpendale suggested—yet a term such as "surface material texture" would make for a clearer distinction.

2.1.2 . Pattern: Repetition and structure

A body of research and practice that has its roots in cartography and statistical graphics interprets *texture* in a different manner, mapping data dimensions directly to graphical features of textures in abstract encodings of quality or quantity. In Figure 2.2 we show examples of this type of "texture." Researchers map data dimensions to the graphical features of these textures. From an appearance perspective, they are clearer, more distinguishable, and more structured than the textures used in rendering. They typically feature repetitive shapes and are generally unrelated to surface materials.

We describe this use of "texture" as a *pattern*, a concept that emphasizes different aspects than *texture*. The term "pattern" originated from the same root as "patron," derived from the Latin *patronus*, meaning "protector" or "defender" [59]. It evolved to signify "an example to be copied" [59], emphasizing the repetition of elements—rather than the tactile or perceived feeling of a material (i.e., a texture). Note that the term *pattern* is not limited to visual elements, it is a structural concept that can be applied to the abstract as well as the physical world. In our daily life, e.g., *pattern* can refer to many physical items and abstract concepts that include repetition, such as a social/behavioral patterns, sound patterns, language structures, or chronologi-

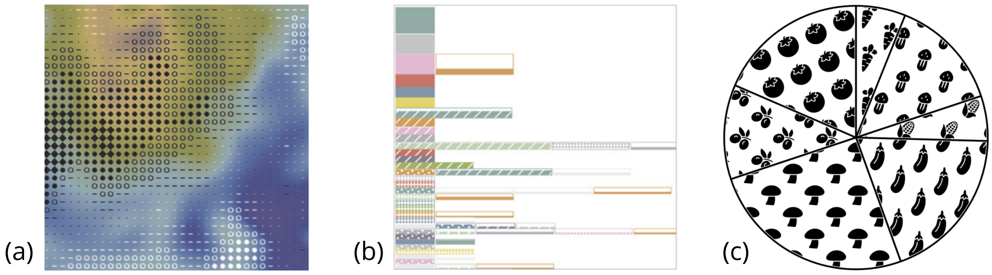


Figure 2.2: Patterns used in the visualization community that are called “texture,” from (a) [179], (b)[46] , and (c) [87]; (a) and (b) © IEEE, (c) ; used with permission.

cal orders.

We focus, however, on the visual aspects of *pattern*. The emphasis on repetition and structure makes the concept of *pattern* particularly suitable for describing visual variables in the form of repeated elements, capturing both their composite encoding and abstract appearance. As Wilkinson [187] in his discussion of visual variables mentioned: “these [visual variables] are not ones customarily used in computer graphics to create realistic scenes. They are not even sufficient for a semblance of realism.” Nevertheless, patterns can also characterize a surface, suggesting that we can view patterns as a specific type of “texture,” one that describes a surface with distinct sub-marks and structured arrangement. When the repeated elements in a texture are clearly identifiable, the texture takes on the characteristics of a *pattern*. This overlap between the two concepts may explain why some researchers use the terms *pattern* and *texture* interchangeably.

2.1.3 . Summary

We can see that the term “texture” is used differently in different visualization contexts, with meanings derived and used in computer graphics and in abstract data representation having some similarities, but important differences. Both can characterize a surface and add visual complexity. *Texture* often describes the appearance of a surface and its material properties, while *pattern* emphasizes the repetition and structure of elements that involves semiotics and is frequently used in abstract data representation and encoding. We acknowledge the overlap of the terms *texture* and *pattern* as well as respect other researchers’ use of both terms. In our case of using it as a visual variable, however, we suggest that *pattern* is a more precise term than *texture*, as *patterns* rely on repetition and are not meant to suggest surface material.

2.2 . Pattern as a visual variable: Three interpretations under the term of "texture"

While *pattern* is a more precise term for describing the visual variable concept, we frequently see "texture" in lists of visual variables. This preference of using "texture" to describe a visual variable can be traced back to Bertin's seminal work, "Semiology of Graphics" [15, 14]. Bertin introduced the first set of visual variables in his book, "texture" among them. Subsequent literature on visual variables has continued to use this term (e.g., [42, 120]), however, with different interpretations. It has been referred as the variation of granularity in a *pattern* (e.g.[15, 14, 105]), the spacing of a *pattern* (e.g.[61, 162]), the shape variation of a *pattern*, or a *pattern* in its entirety (e.g.[106, 170]).[2] This inconsistency has its roots in the translation of Bertin's book, which we discuss in detail below.

2.2.1 . Grain: The original term Bertin used

The French term "grain" is the original word that Bertin used to describe the visual variable, which William J. Berg translated to "texture" in the English version of this book [15]. Bertin defined the visual variable *grain* as follows: "at a given value, the [granularity][3] represents the number of separable marks within a unit area." In the "texture" palettes from his book that we reproduce in Figure 2.3, the variation of granularity along each *horizontal* palette involves changing both the size and spacing of primitives *simultaneously*, while maintaining a given ratio of black to white. As a result, the average *value* of each square stays constant. This effect is similar to what can be achieved by zooming in or out of a pattern or through photographic reduction [14, 15].

Researchers have raised concerns about the translation of Bertin's "grain" variation to the English term "texture," suggesting that "grain" or "granularity" would provide more precise translations. MacEachren [117], for example, suggests that the English term "grain" may be better to describe this variation, as it is similar to the grain in film. Similarly, Wilkinson [187] mentioned Bertin "really means granularity (as in the granularity of a photograph)." Carpendale [42] also commented that this variation is more closely related to a variation of granularity and she directly referred to it as "grain" using the English term. Between "grain" and "granularity," we recommend using "granularity" in English, based on the rationale that it is not the "grain" itself that varies, but rather the size of the grain, which is more accurately described by "granularity." More-

[2]These examples are all textbooks on cartography with lists of visual variables. By observing how they interpret "texture" in various ways we found inconsistencies in the understanding of the term "texture" as a visual variable.

[3]In contrast to the official translation of the book, which uses the term "texture," we intentionally changed the translation here to use "granularity" and also not "grain," for reasons that we explain further below.

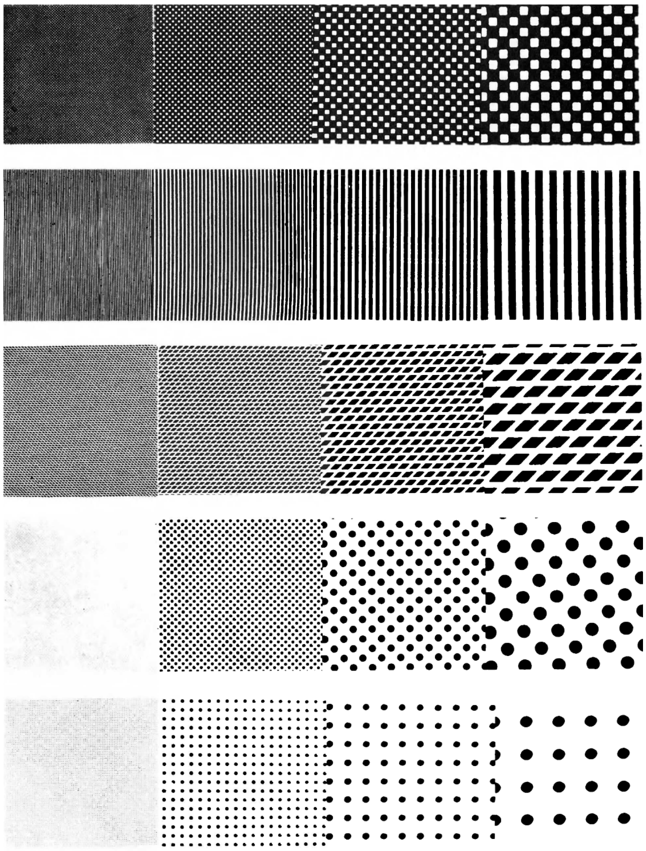


Figure 2.3: Bertin's diagram for granularity variation, described in French as "Horizontalement: grain. Verticalement: valeur et forme" [our translation: horizontal: granularity. vertical: value and shape] [14] and in English as "texture is given horizontally; value and shape [pattern] vertically" [15]; © EHESS, used with permission.

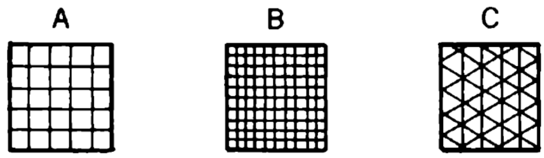
over, in English, "grain" can refer to the longitudinal pattern of wood fibers (i.e., "wood grain"), potentially conveying a sense of direction. The concept of direction, however, is not implied in Bertin's *grain* visual variable, which makes "grain" less suitable in this context.

2.2.2 . Spacing: A misinterpretation in Bertin's book

Another interpretation of the word "texture" refers to the spacing of primitives in a *pattern*. Spacing between primitives can affect *density*—the smaller the spacing, the more densely packed the primitives. This variation is called "spacing" by Brewer [29] and Slocum et al. [162], "density" by Mackinlay [120], or "frenquecy" by Chung et al. [53].

The interpretation of "texture" to relate to spacing may arise from a misinterpretation in a translator's note in the English version of Bertin's book, which we reproduce in Figure 2.4. As we had just discussed, for Bertin changes in

*Bertin draws a rigorous distinction between texture (*grain* in French) and pattern (*texture* in French):



A and B differ in their texture, but there is no difference in pattern. The elementary shapes are the same. The notion of pattern explains the difference between A and C. The elementary shapes are different. A difference in "pattern" is essentially a difference in shape (translator's note)

Figure 2.4: Translator's note in the English edition of Bertin's book [14]; From Semiology of Graphics: Diagrams, Networks, Maps by J. William Berg [14]. Reprinted by permission of the University of Wisconsin Press. © 1983 by the Board of Regents of the University of Wisconsin System. All rights reserved.

granularity (French: "grain," translated in Figure 2.4 to "texture") require that a constant average value is upheld. The translator's note, however, refers to the difference between Squares A and B as a change in "texture" (i.e., "grain" in French or, for us, *granulatity*). Yet, A and B do NOT share the same average value, as A has a lower black-to-white ratio than B. Therefore, A and B would not constitute the same (French) "grain" for Bertin. Instead, if we see the black lines as primitives of the pattern, we can see from the figure that A and B differ only in the *spacing* between primitives.

2.2.3 . Pattern: Not only shape variation

"Pattern," largely in the sense we have established in Section 2.1.2, is a third term often used interchangeably with "texture" when referring to a visual variable—partly because of the overlap of meaning between the two terms as we discussed in Section 2.1 and partly due to the interpretation of the translator of Bertin's book. In his original French book [14], Bertin said about the visual representation we reproduced in Figure 2.3 that the *vertical* change between *corresponding "palette" entries* is a variation of "value and shape" (French: "valeur et forme"). While it is unclear if this interpretation was supported by Bertin, the translator of the book amended this statement to "value and shape [pattern]" in the English version [15]. This amendment seems reasonable: we can see in Figure 2.3 that the differences between palette entries on each column are not just differences in *value* and *shape*, but also include differences in *size* of the elements, *spacing* between the elements, etc.—which are all variations a *pattern* can have. In the same translator's note we just mentioned (Figure 2.4), however, Berg explained that "a difference in 'pattern' is essentially a difference in shape." Carpendale [42] follows this interpretation that *pattern* means the "repetitive use of shape variations (the use of marks upon marks)" and equates the impact of using the visual variable *pattern* in visual interpretative tasks with the visual variable *shape*. This interpretation captures the emphasis of *pattern* on repetition well and the notion of "the use of marks upon marks" touches an apparent inconsistency of Bertin's use of visual variables, which we discuss in Section 2.3.2. The variations of *patterns*, however, should not be limited to the change of shape as we just discussed for Figure 2.3.

2.2.4 . Summary and our recommendation

"Texture" can have multiple meanings, so when the term is used without any further explanation or examples in the context of abstract data representation we cannot be sure which interpretation an author had in mind. We thus recommend to avoid using the term *texture* in lists of visual variables in the future and to, instead, name *granularity*, *spacing*, and *shape of sub-marks in the pattern* when referring to these specific meanings, to reduce ambiguity.

2.3 . Additional related work on pattern variations

We consider *granularity*, *spacing*, and primitives' *shape* merely to be sub-dimensions of *pattern*; with none being able to fully represent variations of a *pattern* on their own. What, then, really constitutes a *pattern*? *Pattern* as a visual variable can include all of the aforementioned dimensions but can also have more. We thus now review previous work on identifying sub-dimensions of *pattern* and then point out an inconsistency in Bertin's use of visual variables; but this inconsistency can inspire us to develop a comprehensive description of *pattern*.

2.3.1 . Pattern description from two perspectives

In the past, researchers have investigated the variations of *pattern* from two perspectives, corresponding to the encoding and decoding process. In the encoding process, visualization designers employ graphical properties of marks (visual variables) to represent differences in data attributes. Conversely, during the decoding process, readers perceive the variation in visual variables and interpret these as differences in data attributes. The description of *pattern* can thus be approached from two directions: what designers can control, and what readers can perceive. Research from the design field has proposed sub-dimensions of *pattern* from a design perspective, and research from the field of vision science has explored dimensions of *pattern* from the perception perspective.

Perception perspective

To be able to use pattern for encoding data effectively, it is vital to understand how the human visual system perceives patterns. Vision science researchers have tried to identify the most important perceptual dimensions that are useful for humans to judge the difference between appearance of textures (also known as texture features).

Tamura et al. [165] proposed six basic texture features, namely, coarseness, contrast, directionality, line-likeness, regularity, and roughness. Amadasun and King [4] approximated 5 perceptual texture attributes in computational form, namely coarseness, contrast, busyness, complexity, and strength of texture. Rao and Lohse [146] identified a Texture Naming System with three most significant dimensions in natural texture perception: "repetitive vs. non-repetitive; high-contrast and non-directional vs. low-contrast and directional; granular, coarse and low-complexity vs. non-granular, fine and high-complexity." Liu and Picard [113] identified three mutually orthogonal dimensions of texture that are important to human texture perception, namely periodicity, directionality and randomness. Cho et al. [52] extended the perceptual research and reported four texture dimensions, namely coarseness, contrast, lightness and regularity.

Although most of these vision researchers [4, 52, 113, 146, 165] have primarily focused on natural textures (e.g., the photographic textures in Brodatz' album [32]), their work—dedicated to understanding how humans perceive texture—can shed light on using pattern for data visualization. In particular, Ware and Knight [183, 184] identified three orderable dimensions for data displays: *orientation*, *size*, and *contrast* (OSC). Healey and Enns [88] built three-dimensional perceptual texture elements, or called pexels, for visualizing multidimensional datasets. Pexels can be varied in three separated texture dimensions, which are height, density, and regularity, and color of each pexel. This perception perspective is highly relevant to the use of *pattern* as a visual variable and we use some of these variables in the model we present later, but it is not our focus. After we build a *pattern* description with the design perspective, we can test it in the context of perception as future work.

Design perspective

Researchers in design, cartography, and visualization have noticed the composite nature of *pattern*, and specified it has multiple dimensions that can be varied to encode data.

From the field of architecture design, Caivano [39, 40] adopted a bottom-up approach to describe patterns. He classifies *simple textures* and *complex textures*, defining the former as "the uniform repetition of a certain element" and the latter as combinations of multiple sets of simple textures [40]. His

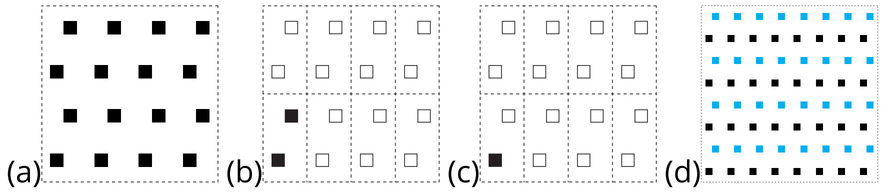


Figure 2.5: Redraw based on Caivano's diagram of composition of a simple texture [39, 40]. (a) A texture, (b) a texture unit, (c) a texture element, (d) two subsets of textures identified from this simple texture composition, colored blue and black, respectively.

simple textures are essentially two elements within a tiling unit. Caivano constructed his simple texture through the tiling of a *texture unit* (the minimal entity for repetition; see Figure 2.5 (b)). In Caivano's model, a texture unit comprises a pair of texturing elements (see Figure 2.5 (c)). He then treats texture as a tripartite variable, including size of the texture elements, directionality (the unit's width-height ratio), and density (the overall black-to-white ratio). Later [39] he refined his theory to describe pattern variation through the shape of texture elements, organization (the relative positions of the two texture elements within the tiling unit), proportionality (the tiling unit's width-height ratio), and density (the overall black-to-white ratio).

Cavaino, however, did not intend to use texture as a visual variable for data encoding. As a result, not all the dimensions he identified are directly manipulable, and his composition of simple textures is unsuitable for our purpose. In addition, we interpret through Caivano's classification that a simple texture should be the most basic form of texture—without any subsets of textures ("uniform repetition of a certain element"). If a texture is combination of multiple sets of textures, we should categorize it as a complex texture. Upon analysis of Caivano's simple texture composition, however, we identified two subsets of texture within it, which appears to contradict our interpretation of his definition of a simple texture. Figure 2.5(d) illustrates the two subtextures identified in a simple texture according to Caivano's composition, with blue and black highlighting, respectively. Thus, while we adopt Caivano's categorization of simple and complex textures, we offer an alternative that covers a wider design space of *pattern*, specifically aimed at encoding data, which we present later.

From the field of cartography, MacEachren in his book "How Maps Work" [117] suggests to "consider 'pattern' as [a] higher-level visual variable, consisting of units that have shape, size, orientation, texture (in Bertin's sense of grain), and arrangement." In the field of visualization, Harris [82] in his book on information graphics design suggests that "there are many variations" within patterns and lists factors that make up patterns: "shape of individual elements," "orientation of individual elements," "texture (sometimes referred to as coarseness)", "size of individual elements," and "spacing between individual elements." Wilkinson [187] wrote that "texture includes pattern, granularity, and orientation," but he does not further analyze *pattern*. Instead, he interpreted pattern as being "similar to fill style in older computer graphics systems, such as GKS (Hopgood et al., 1983) or paint programs" but does not describe the subdimensions of *pattern*. In our own previous work [87] we identified a set of *pattern* properties (as [sic] "textures") but also did not cover all dimensions.

In summary, this prior work provides useful examples for understanding the dimensionality of patterns, even though the concept was not systematically or comprehensively defined. Additionally, none of the previous discussions highlight that a pattern is comprised of sub-marks, except for those by Bertin [14, 15] and Carpendale [42], which we discuss in the next section. This dissatisfaction with the ad-hoc descriptions of *pattern* has motivated us to establish a more rigorous theory.

2.3.2 . Inspiration from Bertin's apparent inconsistency

Bertin himself did not explicitly define or employ the concept of *pattern*, but why then do we see many visual encodings we may intuitively call *pattern* in his charts or maps? One explanation may be that, when Bertin addressed the inherent limitations of line marks and area marks, he used a method of adding an additional mark or a group of repetitive additional marks to the original mark. When he did the latter, he created a *pattern* with repetitive tiling of sub-marks—that's why Carpendale interprets *pattern* as "the use of marks upon marks."

To be specific, line marks cannot change in *orientation* and area marks cannot change in *size*, *shape*, or *orientation* [14, 15, 42, 132], without the area or line encoding changing its meaning. For example, we cannot encode an additional data attribute into the *size*, *shape*, or *orientation* of a region (an area mark) on a map because these attributes are already taken by geographic information. When discussing these constraints, however, Bertin also wrote that, for a line mark, we can change the "orientation of its constituents," and for area marks that, "if the area is visually represented by a constellation of points or lines, these constituent points and lines can vary in size, shape, or orientation without causing the area to vary in meaning" [14]. This adjustment explains why Bertin could apply all his six retinal visual variables—including *size*, *shape*, and *orientation*—onto line and area marks (see his overview in Figure 2.6), and the "constituents" here equates to the sub-marks (the primitives in the pattern).

Let us take the visual variable *size* as an example to explain how he mixed these two approaches. *Size* is applicable to point and line marks, but not to area marks. When applying *size* to point and line marks, Bertin directly adjusts

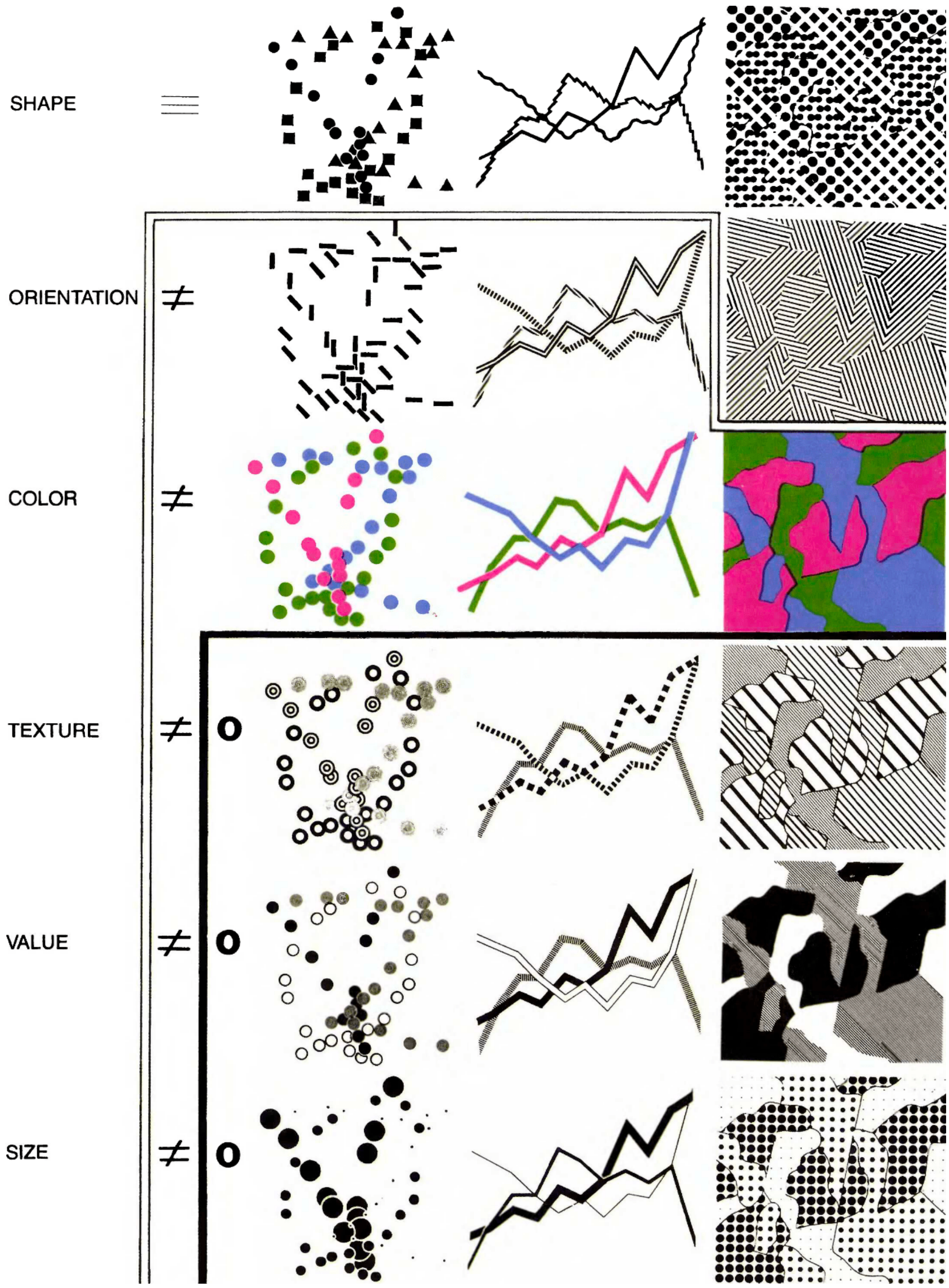


Figure 2.6: Bertin's diagram for visual variables across three mark types [14, 15]. From left to right, the columns represent point mark, line mark, and area mark, respectively; © EHESS, used with permission.

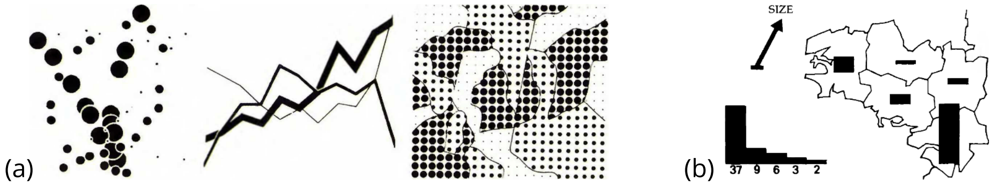


Figure 2.7: Size variations from Bertin's book [14, 15]: (a) Size variations for three mark types: left and middle show Bertin's `Approach 1`, where he directly adjusted the marks' size properties (dot size and line width); right shows Bertin's `Approach 2.2`, where he added repetitive sub-marks (dots) to fill the area mark and varied the sub-marks' size properties (dot size). (b) Size variation for an area mark using Bertin's `Approach 2.1`, where he added a single sub-mark (rectangle) and varied its size property (rectangle size). © EHESS, used with permission.

the mark's intrinsic properties, such as the dot's radius or the line's width.—without introducing sub-marks (Figure 2.7(a), left and middle). We call this approach `Approach 1`: changing the graphical properties of the mark itself, which aligns with the precise definition of a visual variable. *Size* is not applicable to area mark, however, so Bertin takes another approach: introducing new mark(s)—we call this approach `Approach 2`. `Approach 2` includes two options: `Approach 2.1` adding one constituent (sub-mark) or `Approach 2.2` adding repetitive sub-marks ("constellation") to fulfill the mark. For example, he shows the application of *size* to an area mark by adding a rectangle of different size to each area mark (Figure 2.7(b), which aligns with `Approach 2.1`), or by repetitively filling each area mark with circles of varying sizes (Figure 2.7(a)), which aligns with `Approach 2.2`). In summary, when Bertin can use approach (1), he does so. When he cannot use `Approach 1`, he automatically switches to `Approach 2`, yet without clarification. In his discussion, unfortunately, he did not clearly explain why and when to select `Approach 2.1` or `Approach 2.2` either.

The sub-marks Bertin adds to the marks are typically point-marks or line-marks, as more visual variables can be applied to them than to area marks. With `Approach 2.2`, Bertin, in fact, creates point-based patterns and line-based patterns as we understand it, and so that is ultimately why we see many *pattern* examples in Bertin's book.

Bertin's mixing of the two methods actually blurs the meaning of visual variables. Wilkinson [187] pointed out, "Bertin uses size, shape, and orientation to characterize both the exterior form of objects (such as symbol shapes) and their interior texture pattern (such as cross-hatching)." Bertin's approach also limits the use of patterns and does not fully explore the concept. We can, in fact, apply *pattern* across all visual variables and mark types, but Bertin reserved "pattern" for situations where visual variables were not applicable to certain types of marks. In addition, Bertin simply kept the sub-marks arranged in a regular grid and ensured that each sub-mark was exactly repetitive. Similarly, Carpendale [42] equated the variation in patterns to the variation in shapes constituting them, as discussed in Section 2.2.3. Inspired by their idea but go one step beyond, we aim to systematically explore, from a single mark to a composite mark, what new potentials patterns offer for our use in encoding data.

3 - Pattern as a Visual Variable: A Design Space

Based on the previous discussion we can now start to establish a new *pattern* system. Our goal is to identify the most basic visual variables that designers can manipulate to create different patterns. These visual variables should ideally be independent and have no sub-dimensions. It is important to note that our discussion of the independence of visual variables focuses primarily on the design perspective. The independence of variation achieved in design does not necessarily guarantee perceptual orthogonality—human perception may still interpret these variations as being linked or correlated [187].

In this chapter, we conceptualize the notion of a *pattern* along with its potential variations for data encoding. A pattern is composed of graphical primitives. When encoding data within a pattern, we manipulate the graphical attributes of these primitives. Therefore, these graphical elements can also be considered "marks." To differentiate them from the marks to which we apply a pattern, we refer to the graphical elements within the pattern as "sub-marks." Transitioning from a single mark to a composite of sub-marks (patterns), the new graphical attributes that patterns introduce are the rules that describe the relationships between sub-marks. We identify two sets of rules: the spatial relationships among the primitives and their appearance relationships. To complete a pattern, it is also necessary to characterize each primitive's appearance. Accordingly, we have identified three sets of attributes to characterize a pattern: spatial relationships, appearance relationships, and individual appearance characteristics of primitives. These attributes can be used as visual variables to encode data.

3.1 . Pattern configuration: The dimensionality of a lattice

The configuration of a pattern, which is the basic structure for arranging primitives, is fundamental to understanding the spatial arrangement of these elements. Therefore, it is essential to address this configuration before discussing the spatial relationship variables. We start with a type of pattern most commonly seen in our existing visualizations, which is based on the tiling of repeated identical elements in a regular arrangement. We begin with the simplest configuration and use a lattice structure to describe this regular arrangement. A lattice consists of a set of regularly spaced points that can extend infinitely in space. Each point, known as a lattice point, represents a predefined position for a graphical primitive within the pattern.

The number of lattice dimensions influences the parameters required to

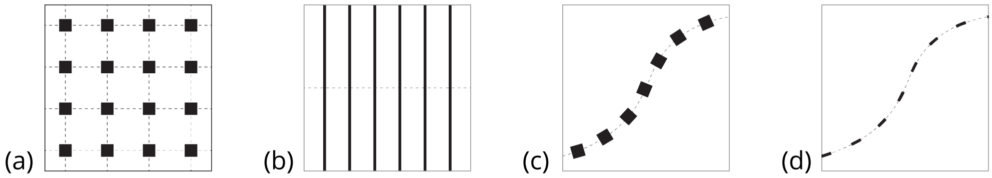


Figure 3.1: Configuration of *pattern* with (a) 2D primitives on a 2D lattice, tiling across an area; (b) 1D primitive on a 1D lattice, tiling across an area; (c) 2D primitive on a 1D lattice, tiling along a line; and (d) 1D primitive on a 1D lattice, tiling along a line. Here, the primitives are in black (they could also be colored); the dashed lines are structural lines to describe the lattice on which we place the primitives; we use them only for descriptive purposes and they are not part of the *pattern* itself.

define the lattice. In this work, we focus on patterns used in maps or charts, which are typically displayed on a 2D plane. Therefore, we can organize the primitives of a pattern into either a 1D or a 2D lattice. It is important to note that the number of dimensions of the lattice (1D or 2D) differs from the number of dimensions that the pattern itself occupies (along a line or across an area), as well as from the number of dimensions of the marks onto which the pattern can be applied (point, line, or area marks). The number of dimensions of a lattice is determined by the directions in which the lattice can extend. We explain these distinctions with four common structures of patterns shown in Figure 3.1.

Figure 3.1(a) and Figure 3.1(b) illustrate two types of patterns most commonly seen in existing visualizations, which we refer to as point-based and line-based patterns, respectively. Figure 3.1(a) displays a pattern arranged in a 2D lattice with point primitives placed at equally spaced lattice points extending in two directions. In contrast, Figure 3.1(b) presents a pattern arranged in a 1D lattice with line primitives of infinite length, oriented differently from the lattice line and spaced equally along a straight line. Both Figure 3.1(a) and Figure 3.1(b) show patterns that have repetitive primitives tiling across an area. However, when applied in charts, they are not limited to use on area marks, but can be used on all three types of marks—point, line, or area marks—because all three mark types practically have an area (e.g., a point mark is not a theoretically point but represented by a circle with size).

Figure 3.1(c) and Figure 3.1(d) show the patterns with a linear configuration. These patterns are arranged in a 1D lattice, featuring repetitive primitives equally spaced along a line, which constitutes the lattice. These patterns with a linear configuration are often used on line marks, for example, to represent boundaries or tracks on maps, trajectories (e.g., [134]), or in charts (such as line charts). Therefore, practically speaking, the lattice representing their spatial arrangement structure is not a straight line but curves along the direction of the line mark. The difference between Figure 3.1(c) and Figure 3.1(d) lies only in the primitives, not the arrangement. Figure 3.1(c) has 2D point primitives, whereas the primitives of Figure 3.1(d) are 1D lines with limited length and no width. Thus, Figure 3.1(d) forms a strict dashed line, a truly "1D pattern." Brath [27], in his blog, characterized patterns in form of Figure 3.1(d) by their length, gaps, and rhythm.

3.2 . Spatial relationship variables

Based on the pattern configuration, we identify the spatial relationship variables of a pattern by following these steps: First, we define a lattice with parameters that include the *shape* and *size* of the unit cell. Next, we position the lattice on the mark, determining its *orientation*. Finally, we place the primitives onto the lattice, considering *positional regularity*. We discuss the variables in each step.

3.2.1 . Define the lattice: Lattice parameters (Θ, a and b)

We follow a method used in crystallography [75] to define a lattice. The central idea of this method is to identify the unit cell of the lattice. The unit cell is the smallest unit of a lattice and the entire lattice can be generated by the repetitive tiling of the unit cells. We call the parameters that define the unit cell and thus the lattice structure "lattice parameters."

Shape of the unit cell. Figure 3.2(a) shows the variation of the shape of the unit cell. In a 2D lattice, we define its shape using *the angles between the edges of the unit cell*. For patterns based on orthogonal lattices, such as square and rectangular lattices, the angle $\theta = 90°$. Angles other than 90° are characteristic of parallelogram lattices, which exhibit various degrees of obliqueness. Theoretically, this angle can range from 0° to 180°. Practically, when θ is very close to 0° or 180°, the unit cell nearly collapses into a line, making the lattice resemble a 1D lattice, which is not very practical for data encoding because it is difficult to place and clearly read primitives on such lattices. In a 1D lattice, no parameter is needed to define its shape, as its unit cell is simply a line.

Note that when varying the angles between the edges, the shape of the unit cell is restricted to different forms of parallelograms. However, shape variation can extend beyond adjusting the angles of the edges to altering the entire geometry of the unit cell. For instance, the unit cell can take the form of a hexagon, resulting in a pattern that is not grid-based.

Size of the unit cell. Figure 3.2(b) shows the variation of the size of the unit cell. In a 2D lattice, we use *the lengths of unit cell edges* define its size, denoted as a and b. These parameters describe the spacing between primitives within the lattice. The simplest form of a 2D lattice is a square lattice where $a = b$ and $\theta = 90°$. The spacing can be modified either uniformly across

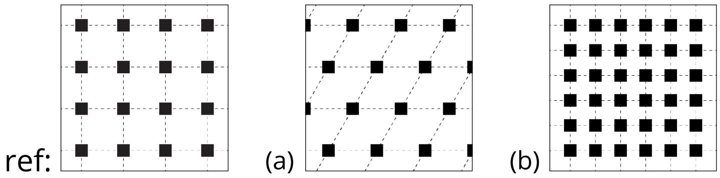


Figure 3.2: Compared to the left: (a) variation on shape of unit cells, (b) variation on size of unit cells

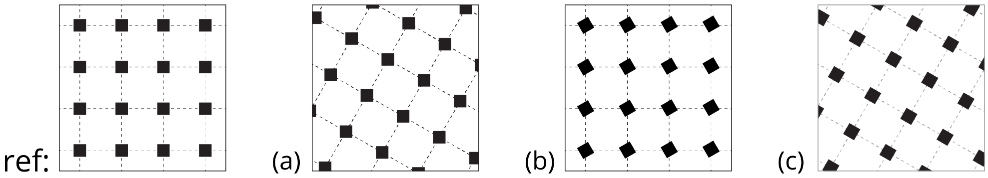


Figure 3.3: Orientation at different level, compared to the left: (a) orientation at arrangement-level, (b) orientation at primitive level, (c) orientation at both levels with same degrees(we can call it orientation of the whole pattern).

both directions—altering a and b simultaneously by the same factor—or independently, allowing for directional variation in the pattern. Independent adjustments in a and b can significantly affect the directionality of the resultant lattice pattern. For a 1D lattice, variations in spacing are constrained to a single dimension, namely along the line of the lattice. By varying the spacing between primitives, one can manipulate the area of the unit cell, which in turn influences the density of primitives within a given area. Theoretically, the range of possible spacings—or unit cell sizes—extends from zero up to the size of the entire marking. Practically, it is crucial to maintain a sufficient number of primitives within the visible area to ensure that the pattern is discernible. If the primitives are too sparse, the pattern may become difficult to perceive effectively.

3.2.2 . Place the lattice onto the mark: Orientation (Φ)

We use lattice parameters to describe the lattice in a self-contained manner, independent of the external environment. When using a pattern as a visual variable in a chart, the external plane is the plane of the chart. Therefore, we need to specify how the lattice is positioned on this plane, introducing the orientation of the lattice as a variable. When placing the lattice onto the plane, we have the option to rotate it. Theoretically, the angle of rotation can range from 0° to 360°. Typically, the center of rotation is the center of the mark onto which the pattern is applied, although it can be set to other points if necessary.

For a pattern arranged in a 2D lattice (Figure 3.1(a)), it is important to distinguish between the orientation of the lattice itself (as shown inFigure 3.3(a)) and the orientation of the primitives within it (as shown in Figure 3.3(b)). If both the primitives and the lattice are rotated by the same angle, this can intuitively be described as a rotation of the entire pattern, as shown in Figure 3.3(c). For patterns arranged in a 1D lattice, theoretically orientation can similarly be applied at two levels. For the three specific cases previously mentioned (Figure 3.1(b), Figure 3.1(c) and Figure 3.1(d)), however, the orientation of the lattice is not applicable. To be specific, for a line pattern (Figure 3.1(b)), the orientation of the lattice has the same effect of the orientation of the primitives. For patterns with a linear configuration applied to a line mark (Figure 3.1(c) and Figure 3.1(d)), their lattice aligns with the line mark and thus cannot be rotated.

Wilkinson [187] describes the orientation of a mark as "rotation" and the orientation of primitives in a pattern (he called it as "texture") as "orientation." He illustrates the concept of "orientation" exclusively with examples of line patterns (Figure 3.1(b)) and does not address the orientation variable of the lattice, which we explore here. Moreover, in our view, distinguishing between "rotation" and "orientation" does not imply a differentiation between method" and result": the outcome of the orientation of primitives is achieved through the method of rotation. Consequently, we recommend referring directly to the orientation at two levels as the orientation of the lattice and the orientation of the primitives.

3.2.3 . Place the primitives onto the lattice: Positional regularity (R)

So far, we have defined the lattice on the plane, establishing a set of predefined position points for the primitives in the pattern—the lattice points. However, when we place the primitives onto the lattice, they can deviate from these predefined points. To describe this deviation, we introduce a new variable called *positional regularity*. *Positional regularity* describes a pattern control that spans from a highly structured, regular layout to an unstructured, randomly dispersed layout (Figure 3.4).

Morrison [130] first introduced this concept of *positional regularity* into visual variables. He referred to it as "arrangement" and adding it as an additional visual variable to Bertin's initial visual variable list. The essence of *positional regularity* variation lies in the degree of deviation allowed for the primitives from these lattice points, ranging from strict adherence to the grid to completely random placement within the mark (Figure 3.4). This deviation can occur in either one direction of the unit cell or both directions. For patterns arranged in a 1D lattice, the primitives can be randomly placed along the lattice line.

Positional regularity is not an atomic variable and has sub-dimensions, including its range, and its dispersion level. **Range** describes how far can we

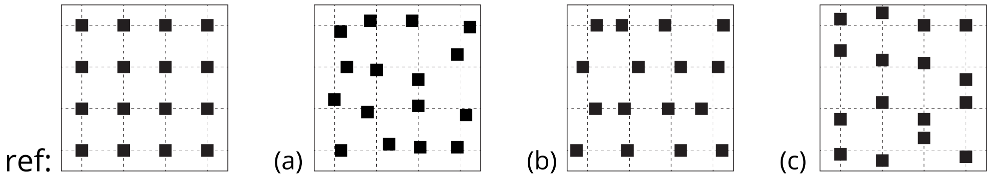


Figure 3.4: Positional regularity variation, compared to the reference on the left: (a) in both directions or (b)(c) only in one direction.

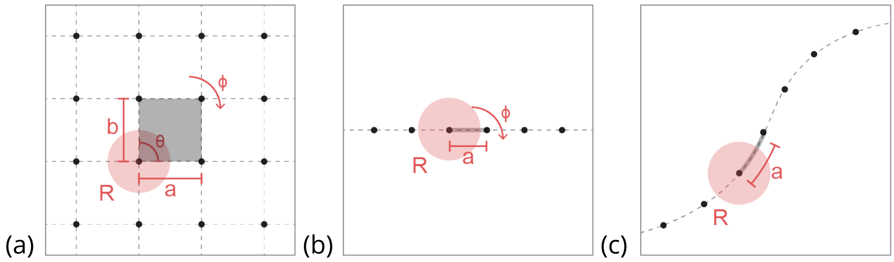


Figure 3.5: The spatial relationship variables of 2D and 1D lattices, (a) 2D lattice, (b) 1D lattice, (c) 1D lattice (along a line). The gray is an example of lattice unit cell, the red indicate what we can vary for the spacial relationship based on the lattice, including: Θ: the shape of the unit cell (included angle), a and b: the size of the unit cell (spacing between primitives), Φ orientation of the lattice and R: positional regularity.

deviate from the predefined point. **Dispersion level** can be understood as the standard deviation or entropy of the deviations among all primitives.

3.2.4 . Summary

We identify three sets of attributes to describe the spatial relationships of primitives in a pattern based on a lattice-based pattern configuration: (1) lattice shape and size, (2) lattice orientation, and (3) positional regularity of primitives. Figure 3.5 shows a summary of these variables.

In this discussion, we use a grid lattice as an example to explain pattern configuration and spatial arrangement variables, as it is the most commonly observed configuration in both historical and contemporary visualizations. However, the arrangement of pattern primitives is not necessarily limited to a grid structure. As discussed in the **shape of the unit cell** section, whether a pattern is grid-based or non-grid-based is a variation of the lattice shape parameter itself. Therefore, the spatial arrangement of primitives in non-grid-based patterns can still be characterized according to these three sets of attributes.

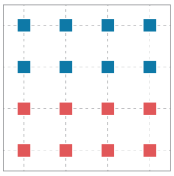
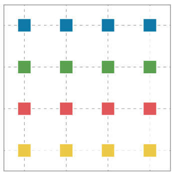
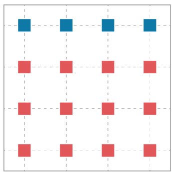
ref:  (a)  (b) 

Figure 3.6: Compared to the left, (a) variation in the number of groups of primitives (changing from 2 to 4), while the ratio between each group stays the same; (b) variation in the ratio between each group (changing from 1:1 to 1:3), while the number of groups of primitives remains 2. The different groups of primitives are differentiated by hue in this example, but we can apply any primitive-level variables to them, i.e., size, shape, etc.

3.3 . Appearance relationship variables

Beyond the spatial relationship, we also need to characterize the appearance of the primitives within the pattern. For non-composite marks, describing their graphical attributes—such as shape, size, and color—is sufficient. These attributes are what Bertin refers to as the "retinal variables." However, a pattern consists of a group of primitives, and we cannot directly manipulate the retinal variables of each primitive. This is because when we use a pattern as a visual variable, it usually fills the entire mark. Consequently, we are often unaware of the total number of primitives within the pattern and thus cannot directly control each primitive's graphical attributes. Therefore, it is necessary to establish rules that describe the relationships between their appearances. For example, for common patterns with repeated primitives, this rule is simply "all primitives look the same." However, the composite nature of patterns gives us more possibilities. We identify a set of new graphical attributes that can serve as visual variables to encode data, describing the internal variation in the appearances of primitives. We discuss this set of variables next.

3.3.1 . Number of primitive groups

Number of primitive groups describes how many primitive groups are created within a pattern, with each group getting a different mapping. Figure 3.6(a) shows an example of variation on this variable. For the most common pattern, the number of primitive groups is 1. Therefore, the appearance of all primitives is the same, meaning that one or more visual variables are applied consistently across all primitives of a given mark to encode data (e.g., Figure 3.7(a)). The composite nature of the pattern, however, allows us to break this consistency. We can apply different variables to recognizable subsets of the primitives (groups) (e.g., Figure 3.7(b), where the number of primitive groups = 2).

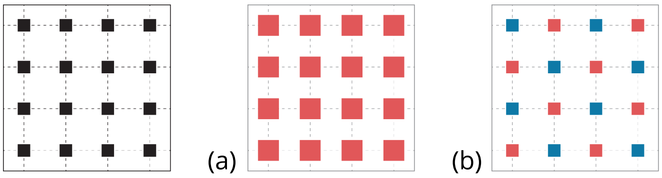


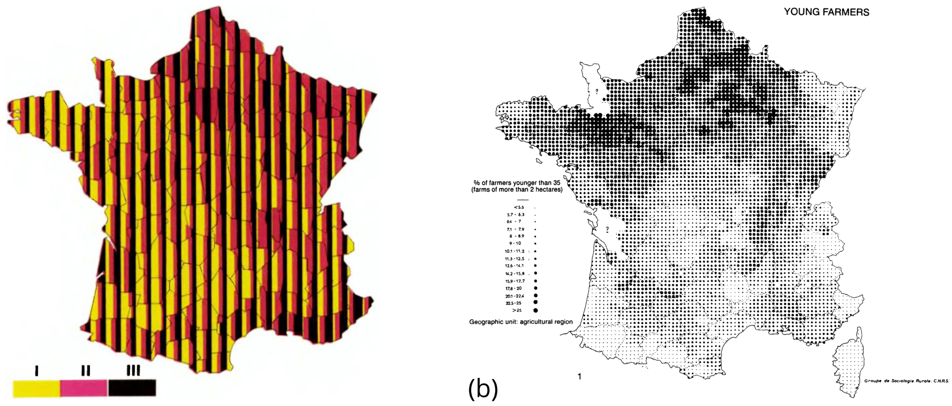
Figure 3.7: Compared to the left, which number of primitives group is 1: (a) global encoding with hue and size, number of primitives group is still 1; (b) pattern with internal variation for hue (subset blue, other subset red), number of primitives group is 2.

Intuitively, adding internal variation of patterns allows us to visualize a new facet of data and represent it within the mark. This new facet introduces a set of keys (categories) and corresponding values. We can use the variable number of primitive groups to encode the number of categories associated with this new facet. However, its application is not limited to this alone; in practice, as it is just a graphical attribute like any other visual variable, it can encode various types of data. This variable is essentially ordered, as it represents a numerical count, making it useful for encoding ordinal data. When using this variable, it is important to ensure that the number of primitive groups is not excessively large to maintain discernibility.

3.3.2 . Ratio between each group

When there are multiple primitive groups, it is necessary to describe the ratio of the number of primitives within each group. We refer this variable as the *ratio between groups*. Figure 3.6(b) shows an example of variation on this variable. Note that this variable is applicable only when the *number of primitive groups* is greater than 1. When the *number of primitive groups* is 1, there is no variation in the interval of appearance of primitives within the pattern; therefore, the attribute ratio between each group is not applicable. In addition, since ratio between each group describes the proportion of primitives of each group, the total of it should add to 1. This variable also theoretically can encode ordered data, because it has a numerical nature.

A straightforward way to use this new facet is to form primitive groups and encode categories (i.e., keys). For example, all red primitives encode data for category A, and all blue primitives encode data for category B. If these categories have a certain distribution (e.g., 75% of data items are of type A, and 25% are of type B), then we can (but do not have to) reflect this split in the primitive group ratio. Figure 3.8(a) from Bertin's book [14, 15] shows a good example of using *ratio between each group* to encode distribution of categories. It shows 3 categories of data for France, with differently colored primitives that encode data by region. Here, the width of each colored primitive encodes the proportion of the respective category, whose totals add to



(a) (b)

Figure 3.8: Examples of using regular arrangement pattern with internal variation. Within the patterns, the variations (a) show a facet of data (described in Section 3.3.2), (b) based on geographical information (described in Section 3.5.2); © EHESS, used with permission.

Figure 3.9: Unit visualization that can be considered to be using internal variation. Image 'The Great War' by Otto Neurath; the image is in the public domain.

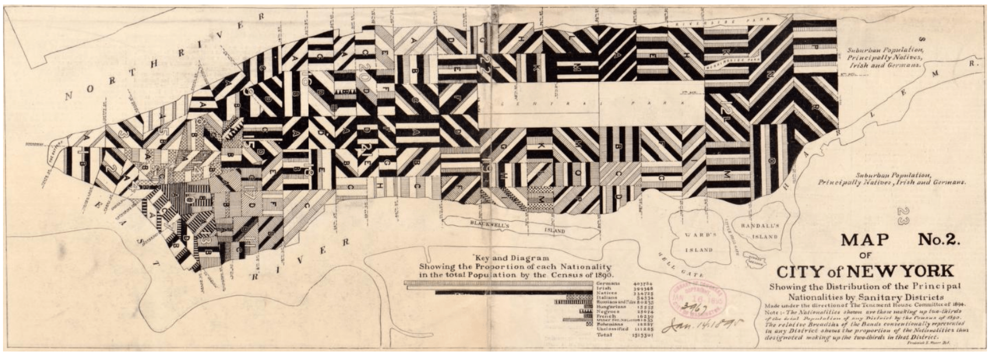


Figure 3.10: Map of nationality distribution in NYC [141] from 1895, illustrating patterns with internal variations from an additional facet, namely, "nationality." It depicts the distribution of different nationalities across sanitary districts in Manhattan. 🄍 the image is in the public domain.

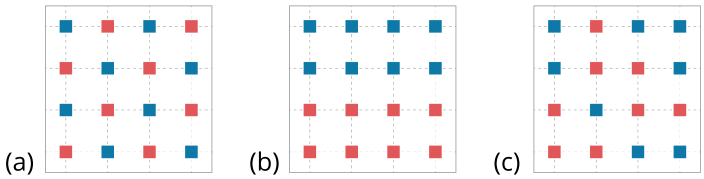


Figure 3.11: Pattern with internal variation with different arrangment of groups of primitives (a) negative autocorrelation, (b) positive autocorrelation, and (c) no autocorrelation.

100%. Figure 3.10 shows another example, employing the number of groups of primitives to encode the number of categories. The ratio between groups (indicated by line width) encodes the percentage of each category. Unit-based visualization with sub-groups an also be considered as using patterns with internal variation—where the variable *shape* is used to represent the categories. Figure 3.9 shows an example of a unit-based visualization. In this figure, if we view each diamond region as a pattern, it exhibits internal variation derived from a new facet, "type of soldiers". Within each pattern, the number of groups of primitives encodes number of categories in this facet, the ratio between groups represents the percentage of each category.

3.3.3 . Distribution style of different primitives

The *distribution style of each group* refers to how we place each group of primitives within the pattern. We should differentiate it from the spatial arrangement of primitives, which concerns the predefined spatial positions of all primitives. Here, we discuss how, after defining all primitives' positions, to further specify which primitive belongs to each group.

Figure 3.11 illustrates three different choices of distribution style (note that they are same in terms of spatial arrangement primitives). Both Figure 3.11(a) and Figure 3.11(b) feature regular arrangements. In Figure 3.11(a), the two groups of primitives are distributed with negative autocorrelation, resulting in a uniform distribution, as exemplified in Figure 3.10. Conversely, Figure 3.11(b) exhibits positive autocorrelation, with primitives within the same group clustering together, as seen in Figure 3.9. Figure 3.11(c) represents a random distribution, where the primitives of the pattern within each group are arranged irregularly.

3.3.4 . Summary

We identify three attributes to describe the appearance relationship of primitives in a pattern, opening many new opportunities for visualization design. Although patterns with internal variation may pose perceptual challenges [117], historical examples (e.g., Figure 3.8(a), Figure 3.9, Figure 3.10) demonstrate their potential in encoding data, making them worth exploring in design and empirical studies.

3.4 . Retinal visual variables on each primitives

In the previous two sections, we used two sets of parameters to describe the relationships between primitives, including their spatial and appearance relationships. After establishing these rules, we still need retinal variables to characterize the appearance of each primitive to complete the pattern. For example, these two patterns  are identical in terms of spatial relationship and appearance relationship, but they differ in the choice of retinal variables (the first uses color to differentiate two groups of primitives, maybe for encoding categories; the second uses size, maybe for encoding quantities). In this section, we explore the application of retinal variables to primitives within a pattern, as well as the additional parameters and effects that arise from their utilization.

3.4.1 . Retinal variables for primitives

Bertin [14, 15] used the term "retinal variables" to describe the graphical attributes that elevate marks above the plane, and point out that these variables are independent of position. Following Bertin's definition, we use the term retinal variable to describe non-spatial graphical attributes. However, we further clarify these attributes to those applicable to individual, non-composite graphical elements, thereby distinguishing them from variables in our previous two aspects.

Bertin identified six initial retinal variables: *shape*, *size*, *orientation*, *value*, *color*, and *texture* (*granularity*). In Bertin's list of visual variables, *granularity* notably comprises two sub-dimensions: *size* and *spacing*, as discussed in Section 2.2.1. This categorizes *granularity* as a composite visual variable rather than an atomic one. Strictly speaking, *size* also comprises two components—*width* and *length*. Similarly, Bertin's *color* combines *hue*, *saturation*, and *value/lightness*. We have therefore revised Bertin's list, identifying the most commonly used retinal variables as *shape*, *size* (1D size), *orientation* (primitive-level orientation), and *color* (*hue*, *saturation*, *value/lightness*).

Theoretically, we could also apply a *pattern* to the primitives of a pattern, with the possibility of adding multiple layers of additional patterns ad infinitum. Figure 3.10 shows an example. It depicts the distribution of different nationalities across sanitary districts in Manhattan. The designer uses lines pattern with variations in orientation to distinguish the districts of the city and use patterns on each line to distinguish different categories. However, it is important to acknowledge this recursive application can cause high visual complexity which may make interpretation challenging, so needs to be designed thoughtfully, and in light of evidence that supports the approach.

Unlike the variables on spatial arrangement and on internal variation of appearance discussed in the previous two chapters, these retinal variables are not new variables introduced by *pattern*. Therefore, this list can extend to any visual variable that is applicable to individual marks. For example, researchers have expanded Bertin's initial list to include additional variables such as *resolution*, *transparency* and *crispness*. For non-static charts, the retinal variables can also have [117] *motion* parameters [117, 181]. We can apply all these visual variables to the primitives within a pattern if needed.

Previous work (e.g., [14, 15, 117, 132, 153]) has investigated the use of these variables and proposed guidelines on their syntactics for mapping (such as which variable is suitable for which type of data), we assume that the use of retinal variables for primitives within a pattern is similar to their use for individual marks. Therefore, we do not introduce each retinal variables one by one. Instead, we focus on issues related to these variables that arise from the repetitive use of primitives.

3.4.2 . Regularity of retinal variables: A secondary visual variable characteristic

While retinal variables themselves do not constitute new variables introduced by patterns, their repetitive use within patterns leads to a series of new variables: the regularity of each retinal variable. These regularities are, in fact, secondary characteristics for each of the visual variables at the primitive level, for which examples are shown in Figure 3.12. Similar to positional regularity, we can describe their range and dispersion level.

For variables that can carry numerical values (e.g., size, orientation, value, lightness), similar to positional regularity, we can quantify the range using the maximum deviation, and quantify the dispersion level using the standard deviation. For variables that do not carry numerical values (e.g., hue, shape),

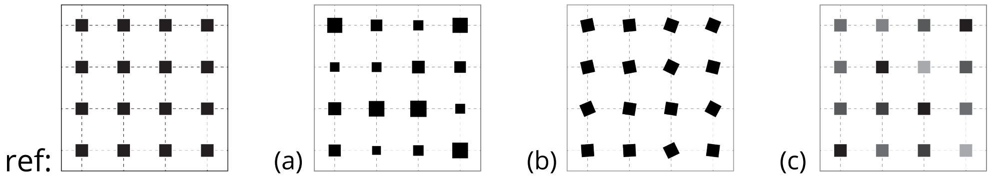


Figure 3.12: Primitive regularity variation, compared to the left: (a) for size, (b) for orientation, and (c) for value.

how to quantify the range and dispersion level requires specific examination. For example, we can use entropy to describe the degree of their regularity.

Related to this concept is work by researchers in the field of non-photorealistic rendering (NPR), who have investigated the generation of non-repetitive patterns (e.g., [7, 94, 123, 154, 188]). These patterns have non-regularity both in their primitives and the primitive's specific placement.

3.4.3 . Dependency between variables

Retinal variables are independent of variables in spatial and appearance relationship. However, when retinal variables are used in the context of patterns, they are constrained by the variables in other aspects. For example, size is influenced by the spatial arrangement. Theoretically, a graphical elements *size* can range from 0 to infinity, but in the context of pattern, a primitive cannot have 0 size and increasing the size of primitives beyond a certain point leads to overlap. This overlap threshold is based on the spatial relationship of the primitives. As soon as primitives with tessellating shapes (e.g., 2D squares or dashed lines in a line pattern) and arrangements touch each other, they form a seamless tessellation and directly convert the pattern into a solid fill. For non-tessellating shapes (e.g., dots), in contrast, an overlapping results in the merging of primitives without necessarily resulting in an immediate solid fill. Drawing on Gestalt principles, even as primitives merge and lose their individuality, our brain is often still capable of perceiving the shape of primitives to some extent through mental completion. Regardless of the specific primitive shape, as their size continues to increase, the pattern ultimately becomes completely saturated, effectively turning into a solid fill. The range of *size* variation that can be effectively utilized in visualization thus spans from just noticeable differences to a threshold where the pattern is no longer identifiable.

There are also dependencies between retinal variables. The primitive *shape* affects both the range and steps of the orientation of the primitive. When the primitive is a round dot, the primitive's orientation cannot produce any variation. The more elongated the shape is, the better we can perceive its orientation [14, 15]. We can thus always use orientation variation on line patterns. For these, however, the orientation at both the primitive level and the

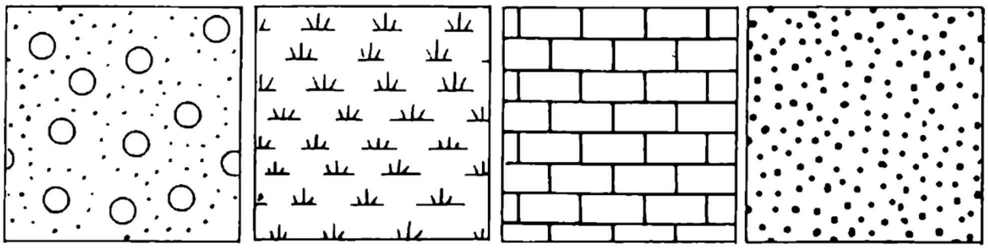


Figure 3.13: Examples of "patterns have achieved the status of symbols" from Bertin's book [14, 15]; © EHESS, used with permission.

arrangement level essentially refer to the same aspect.

3.4.4 . Using multiple variables

We can use more than one visual variable in a pattern. Bertin [14, 15] refers to this as a combination of variables. We vary multiple visual variables for representing the same dimension of data, which is known as a redundant combination. On the other hand, when we represent different dimensions of data, it is referred to as a meaningful combination. In Bertin's discussion on the combination of variables, he only combines the retinal variables. Since we have identified more variables for patterns, we offer more possiblities based on Bertin's original concept.

In addition, we can also combine multiple variables to generate semantic meaning in patterns. Bertin [14, 15] stated that "patterns have achieved the status of symbols." He classified this variation as shape variation, as shown in Figure 3.13. From the examples, however, we can see that they not only vary in shape but also in spatial relationships. Therefore, they combine multiple visual variables. For more examples, refer to Figure 3.14. These include the *hatching* used in technical or architectural drawings, which are well-established pattern sets used for indicating specific materials of objects or surfaces of plans (e.g., standardized by ANSI and ISO). We have also explored the aesthetics and effectiveness of geometric versus iconic patterns [87], as illustrated in Figure 2.2(c).

3.4.5 . Emergent phenomena

When we directly manipulate the pattern attributes mentioned in the previous chapters, it may also affect the appearance of the pattern beyond the attributes we control. We refer to these unintended effects as *emergent phenomena*. These phenomena primarily arise from the composite nature of the pattern.

Regional value. The concept of *regional value* refers to the ratio of black (or colored) to white across the entire pattern, differing from the *value* of in-

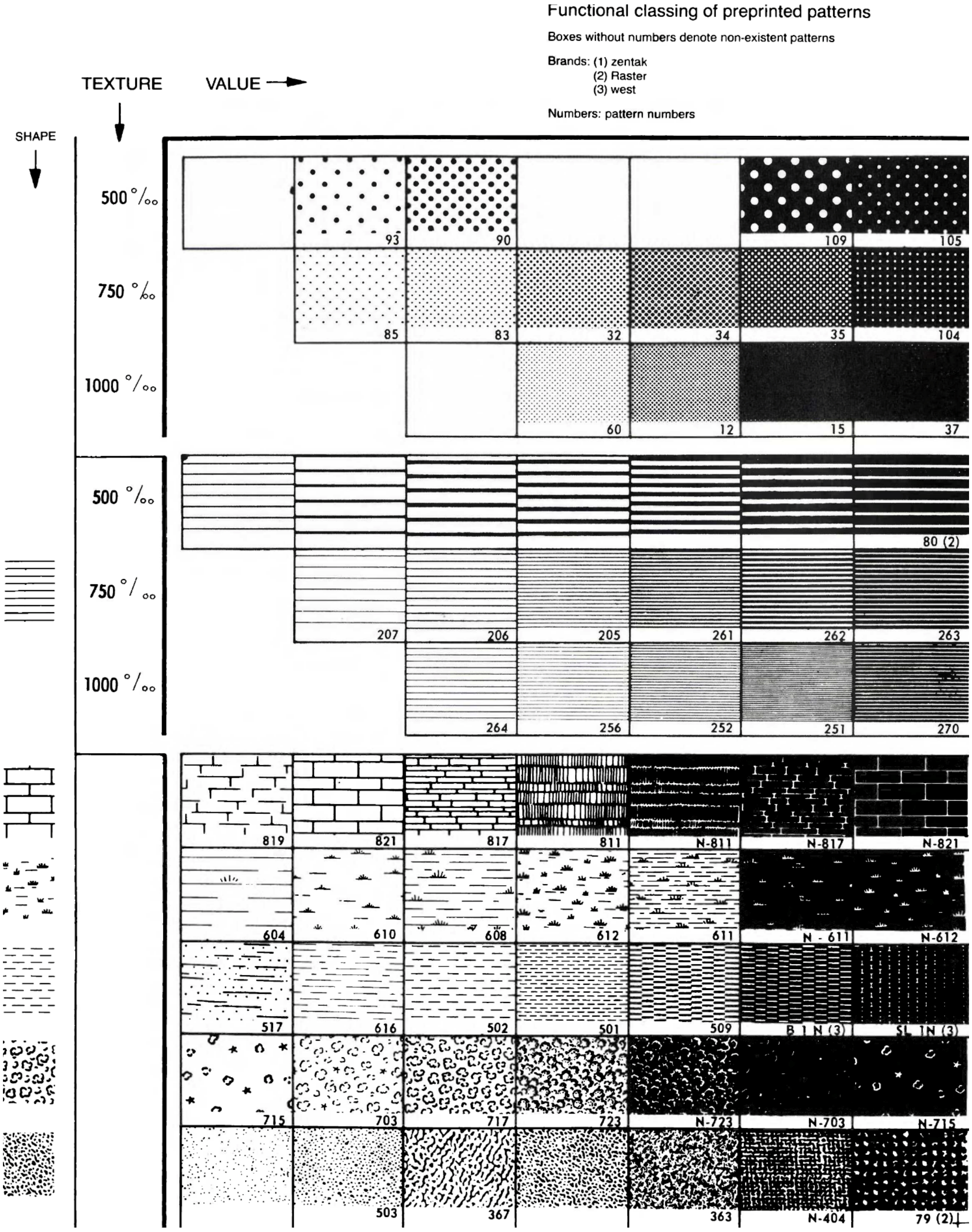


Figure 3.14: Examples of pre-printed hatchings from Bertin's book [14, 15]; © EHESS, used with permission.

dividual primitives. We adopt Bertin's definition of *regional value* and understand it as the overall ratio across the pattern. Bertin's approach to controlling *value* employs a traditional halftoning technique to create varying levels of gray. Halftoning [171] creates the illusion of various shades of gray by adjusting the density of numerous black dots on a white background. Given its composite nature, a pattern can inherently produce a regional *value* that aligns with the logic of *value* as perceived from halftoning.

Value variation is a dominant variation for conveying order [14, 15]. Even though *regional value* is emergent and cannot be controlled directly, we thus need to pay attention to the *regional value* of patterns when using them for encoding data. It is, therefore, important to know which independent variables of pattern affect or do not affect *regional value*.

Among the independent variables we discussed, both *orientation* (at the primitive and arrangement levels) and carefully designed *shape* variations (which essentially maintain a constant number of black pixels) can preserve a constant regional value. In addition, employing combination variables such as *granularity* variation can also preserve *regional value*. *Size* variation usually affects *regional value*, only the special case of changing the sub-paramateters *width* and *height* in opposite directions can keep *value*. Conversely, a variation of *spacing* and of the individual primitive's *value* always also influence *regional value*.

These phenomena help us to reason about the encoding of data, yet without *regional value* variation. For example, one recommended use of patterns [180] is to overlay a *pattern* on a *color* encoding to represent a bivariate scalar field, with one data dimension mapped to *pattern* and the other to *color*. Using this concept, Retchless and Brewer [149] compared eight ways to show uncertainty, as shown in Figure 3.15. Among them, most participants preferred the design using a random dot *pattern* overlaid on *color* (Figure 3.15(g)). This design exemplifies using the pattern's *positional regularity* to encode uncertainty. Yet Ware [180] pointed out that when *patterns* are overlaid on *color*, the bandwidth of the luminance channel is shared between the two. We assume this is due to changes in the *regional value* of the *pattern*, which affects the perception of the underlying *color* layer. Therefore, when using a pattern to represent one of the bivariate variables, the (ordered) data dimension should be represented by a *pattern* variation with a constant *regional value*, in order to minimize its impact on the perceived value of the *color* layer.

Regional color. If all primitives in a pattern are the same color, the regional color is simply the color of the primitives mixed with the (white) background. However, if there are multiple color primitives, we introduce a *regional hue* to the pattern. Incorporating internal *hue* variations among different primitives (e.g., some primitives are blue while others are yellow) can result in a *regional hue* (e.g., green) due to color mixing, similar to the process

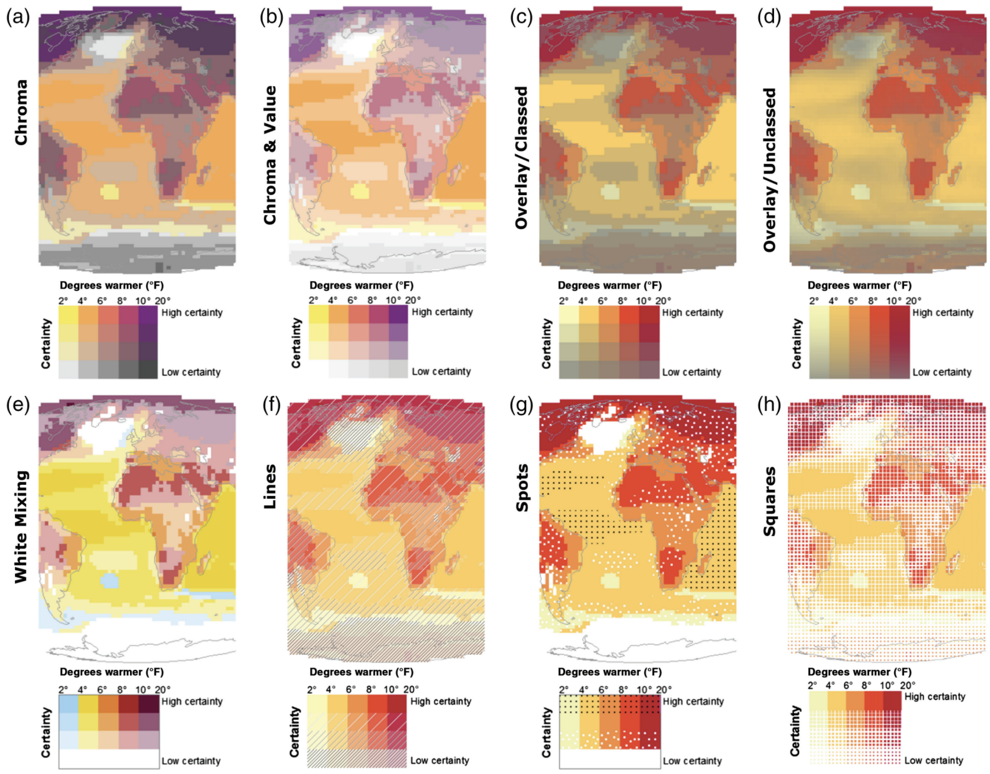


Figure 3.15: Comparison of eight uncertainty representations by Retchless and Brewer. Most participants prefer (g). Reproduced from [149].

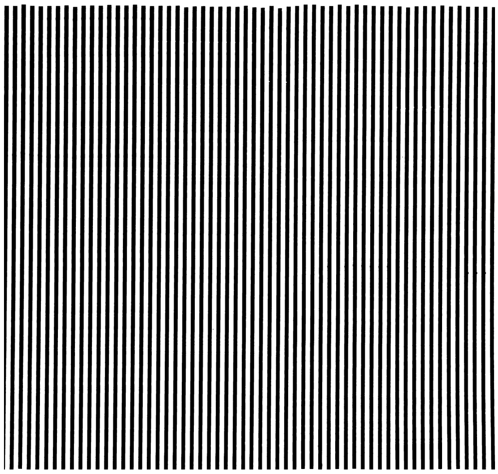
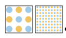


Figure 3.16: An example of Moiré effect from Bertin's book [14, 15]; © EHESS, used with permission.

of color halftoning .

Optical illusion. Repeated patterns can cause a sense of instability, known as the Moiré effect [14, 15] (see Figure 3.16 for example). In addition, there are many Op artworks based on patterns (e.g., Movement in Squares by Bridget Riley). These works vary the size and spacing of pattern primitives to create a sense of movement.

3.5 . Pattern from geographical information

In our discussion so far we explored patterns based on a regular arrangement. We used a lattice to arrange the primitives such that, at most, the relative position between primitives was considered as a visual variable, and the absolute position of primitives became meaningless. This approach is widely accepted in the community for encoding data using patterns. An intriguing alternative, however, is to make use of each primitive's position and use it to encode geographical data. While doing this, do the other parameters of the pattern (i.e., parameters for appearance relationship and retinal variables of each primitive) tell us anything? Do they implicitly encode anything?

3.5.1 . Geographic pattern: Both spatial arrangement and internal variation driven by geographical information

One intuitive approach is to directly encode geographical position into the position variable of each primitive, which leads to symbol maps, in this case the "pattern" is less intuitive and is not created directly. Consider, for example, Figure 3.17, which depicts a symbol map, where each dot represents a city, and the position of each dot is the city's actual geographical location on the

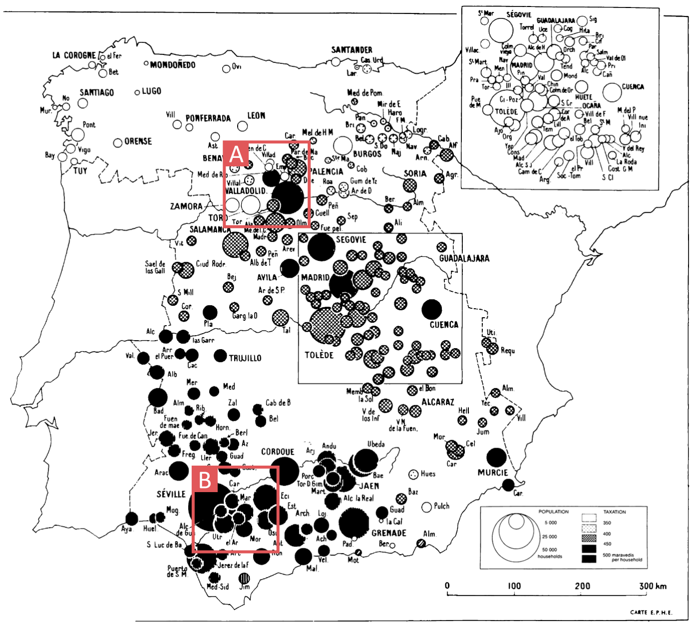


Figure 3.17: Symbol map example, edit based on a map about Population and Taxation in Castille from Bertin's book [14, 15]; © EHESS, used with permission. A and B can be considered as patterns whose primitives encoding geographical information.

map. When we read this map, we can read at individual dot level—get a certain city's population (from the dot's *size*) and its tax rate (from the dot's value). It is also very common for us, however, to read the map beyond the individual dots and look at regions. We may be interested in a specific region such a Region A on the map in Figure 3.17. When we focus on this region we, in fact, visually focus on a pattern—the pattern highlighted inside the red frame. It consists of a group of dots, which are the pattern's primitives. We can see that the pattern of Region A has internal variation and conveys comprehensive regional information. From the pattern, we can discern (1) **where** the cities are located in this region (from the dot *positions*), (2) **how many** cities there are (from the dot *density*), and (3) **what** their characteristics are (with dot *size* representing population and *value* representing tax rate). Among them, (1) and (2) are emergent variables that come from geographic information, which uses arrangement-level visual variables, while (3) is directly encoded in primitive-level variables. The pattern also allows us to compare different regions. We can see, for example, that the pattern in Region A is different from the pattern in Region B, and we can find, e.g., that the taxation levels within Region A might have a greater diversity compared to those in Region B. This information also emerges from the encoding of geographic data to primitives. In this way, when we read this map, we can visually select different patterns at multiple scales and multiple places concurrently to understand geospatial data based on the emergent visual patterns. This process aligns with the goal of cartographic visualization pointed out by MacEachren [118]: to "assist an analyst in discovering patterns and relationships in the data."

We should note that here the "geographic information" we encode to primitive positions can go beyond real-world geographic data, which is typically limited to maps. In fact, what we are doing is encoding positional information relative to a coordinate axis. For maps, this pertains to geographical locations, but for a scatterplot, for instance, we can also consider the points as patterns, with the position being the x- and y-dimensions of the data. We can thus use a similar way to interpret the emergent "pattern" on scatterplots.

3.5.2 . Part-geographic pattern: Only internal variation driven by geographical information

For maps, actually placing a primitive at any point corresponds to geographical information (within the accuracy of the map). Therefore, another approach to make use of the primitives' position is to just keep the spatial arrangement of primitives consistent among the patterns (or, say, across the entire map). In this case, we fix the visual variables in the spatial relationship aspect and do not use these to encode information. We visualize geographical information using the retinal variables of primitives, and the variation in the appearance relationship of primitives emerges.

Bertin calls this specific type of maps with consistent spatial arrangement dot as "semis (seedbed)." Then, we can let each primitive's primitive-level variable change according to the corresponding information of its location, which is called "a regular pattern of graduated circle." For instance, Figure 3.8(b) shows the use of dot size to represent the local population. On this map, the pattern in each map region (departments of France) we see has internal variation.

3.6 . Conclusion

We have elucidated the underlying thoughts in Bertin's works, addressing internal inconsistencies of Bertin's methods (described in Section 2.3.2). We identify three sets of attributes of patterns. The first set of attributes describes the spatial arrangement relationships of primitives. Previous works have proposed some variables that can be included in this set, such as density and positional regularity. However, these works do not systematically describe these variables in the context of patterns, nor do they fully summarize all spatial arrangement variables of patterns. Next, we propose the attributes describing appearance relationships between primitives, which introduce internal variations within patterns. This is a novel concept not discussed in previous works. We found some good examples from Bertin and other older visualizations, but these examples are scattered and not systematically analyzed. Lastly, we discuss the retinal variables on primitives. While these sets of visual variables have already been investigated by previous researchers, we introduce new variables brought by patterns, the regularity of the retinal variables, and the visual effects caused by using retinal variables repeatedly.

In summary, our approach is the first to systematically describe that, compared to single marks, how patterns—as visual variables consisting of multiple marks—provide additional variations on relationships compared to single marks. The visual variables we have identified offer visualization designers with a toolkit for encoding data through patterns and lay the groundwork for future empirical studies and the development of visualization libraries. Moreover, by exploring how patterns emerge from positional information without compromising their essence, we employ patterns as a theoretical lens to compare, explain, and connect different types of visualizations.

4 - Empirical Studies on Black-and-White Patterns for Categorical Visualization

As shown in the pattern design space in Chapter 3, patterns have various attributes that we can manipulate for encoding data. However, existing guidelines and empirical evidence on how to effectively use these pattern attributes are limited. It remains unclear how these attributes interact within a single data display and how the use of patterns affects perceived aesthetics and chart reading effectiveness.

To address this gap, we conducted three empirical experiments to explore the aesthetics and effectiveness of different combinations of pattern attributes for data encoding. Theoretically, the instances of patterns can be infinite. As this is the first study in this area, we narrowed our research scope to a specific subset: black-and-white patterns for categorical visualization. We focused on three simple chart types (bar charts, pie charts, and maps) and two pattern types (geometric patterns and iconic patterns).

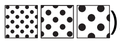
First, we invited 30 visualization experts to design geometric and iconic patterned bar charts, pie charts and maps by adjusting parameters of each pattern attribute. We collected 66 designs and experts' design strategies and opinions on using patterns for visualizations. Then, we conducted a crowd-sourced experiment, in which we had 150 participants rate the designs we collected for their aesthetics. Finally, we conducted another crowd-sourced experiment with 150 participants to perceptually assess how quickly and accurately people can read the bar and pie charts filled with the top-rated geometric and iconic patterns as well as a unicolor fill. In this chapter, I present these three experiments in detail.

This chapter is an updated version of my original article published at IEEE Transactions on Visualization and Computer Graphics [87]. The work was led by myself in collaboration with Yuanyang Zhong, Petra Isenberg, and Tobias Isenberg.

4.1 . Related work

In this section, we first examine previous work on the use of patterns in visualizations, with a focus on traditional geometric patterns. Next, we describe research on pictographs, which inspired our use of iconic patterns.

4.1.1 . Using pattern for visualization

In his seminal book, Bertin [14, 15] comprehensively discussed how to use 2D geometric patterns for visualizations. Bertin referred to visual channels as *retinal variables* and proposed 7 key ones, including *planar position*, *size*, *value* (black/white ratio), *texture*, *color*, *orientation*, and *shape*. These visual channels are mainly used to manipulate 2D marks such as points, lines, and polygons in printed data graphics. As we discussed in Section 2.2.1, we note here that Bertin's terminology differs from what we commonly use today. He used the term *texture* to refer to the number of distinct marks in a given area, which is similar to what we call *grainularity* (e.g., ). Our notion of *pattern* encompasses several visual variables mentioned by Bertin (texture (granularity), size, orientation, shape), so his ideas on the use of these variables are important for us. For instance, Bertin identified four perceptual qualities—*associative*, *selective*, *ordered*, and *quantitative*—to determine which visual channels are suitable for representing different types of data. Both associative and selective qualities are important for nominal data. Associative perception helps designers to balance variations and groupings across all categories of a given variable, while selective perception indicates that a variable has enough diversity for people to distinguish all the elements of this category from others. Bertin found that texture (granularity) as a visual variable is both selective and associative, making it ideal for encoding categorical data.

More visual channels were proposed and evaluated after Bertin. Cleveland and McGill [54] evaluated various channels for accuracy, but excluded pattern and texture. Mackinlay [120] extended this research to 13 visual channels, ranking them based on their effectiveness in encoding quantitative, ordinal, and nominal data. For nominal data, texture ranked third, outperformed only by position and hue.

The use of pattern in visualizations has not been extensively researched. There are several design guidelines on how to use pattern in visualizations, but they are limited and mostly borrowed from the psychophysics field directly, without empirical research using visual data representations—which is what we provide. Some visualization design books [104, 180] recommend ensuring that visual properties are distinguishable when using pattern. For instance, it is suggested that orientation varies by at least 30° and that the spacing of primitives with similar orientations varies by at least a ratio of 2 to 1. Both Tufte [169] and Bertin [14, 15] mentioned that patterns may produce the vibratory effect. Bertin pointed out that this visual effect represents a remarkable selective possibility, so designers can make good use of it. Tufte [169], however, believed this effect should be avoided altogether. We empirically investigate this effect further in our own work.

4.1.2 . Research on pictographs

Pictographs, or pictorial visual representations, use an icon-based language to represent data visually [194]. They have a long history and have been shown to have many positive effects. The ISOTYPE system, an icon-based visual language developed by Otto Neurath, Marie Neurath, and Gerd Arntz in the mid-1920s, is a well-known example of pictographic visualization. ISOTYPE visualizations feature rows or arrays of icons, using repetition rather than size of icons to represent quantitative data [135]. Chen and Floridi [48] organized over 30 visual channels into a simple taxonomy consisting of four categories, namely geometric, optical, topological, and semantic channels. Icons and ISOTYPE are classified as semantic channels in this taxonomy.

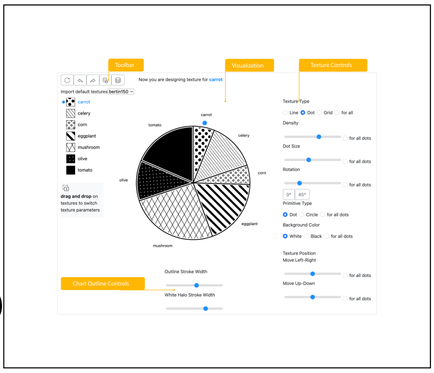
Studies by Haroz et al. [81] on bar charts with ISOTYPE found that pictographs are beneficial for working memory and engagement, and do not significantly impact chart reading performance. Burns et al. [35] conducted a comparison between part-to-whole visualization using pictographs and found that pictographs made it easier for people to envision what was happening in the charts.

Since icons have lots of shape attributes, researchers also investigated how to support the design of pictographs. Borgo et al. [22] did a comprehensive survey of glyph-based visualization and proposed a set of design guidelines. Morais et al. [129] created a design space for anthropographics, a type of visualization that incorporates human-related information. One common approach in anthropographic design is to use pictographs in the shape of humans. Shi et al. [160] explored the design patterns of pictorial visualizations that can be used to guide their generation. All these studies and the established pictograph qualities inspired us to investigate the use of icons as pattern primitives.

Pictographs, however, can also be seen as a type of visual embellishment (or 'chart junk'), which are extraneous elements in a chart or visualization that do not represent data [9]. Tufte's [169] design principles suggest to maximize the data-ink ratio and to avoid chart junk. To investigate this issue, Bateman et al. [9] conducted a study comparing plain and embellished charts. They discovered that adding embellishments did not have any impact on interpretation accuracy, but it did improve long-term recall, made the topic and details of the chart more memorable (an effect later confirmed by Borkin et al. [23, 24]), and embellished charts were preferred by participants. These results also led us to investigate icon-based patterns more closely.

4.2 . Experiment 1: Design

To better understand how to effectively combine pattern properties in designing patterns for visualization, we conducted a series of experiments. In

(a) 

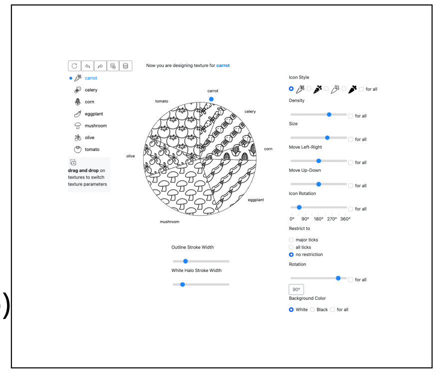
(b) 

Figure 4.1: Technology probe for designing patterns used in charts: (a) for geometric patterns, and (b) for iconic patterns. The annotations highlight the elements discussed in Section 4.2.1.

our first experiment, we focused on the perspective of visualization professionals. We reached out to visualization experts with a design background and asked them to create designs using patterns to identify the characteristics of effective textured visualizations in their eyes and to study their approaches to parameter arrangement. To keep the workload manageable, we narrowed our scope to three basic chart types (bar charts, pie charts, maps) and two pattern categories (geometric, iconic).

4.2.1 . Pattern design interface as a technology probe

To collect input from professionals, we developed a web-based technology probe [95]. This tool allowed experts to create chart designs using black-and-white patterns by adjusting various parameters. The probe comprised three main views: the visualization itself, the controllers, and the toolbar.

Using our web-based technology probe, designers can create patterns by adjusting parameters via buttons and sliders. Figure 4.1 shows screenshots of our technology probe for designing geometric patterns and iconic patterns used in pie charts, with annotations for each part of the probe.

Visualization view

In the central view, we show the chart—a bar chart, a pie chart, or a map "colored" with black-and-white geometric or iconic patterns—and its legend. The chart represents unspecified quantities for seven vegetable items (carrots, celery, corn, eggplant, mushrooms, olives, tomatoes).

When opening the interface, we showed the chart with default patterns and dataset. For geometric patterns, we provided five default pattern sets, all sourced from Bertin's book [14, 15] (see Figure 4.2). Bertin used these patterns to encode nominal and ordered data. We picked the default pattern set from the Bertin set randomly per participant.

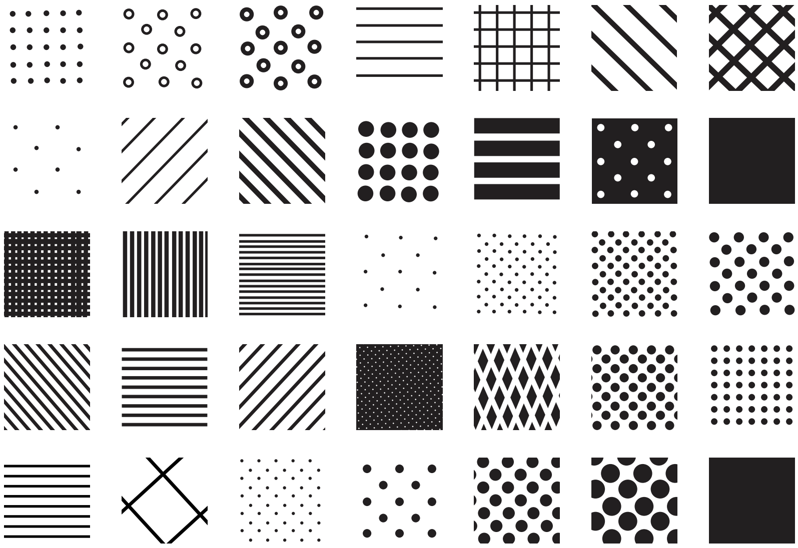


Figure 4.2: The five pattern sets (rows) we included in Experiment 1 as defaults, inspired by visualizations from Bertin's book [14, 15].

For iconic patterns, we chose two professionally designed, neutral, and stylized icon sets from Icon8.com [2] to represent the vegetable items, as we show in the top two rows in Figure 4.3 (one light one and the corresponding dark variant). In addition, we wanted to provide the participants with two corresponding simplified pattern sets. As we did not find complete, matching sets on Icon8.com, we created the simplified version by eliminating details and streamlining the outlines of the original, detailed icons, as shown in the bottom two rows of Figure 4.3. The only icon that we did not change is that for the mushroom, as there was no detail that we could reasonably remove. In total, in Experiment 1, we thus provided participants with four distinct icon sets (Figure 4.3).

The visualization experts could then edit any given vegetable's pattern by clicking the corresponding section of the chart (e.g., the bar or pie piece) or the vegetable's legend entry. We showed a blue round dot next to the vegetable on the chart and the legend to indicate the vegetable currently being edited. The experts could also swap patterns by dragging and dropping, such as dragging the pattern from the carrot's bar and dropping it on the mushroom's bar. For iconic patterns, naturally, we then switched only the parameters and not the vegetable icons themselves (e.g., the carrot bar always used carrot icons).

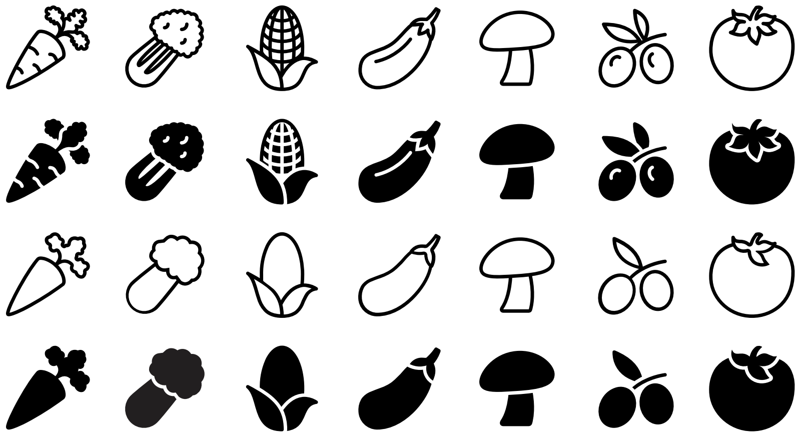


Figure 4.3: Icon sets included in Experiment 1. The first and second rows of icons are collected from Icon8.com, the third and fourth rows of icons are simplified versions we created outselves. The icons in the top two rows are © Icon8.com, used with permission.

Controls for adjusting the patterns

Our interface relied on buttons and sliders. After selecting a vegetable's pattern, the experts could modify the chart's patterns using these controls by first choosing a primitive type and then adjusting its properties.

Primitive shapes. For the geometric patterns, we provided three primitive types: lines, dots, and a grid. For the iconic patterns, we selected two professionally designed, neutral, stylized icon sets from Icon8.com [2] (ensuring we would have icons for all data items). We also provided two matching simplified pattern sets, created by removing internal details and simplifying outlines from the original versions. In total, we offered four sets of icons (all shown in Figure 4.3).

Properties. The visualization experts could adjust the various pattern properties [1], including primitive type, density, size, orientation, the pattern position in the chart, and the chart outline width.

In addition to these common properties, dot patterns could be modified to display circles, while grid patterns allowed angle adjustments between two lines. For icons, the entire pattern could be rotated and the individual icons themselves as well. For pie charts and maps with connected regions, we also added an optional white halo between the pattern and the black outline and allowed the experts to adjust its width.

[1]These properties are commonly used in patterns in current visualizations, as summarized based on a review of historical patterns and prior literature. They do not fully include the pattern properties summarized in Chapter 3, because we first conducted the experiments described in this chapter and then generalized the results to the design space in Chapter 3.

We pilot-tested our technology probe within our research group and, based on this pilot, chose reasonable value ranges for density, size, outline, and the white halo width. For other parameters such as orientation we allowed the full spread of possibilities (i.e., a full 360° rotation). We also offered controls to quickly set certain properties to special values, such as rotating the pattern in steps of 45°. We selected these special values because they are common in historical visualization examples. We also added a "for all" checkbox to the property controllers that, when checked, applies changes across all patterns of the same type (for geometric patterns, e.g., all grid patterns; for iconic patterns for the patterns of all seven vegetables).

Toolbar

At the top of the interface we offered a toolbar for managing operations on patterns and datasets, loading default pattern sets, as well as undo and redo functionality. A reset button allowed the visualization experts to revert all patterns to their respective default settings. We also provided a button to load a new, random dataset or to return to the default dataset (that we use throughout this chapter; e.g., Tables 4.2–4.7).

User feedback on the tool

Although we did not specifically request participants to comment on our tool, four participants voluntarily commented in their free-text answers in Experiment 1, and nine participants provided voluntary, unprompted comments in response to the invitation e-mail. They said that they enjoyed using our tool (mentioned 10×) and found that the interface was well-designed (1×), that the controls made it easy to manipulate the patterns (1×) and allowed them to create expressive patterns (1×).

4.2.2 . Method and procedure

We used a mixed design with the between-subjects variable *chart type* (bar, pie, map) and the within-subject variable *pattern type* (geometric, iconic). The experiment was pre-registered (`osf.io/r4z2p`) and IRB-approved (Inria COERLE, avis № 2023-01).

We recruited participants by reaching out to visualization experts with design expertise within our network via e-mail. We also requested that these experts share the e-mail with their colleagues, friends, or students. Furthermore, we sent our experiment link to the design-related Slack channels of the Data Visualization Society [1].

We started the study by asking participants for their informed consent and background information. Following a tutorial to familiarize them with the interface, we assigned participants randomly to a chart type and instructed them to design two charts, one with geometric and one with iconic patterns, in random order. We asked them to adjust the parameters to create effective visualizations. Subsequently, we asked them about their goals and design strategies, their opinions on the two pattern types, and their thoughts on the transferability of their designed patterns to the other two chart types by showing them their designs automatically applied to the respective other charts. After completing the experiment once, we gave the participants the chance to continue. For any repetition they could select their preferred chart type to use, while we still randomly assigned the pattern type order.

4.2.3 . Results

We collected 66 designs from 30 experts (12 female, 18 male; ages: mean = 40.1, SD = 14.4; prior experience in visualization design: mean = 13.4 years, SD = 11.0 years). The designs consisted of 14 bar charts, 30 pie charts, and 22 maps. Six of the pie charts were from participants who had completed this experiment at least once before. Half of the designs used geometric patterns, while the other half used iconic patterns. We show all created designs in Section A.2 and qualitatively coded the free-text answers using open coding. We discuss our observations and findings next.

Design strategies

We broadly categorized the main objectives of experts into two classes: those related to data readability (e.g., distinguishing between categories, ensuring the clarity of the chart, creating semantic associations) and those focused on aesthetics (visual pleasure, balance).

Distinguishability. 27 participants mentioned wanting to make the categories distinguishable (5× bar, 12× pie, 10× map). To achieve this goal, the use of varied visual channels was the most commonly used method (mentioned 12×). For differentiating geometric patterns, most participants used background color, density, and size as the key visual channels. For iconic patterns, background color, orientation, icon style, and density were generally considered helpful. In addition, participants mentioned that, for designing pie charts, outlines (1×) and white halos (3×) contributed to creating a more distinct separation. We indeed observed many designs with thick outlines (11×) and white halos (10×) in pie chart designs, which is not common in other chart types. For iconic patterns, specifically, 5 participants found it important to show complete icons in the chart. One response also mentioned that upright icons were generally easier to recognize.

Clarity. 14 visualization experts tried to make the chart clear and readable (4× bar, 4× pie, 6× map). To be specific, 5 responses mentioned they participants focused on avoiding clutter and overwhelming elements. Fading icons into the background is considered as a way to avoid icons being overwhelming and distracting (2×). The white halo was also considered useful in preventing a perception of clutter (1×).

Semantic association. Five participants tried to create a semantic association between the patterns and the vegetable items (2× bar, 2× pie, 1× map). With iconic patterns, people applied the vegetables' relative size to the icons of their representative patterns (4×), such as making the tomato icon larger than the olive icon due to their physical size difference. In addition, in 2 designs the visualization experts selected the patterns for vegetables (dark vs. bright) based on their respective colors. Remarkably, 4× the experts sought to establish conceptual matches between the vegetable items and the geometric patterns. One did this by considering the vegetables' color, while two others tried to elicit visual associations by incorporating various visual channels. Furthermore, one employed dots to signify vegetables typically planted in rows such as carrots, celery, and corn.

Visual pleasure. In 13 responses the participants tried to make the chart visually pleasing (4× bar, 5× pie, 4× map). One common strategy was to maintain a consistent visual style throughout all categories by applying a uniform orientation, line width, density, or icon style (9×). Other strategies included selecting an aesthetically pleasing default pattern set (2×) and striving to create a visual experience that was harmonious (1×), clean and elegant (1×), or sketch-like (1×).

Visual balance. In 12 responses the visualization experts mentioned to attempt a visually balanced chart (2× bar, 7× pie, 3× map). To achieve this objective, a strategy was to use a consistent ink density across all categories such that the patterns maintain a roughly equal visual weight, preventing one pattern from dominating or becoming too weak (8×). Notably, in 3 responses the participants emphasized that, since our designs were aimed at general datasets, patterns should be effective for small areas without being overpowering in larger ones, indicating that the pattern should remain recognizable even when a category represents a small data point.

Other design strategies. Apart from these primary design goals, our participants employed several other noteworthy strategies.

Abstracting iconic patterns: One person aimed to create an abstract representation of iconic patterns by making the icons overlap (BI4 in Table 4.3 or Figure A.5(d) in Section A.2). This approach produced an interesting pattern-like style, in which the vegetables are still distinguishable.

Avoiding conflicts with chart outlines: Another participant avoided using vertical line patterns when designing bar charts with geometric patterns, as these would conflict and compete with the vertical bars.

Using dense icons for iconic maps: When designing iconic maps, people often used small and dense icons. Two participants mentioned to make an explicit effort to incorporate this design approach. We observed 8 out of 11 iconic maps with dense icons.

Connecting areas: Two participants removed borders to allow the same patterns to connect between areas on a map. Unfortunately, this visual grouping of regions in the maps (Figure A.9(g) in Section A.2; to some degree also MG4 in Table 4.6 or Figure A.8(d) in Section A.2) may be misleading, resembling a pattern version of the rainbow color map [25].

Avoiding negative pattern effects: Participants also employed various strategies to address the potential negative effects caused by patterns. For example, one participant attempted to avoid the vibratory effect, while another was cautious not to incorporate too many patterns that could generate an aliasing effect. In addition, one participant adjusted the density of dot patterns to minimize spatial density associations with adjacent patterns, thereby reducing the adverse effect of densities altering the perception of grouping.

Using geometric and iconic patterns

After designing patterns for both geometric and iconic shapes, we asked participants to share their thoughts on using these pattern types in data representation. The most notable difference that was mentioned by participants was the semantic association provided by iconic patterns (10×), which made iconic patterns self-explanatory. In addition, participants generally found geometric patterns easier to handle (3×), had more variation (2×), and better for distinguishing bar chart columns (1×). Despite the novelty of iconic patterns (2×), they were perceived as more cluttered and harder to read (7×).

Application of patterns to other charts

We also applied the patterns designed by participants to the two other chart types and asked the participants whether they thought that the patterns still worked and to provide their reasoning. Table 4.1 summarizes the percentage of designs that participants considered to still work in each condition. We can see that patterns designed for bar and pie charts were rarely considered to work well on maps. Patterns designed for maps, in contrast, were considered to be quite suitable for both bar and pie charts. The primary reason for this discrepancy is that the space available for filling patterns in maps can be relatively small compared to bar and pie charts. Applying patterns designed for bar and pie charts to maps can thus lead to visual clutter or generally bad readability. This observation highlights the significant impact that the available space in a chart has on the effective use of patterns. Experts should therefore tailor their patterns specifically to the target chart.

4.3 . Experiment 2: Rating

Table 4.1: Percent of designs that still worked for another chart type.

texture design \ applied to	bar	pie	map
geometric bar	/	57.1%	28.6%
iconic bar	/	100%	28.6%
geometric pie	53.3%	/	26.7%
iconic pie	73.3%	/	13.3%
geometric map	90.9%	90.9%	/
iconic map	72.7%	81.8%	/

After we collected a diverse set of pattern designs, we wanted to know how the general public would experience them in terms of their visual appeal. We asked participants about the collected designs' aesthetics, vibratory effect, and overall preference. We included questions about the vibratory effect because it is a well-known negative effect that patterns can produce. According to some experts [14, 15, 169], its negative impact makes the use of patterns for visualization undesirable (see Section 4.1.1). This experiment was also preregistered (`osf.io/nyru7`) and IRB-approved (Inria COERLE, avis № 2023-01).

4.3.1 . Participants

We recruited 150 valid participants (fluent English speakers, of legal age—18 years in most countries) through the Prolific platform. Participants received a compensation equivalent to 10.20 euros per hour.

4.3.2 . Stimuli selection

To avoid a lengthy experiment and given the similarity between some designs, we chose a subset of aesthetically appealing designs that represented a diverse range of aesthetic styles for our experiment. To facilitate this selection process, we first printed each of the 66 designs from Experiment 1 (Section A.2) using the default dataset on individual A4 paper sheets. Subsequently, we classified these designs based on their distinguishing aesthetic characteristics. Some of these attributes included unique pattern properties such as the use of a predominantly black background or overlapping icons. We also looked at the overall impression the design conveyed such as an appearance of regularity or a sense of calmness. While this classification process was inherently subjective, we made an effort to ensure a balanced representation of various aesthetic styles. After identifying different styles, we selected 24 designs we considered aesthetically pleasing with four images representing each combination of chart type and pattern type (see Tables 4.2–4.7).

4.3.3 . Method

We employed a mixed design using the between-subjects variable *chart type* (bar, pie, map) and the within-subjects variable *pattern type* (geometric, iconic). We randomly assigned participants to one chart type.

We started the study by asking participants to complete a consent form and to provide their background information. We then gave them a brief explanation of the vibratory effect, and instructed them to focus only on the visual appearance of the charts. Subsequently, we asked them to evaluate a total of eight images, presented in two separate blocks: one containing geometric and the other iconic patterns. Each block contained four images, with the block order and the images within them randomized. For each block, we asked participants to rate the aesthetics of each visualization using a 7-point Likert scale via the 5 items of the BeauVis scale [85], a validated measure we developed to compare the aesthetic pleasure of visualizations, as explained in Chapter 5. We also added 1 item to assess the degree to which they perceived a vibratory effect. We included one attention check question in this section. Following the rating section, we asked participants to rank the four visualizations they had just evaluated based on their overall preference. In addition, we asked them to provide a rationale for their selection of the highest-ranking visualization.

4.3.4 . Data analysis and interpretation

For each design, we computed the BeauVis score as the mean of the five BeauVis Likert items. We then calculated the average BeauVis and vibratory scores for each design across all participants. We also counted the number of times a design was ranked first for overall preference.

For each chart type, we also computed the average BeauVis score for both the four geometric and the four iconic pattern designs per participant. We report the sample means of BeauVis scores along with their 95% Bootstrap confidence intervals (CIs; 10,000 bootstrap iterations, indicating that we have 95% confidence that the calculated interval encompasses the population mean). We also first averaged the question on the vibratory effect across the four images per pattern type, and then across all participants, and report the sample mean with its 95% CI. We present the CIs of the mean differences between two pattern types for each chart type for BeauVis score and vibratory score.

In our analysis, we derive inferences from the graphically presented point estimates and interval estimates, thus eliminating the need for conducting significance tests or reporting p-values. As suggested in the literature [16, 17, 55, 60, 63], we interpret CIs as providing different levels of evidence for the population mean. To compare different techniques, we examine the CIs of mean differences. When the CI bar of the mean difference between two techniques does not intersect with 0, we can conclude that there is evidence of a difference between these two techniques, which is equivalent to the results being statistically significant in traditional p-value tests.

4.3.5 . Results

We received 170 responses from Prolific. After excluding those who failed our attention check question, we obtained 150 valid responses for our analysis (75 female, 75 male; ages: mean = 28.2, SD = 8.9; education: 87 Bachelor's or equivalent, 27 Master's or equivalent, 3 PhD or equivalent, 33 other). Among them, 53 participated in the bar condition, 44 in the pie condition, and 53 in the map condition.

Tables 4.2–4.7 show the BeauVis score (and its respective distribution), the number of times a design was ranked first, and the vibratory score for each design. While we calculated these scores primarily for selecting stimuli for our next experiment (Section 4.4), they can also provide insight into the general public's opinion on each design.

Looking at the pairwise differences of the two pattern types for each chart (Figure 4.4 and 4.5), we only found evidence of a difference between iconic and geometric patterns for maps, where geometric patterns were perceived as more aesthetically pleasing. Participants perceived iconic patterns to have a lower vibratory effect than geometric patterns across all three chart types. The average BeauVis scores were lowest for the iconic maps at just below average on the 7-point scale and hovered around or just above average for most other designs. The chart with the highest BeauVis score was an iconic bar chart with a rating of 5.07 on average. This finding is particularly intriguing, prompting us to delve deeper into the data to examine the distribution of BeauVis scores for each design, which we included as word-scale histogram visualizations [77] alongside the BeauVis scores in Tables 4.2–4.7. From these, we see that, in each condition except for iconic maps, the highest average score one (located on the leftmost side of the table) all have a normal-like BeauVis score distribution, which means that people's opinions are consistent. This consistency gives us confidence in utilizing the BeauVis score as a reliable reference indicator for selecting the most suitable pattern within each condition to serve as stimuli. But we can also see that opinions diverge for designs that received lower average scores, such as BI3 and BI4. Notably, the BeauVis score distributions for PI3, PI4, and MI1 are uniform or even bimodal, suggesting that participants hold varying views about these designs. Therefore, patterns with lower average scores should not be directly counted as bad since they may appeal to certain individuals, as also demonstrated by the fact that each chart was ranked as the top choice by some participants.

4.4 . Experiment 3: Chart reading

Beyond this feedback on visual appearance, however, it is also important to understand how the use of patterns influences chart reading.

Lin et al. [112] found that employing semantically-resonant colors can improve performance in chart reading tasks, while Haroz et al. [81] found that

Table 4.2: BeauVis score with distribution, # ranked first (total: 53), and vibratory score for geom. bars BG1–4 (left–right; larger in Section A.2).

	BG1	BG2	BG3	BG4
BeauVis (1–7)	4.70	4.45	3.92	3.84
ranked first	16	20	13	4
vibratory (1–7)	3.83	3.66	3.00	5.13

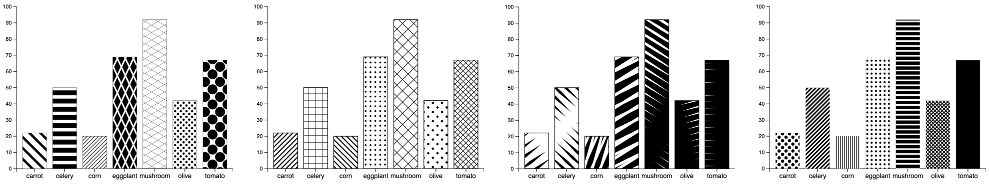


Table 4.3: BeauVis score with distribution, # ranked first (total: 53), and vibratory score for iconic bars BI1–4 (left–right; larger in Section A.2).

	BI1	BI2	BI3	BI4
BeauVis (1–7)	5.07	4.71	4.29	3.79
ranked first	16	13	19	5
vibratory (1–7)	2.89	2.02	3.42	2.92

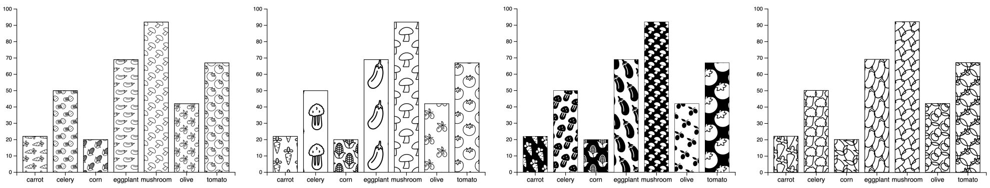


Table 4.4: BeauVis score with distribution, # ranked first (total: 44), and vibratory score for geometric pies PG1–4 (left–right; larger in Section A.2).

	PG1	PG2	PG3	PG4
BeauVis (1–7)	4.95	4.40	4.37	4.33
ranked first	17	13	4	10
vibratory (1–7)	4.30	3.73	5.02	3.64

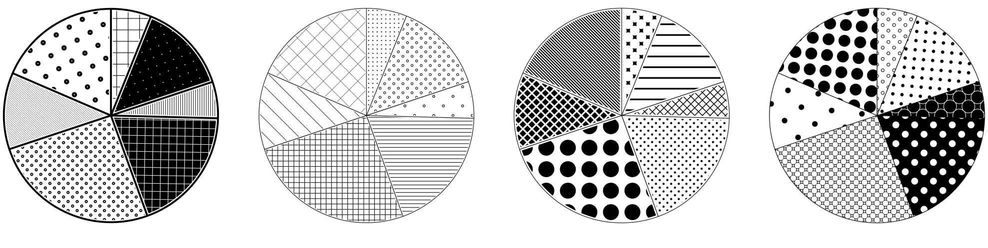


Table 4.5: BeauVis score with distribution, # ranked first (total: 44), and vibratory score for iconic pies PI1–4 (left–right; larger in Section A.2).

	PI1	PI2	PI3	PI4
BeauVis (1–7)	4.81	4.69	4.60	4.48
ranked first	13	9	10	12
vibratory (1–7)	2.55	2.95	2.59	3.57

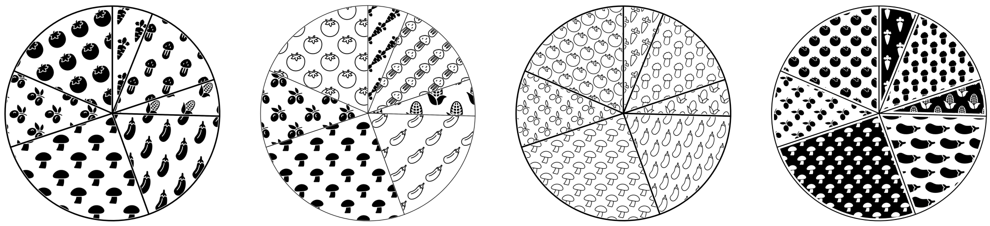


Table 4.6: BeauVis score with distribution, # ranked first (total: 53), and vibratory score for geometric maps MG1–4 (left–right; larger in Section A.2).

	MG1	MG2	MG3	MG4
BeauVis (1–7)	4.27	4.25	3.57	3.15
ranked first	21	18	6	8
vibratory (1–7)	3.42	4.43	4.38	3.08

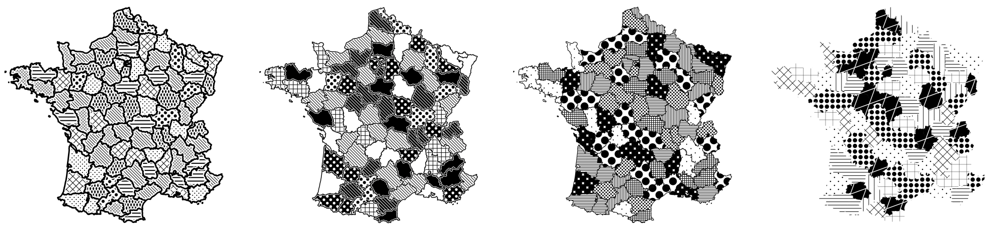
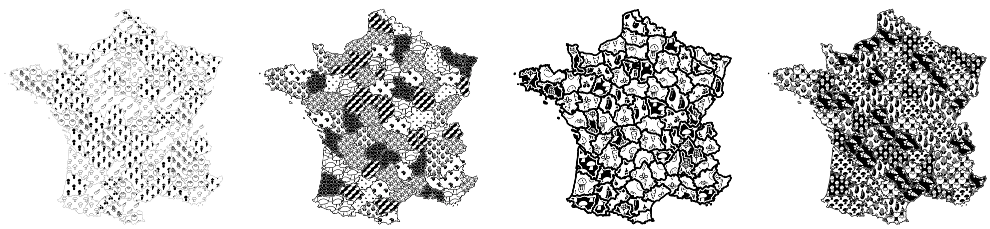


Table 4.7: BeauVis score with distribution, # ranked first (total: 53), and vibratory score for iconic maps MI1–4 (left–right; larger in Section A.2).

	MI1	MI2	MI3	MI4
BeauVis (1–7)	3.58	3.55	3.32	2.66
ranked first	17	18	16	2
vibratory (1–7)	2.81	3.68	2.32	3.55



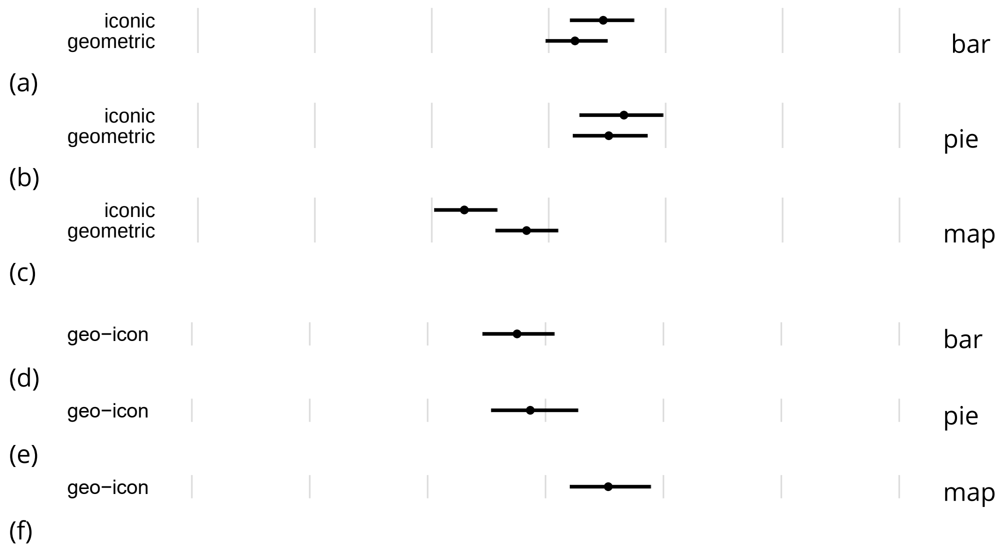


Figure 4.4: Aesthetics analysis: BeauVis score for each fill type for (a) bar charts, (b) pie charts, and (c) maps; (d)–(f) corresponding pairwise comparisons between the two fill types. Error bars are 95% Bootstrap confidence intervals (CIs).

pictographs do not significantly affect chart reading time. When we initially pre-registered this experiment, we assumed that iconic patterns, like pictographs, would have no impact on chart reading speed. However, given the emphasis by experts in our Experiment 1 on the semantic association characteristic of iconic patterns, we revised our hypothesis before beginning the experiment so that iconic patterns may also enhance chart reading speed. Bertin [14, 15] proposed that geometric patterns possess selective qualities, enabling them to assist viewers in distinguishing between categories. Consequently, we hypothesized that these patterns may also have a positive influence on chart reading speed. With this in mind, we hypothesized (**H1**) that *both iconic and geometric patterns can lead to faster chart reading*. Earlier studies, however, demonstrated that pictographs can improve engagement [81] and that people tend to find embellished charts more attractive than those without [9]. Interestingly, our previous experiment (Section 4.3) showed no evidence of a difference between geometric and iconic patterns in terms of aesthetics for bar and pie charts. This contrast led us to question whether the focus on participants' first impressions in our prior study may be a factor. We thus decided to investigate if aesthetic preferences changed after actually using the visualizations and formulated our second hypothesis **H2** that *iconic patterns will be perceived as more aesthetically pleasing compared to geometric patterns, after people have completed chart reading tasks.*

To test our hypotheses, we conducted a third experiment to compare the

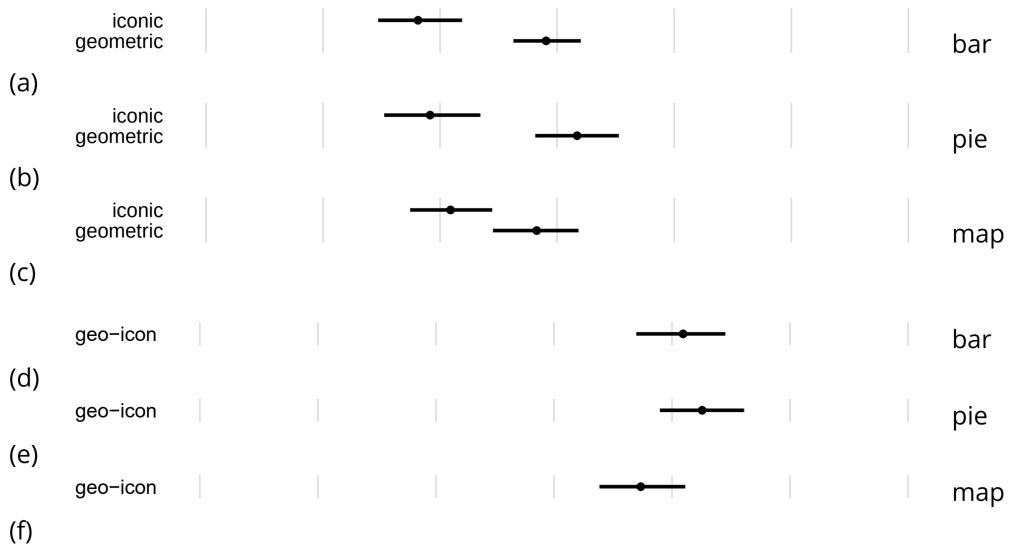


Figure 4.5: Vibratory effect analysis: vibratory score for each fill type for (a) bar charts, (b) pie charts, and (c) maps; (d)–(f) corresponding pairwise comparisons between the two fill types. Error bars: 95% CIs.

most preferred geometric and iconic patterns with respect to effectiveness, aesthetics, and readability. We limited the chart types to bar and pie charts as they are suitable for the chart reading tasks studied in previous research [81], and maps overall received a lower BeauVis score in our Experiment 2. Specifically, participants answered which one of two specific data values represented more or fewer items. This experiment was again pre-registered (osf.io/8cy62) and IRB-approved (Inria COERLE, avis № 2023-01).

4.4.1 . Participants

Following the sample size used in previous experiments[81, 112], we recruited 150 English-fluent, legal-age participants and compensated them at a rate of 10.20 euros per hour.

4.4.2 . Pattern selection

To select the best patterns for bar and pie charts in this experiment, we considered their BeauVis scores and the number of times each was ranked first in Experiment 2. In instances where the BeauVis scores and ranking counts did not align, we took into account the vibratory effect scores for each image and the open responses to the strategy question. Only if the result remained inconclusive, we prioritized the BeauVis score.

To be specific, for both geometric and iconic patterns for pie charts, the pattern with the highest BeauVis score and the highest number of being ranked first were consistent. We thus confidently selected these top 2 designs (PG1 in Table 4.4 resp. Figure A.6(a) and PI1 in Table 4.5 resp. Figure A.7(a)).

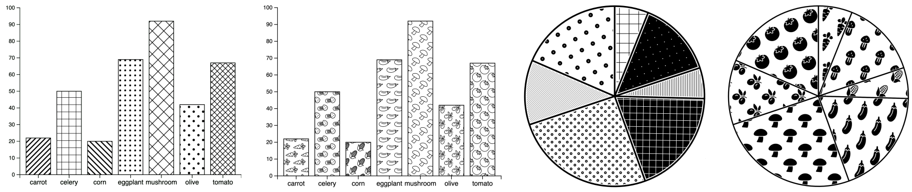


Figure 4.6: The bar chart, pie chart designs with geometric and iconic textures with the highest ratings in Experiment 2.

For iconic patterns for bar charts, despite the BeauVis score and top-ranking frequency being inconsistent, the choice was clear. The most aesthetic design (BI1 in Table 4.3 resp. Figure A.5(a)) had a much higher BeauVis score than the most frequently ranked first design (BI3, shown in Figure A.5(c)), and their top-ranking frequencies were similar. In addition, the most aesthetic design received a significantly lower vibratory score, leading us to choose it as the best iconic pattern for bar charts.

Selecting the geometric pattern for bar charts, however, was challenging as we had to decide between the first (BG1, shown in Figure A.4(a)) and second (BG2, shown in Figure A.4(b)) designs (comparison in Table 4.2). BG1 had the highest BeauVis score (4.70), ranked first 16×, and a vibratory score of 3.83. BG2 had a BeauVis score of 4.45, ranked first 20× (the highest), and had a better vibratory score (3.66) than BG1. To make a decision, we conducted a qualitative coding analysis of the reasons participants provided for ranking these patterns as their top choice. For BG1, the most frequently mentioned reasons were aesthetics (7×) and ease of distinction (5×), while for BG2 they were aesthetics (9×) and visual comfort (6×). Considering these reasons collectively and factoring in the lower vibratory score of BG2, we decided on BG2. Notably, due to technical issues, the pattern in BG2 was slightly shifted in our previous experiment, suggesting that the original version might have received even higher ratings. We thus chose to use the originally designed version in this experiment.

This process resulted in the four designs we show in Figure 4.6. We added a light gray fill for bar and pie charts as a baseline.

4.4.3 . Method

We used a mixed design with a between-subjects variable *chart type* (bar, pie) and a within-subjects variable *fill type* (geometric, iconic, unicolor). We also used two question types (more, fewer). At the beginning of the experiment, we asked participants to complete a consent form and to provide background information.

Inspired by the studies of Haroz et al. [81] and Lin et al. [112] who measured chart reading speed and accuracy, we asked each participant to complete 60 trials, consisting of 2 question types × 3 fill types × 10 repetitions.

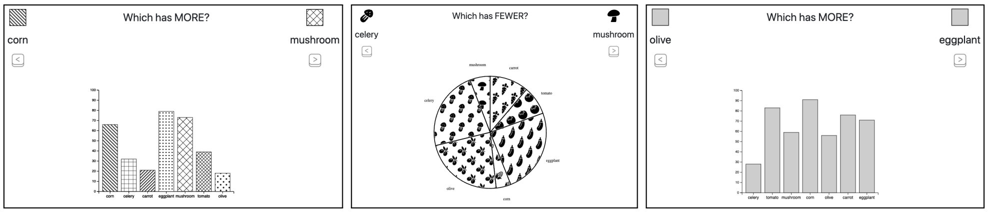


Figure 4.7: Screenshots of a trial in Experiment 3 under different conditions. Left: One trial in Experiment 3 with bar charts and geometric textures, asking participants to identify the item with a higher value ("MORE"). Middle: One trial in Experiment 3 with pie charts and iconic textures, asking participants to identify the item with a lower value ("FEWER"). Right: One trial in Experiment 3 with bar charts and unicolor fill, asking participants to identify the item with a higher value ("MORE").

We grouped the trials by question type and sub-grouped by fill type. At the beginning of each block, we presented participants with instructions that explained the task and instructed participants to complete the tasks as quickly and accurately as possible. In each fill type block, we asked participants to first examine a chart with the pattern type to familiarize themselves with the chart fill and then to proceed to the training. We required the participants to complete three correct training trials, before they could advance to the real experiment. We randomized the chart type, the order of each block, and the stimuli.

During each trial, we presented two targets (e.g., *olive* and *corn*) and one of two questions: "Which has MORE?" or "Which has FEWER?" We represented the targets as a vegetable name and an image, the latter being a geometric pattern, an icon, or a blank light gray square depending on the chart fill condition. Participants needed to press the space bar to initiate the trial, reveal the chart, and start the timer. Figure 4.7 shows three screenshots taken during a trial in Experiment 3, representing varying chart types, fill styles, and question categories. We instructed them to press the left or right arrow key to indicate which target answered the question. We ensured that, for both bar and pie charts, the item designated by the left arrow key consistently appeared on the left side relative to the item identified by the right arrow key. After 5 seconds, the question and chart disappeared, and we showed participants the result of their response (correct, incorrect, or timed out). We conducted a pilot within our research group and determined that 5 seconds was a reasonable time to be able to give an answer.

Finally, we showed participants three charts with default data values, each featuring a different fill type, in random order. We asked them to rate each chart using the 5 items of the BeauVis scale and an additional readability item on a 7-point Likert scale.

Table 4.8: Number of trials per condition that timed out in Experiment 3.

chart \ fill	geometric	iconic	unicolor
bar	12	26	8
pie	23	31	25

4.4.4 . Dataset generation

Following the approach used by Lin et al. [54, 112], we generated 10 datasets for our experiment, with seven data values each. We randomly selected these seven values from a range of 5 to 95 on a 0–100 scale, ensuring that the values of two targets for comparison were separated by at least 5 points on the scale. With the 10 datasets, we generated images for each fill type $\times$ chart type condition, resulting in 60 images in total. In the experiment, we used the 30 images of bar or pie charts twice due to the two question types. For each image, we randomly shuffled the order of the seven vegetable items on the chart (e.g., in a bar chart, the carrot bar could appear at any position). We also generated additional stimuli for training trials, following the same rules.

4.4.5 . Data analysis and interpretation

We calculated average correct rates, response times, readability, and BeauVis scores for each fill and chart type combination (e.g., geometric bars) across participants. We report sample means and pairwise mean differences of our three fill types with 95% CIs. We adjusted the CIs of pairwise differences using the Bonferroni correction to reduce the risk of type I errors when doing multiple comparisons simultaneously [90]. We interpret the results in the same way as in Experiment 2. (Section 4.3.4).

4.4.6 . Results

We received 150 valid responses (67$\times$ bar, 83$\times$ pie), which we used for our analysis (74 female, 76 male; ages: mean = 28.0, SD = 8.1; education: 99 Bachelor's or equivalent, 23 Master's or equivalent, 1 PhD or equivalent, 27 other). We should have received 9000 valid experiment trials, but we lost data from 12 trials due to log file issues. Among the remaining 8988 trials, there were 125 timed-out trials. Table 4.8 shows the distribution of time-out trials.

Accuracy rate. Figure 4.8 shows the mean values and pairwise comparisons of the accuracy rates for all fill types in bar and pie charts. All conditions yielded high average accuracy rates, exceeding 85%, much higher than the 50% correct rate for random guessing. Pairwise comparisons, shown in Figure 4.8(c, d), reveal that for bar charts, unicolor and geometric patterns outperform iconic patterns, while for pie charts, unicolor surpasses both patterns. We note, however, that the difference is quite small in practice ($<3.6\%$).

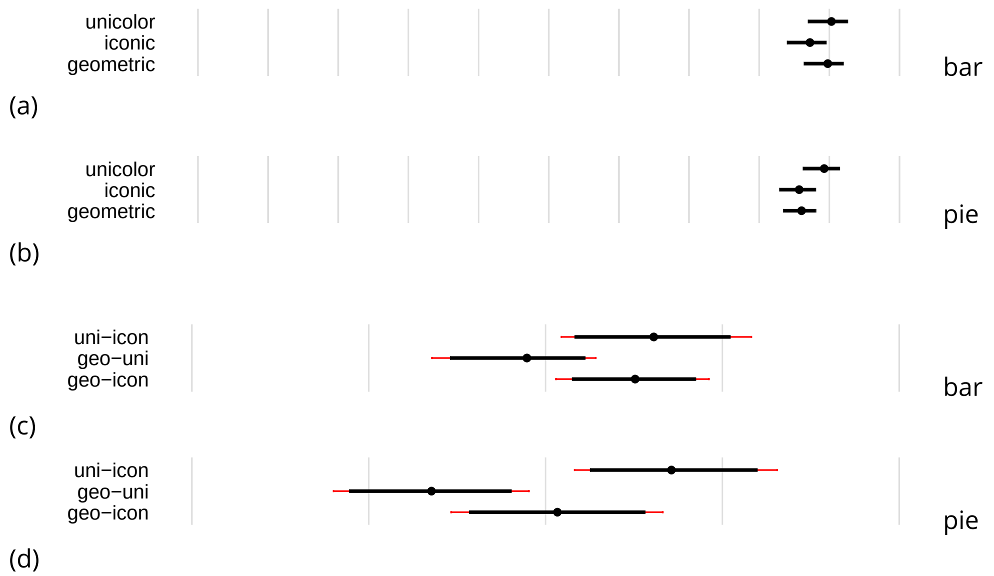


Figure 4.8: Correct answer rates in % for (a) bar and (b) pie charts; (c), (d) corresponding pairwise comparisons between the fill types. Error bars: 95% CIs. Red bars: CIs for Bonferroni-corrected pairwise comparison.

After examining individual correct rates, we revised our pre-registrated analysis plan of including all participants (see Section A.1) to only include the 86 participants who achieved $\geq$ 90% overall accuracy (45$\times$ bar, 41$\times$ pie) for the following analysis, minimizing the effect of random guesses. We counted 2 trials recorded with correct answers but durations slightly over 5s as correct.

Response time. We only counted the response times of correct trials from the 86 participants to ensure the interpretability of our results. Figure 4.9 shows the mean values and pairwise comparisons of response times for all fill types in bar and pie charts. The analysis of the pairwise differences shows that, for bar charts, we have evidence that both patterns have a longer response time than unicolor. For pie charts, we see evidence that geometric patterns have shorter response times than the other two fill types. There was no evidence of a difference for any other combination of fill types. Again, we note that the differences are minimal, within a range of $<$255 ms.

Readability. Figure 4.10 presents the mean values and pairwise comparisons of readability scores for all fill types for bar charts and pie charts, which we measured using a 7-point Likert item. For bar charts, the pairwise differences in Figure 4.10(c) indicate that unicolor filling was considered more readable than the other two types; however, we have no evidence for a difference between the two patterns. We observe a consistent trend across all three analyses (correct rate, response time, and readability) for bar charts, showing that unicolor outperforms geometric patterns, which in turn outperform

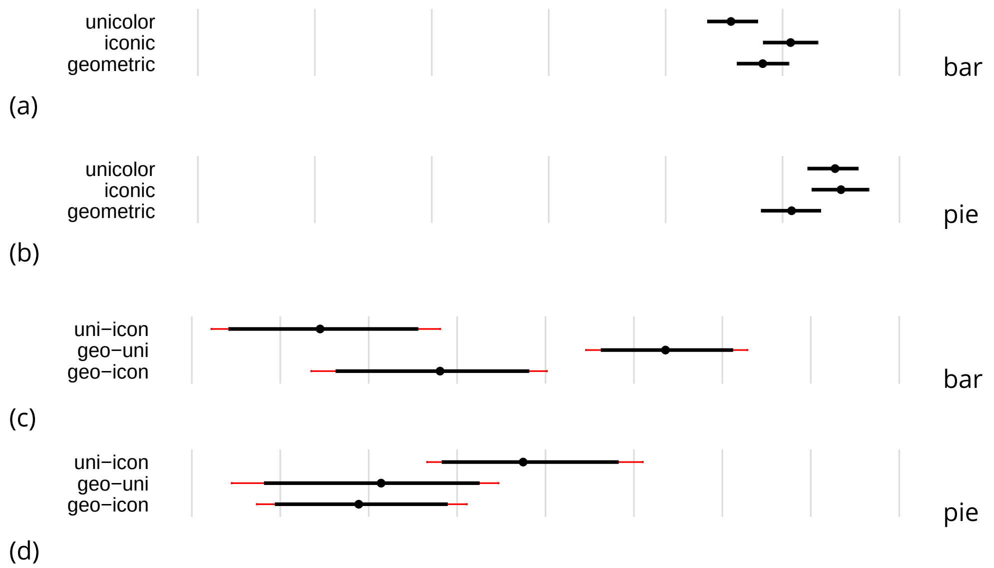


Figure 4.9: Response times in ms for (a) bar and (b) pie charts; (c), (d) corresponding pairwise comparisons between the fill types. Error bars: 95% CIs. Red bars: CIs for Bonferroni-corrected pairwise comparison.

iconic patterns. This trend aligns with the distribution of the number of timed-out trials. Regarding pie charts, the pairwise differences in Figure 4.10(d) reveal no evidence of differences in readability among the three fill types.

Aesthetics. Figure 4.11 displays the mean values and pairwise comparisons of the BeauVis score for all fill types separated by bar and pie charts. For bar charts, the pairwise differences in Figure 4.11(c) reveal no evidence of a difference between either geometric or iconic patterns and unicolor, although iconic patterns were considered more aesthetically pleasing than geometric patterns. For pie charts there was evidence suggests that both geometric and iconic patterns were perceived as more aesthetically pleasing than unicolor; no evidence, however, supports a difference between geometric and iconic patterns in terms of aesthetics.

Summary. Our results show that for, bar charts, iconic patterns performed worse than the other two types, resulting in more errors and slower responses. While geometric patterns did not reduce accuracy, they did slow down response times. For bar charts our hypothesis H1 is thus incorrect, but, since geometric patterns were perceived as less aesthetically pleasing than iconic patterns, H2 is supported. For pie charts, the situation is reversed; geometric patterns performed well, demonstrating faster response times and being considered more visually appealing than unicolor patterns. There was also a trend towards higher readability for geometric patterns. For pie charts, however, the iconic patterns did not have a positive effect on chart reading effec-

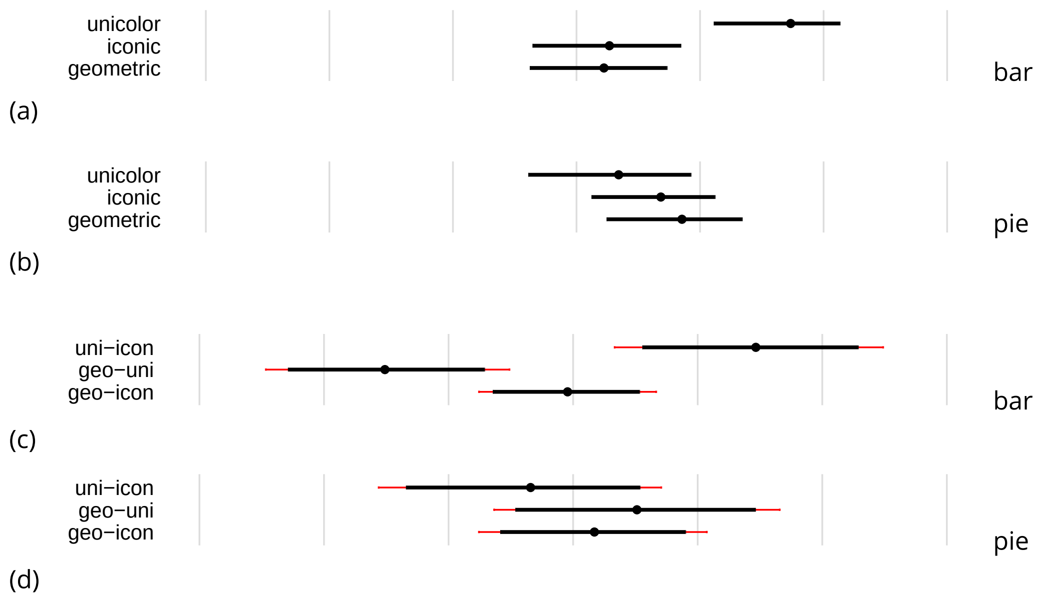


Figure 4.10: Readability scores for (a) bar and (b) pie charts; (c), (d) corresponding pairwise comparisons between the fill types. Error bars: 95% CIs. Red bars: CIs for Bonferroni-corrected pairwise comparison.

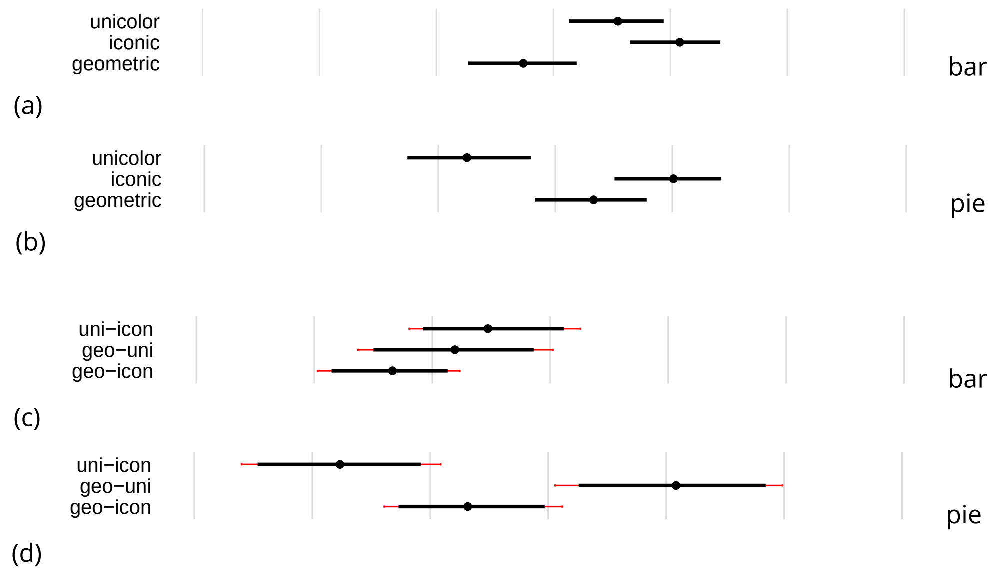


Figure 4.11: BeauVis scores for (a) bar and (b) pie charts; (c), (d) corresponding pairwise comparisons between the fill types. Error bars: 95% CIs. Red bars: CIs for Bonferroni-corrected pairwise comparison.

tiveness, supporting H1 only partially. Since there is no significant difference in aesthetics between geometric and iconic patterns, H2 is not supported.

4.5 . Discussion and limitations

The results of Experiments 2 and 3 slightly deviated from our expectations, but the overall differences were marginal. In Experiment 2, the average BeauVis scores hovered around 'neutral,' with a range of opinions causing this median result. Experiment 3 saw the unicolored bar chart surpassing the two patterns in terms of readability, time, and accuracy, but the differences were relatively minor (less than 3.6% in accuracy, and under 255ms in response time). Practically speaking, these differences may be too small to be substantial. In addition, the results from this simple test of Experiment 3 should **not** be overgeneralized to broad conclusions that "patterns reduce accuracy." Since patterns are considered to be as aesthetically pleasing as unicolor in bar charts, and even more aesthetically pleasing than unicolor in pie charts, the use of patterns could be recommended for those who have a strong preference for aesthetics or specific needs to incorporate patterns into their charts.

Our hypothesis in Experiment 3 about the effects of semantic association on patterns, although failed, is still intriguing. Experiment 1 demonstrated that semantic association is a quality valued by experts, as they sought to achieve semantic association, not only for iconic patterns but also for geometric ones. Interestingly, despite the evident semantic association of iconic patterns, previous research on pictographs [35, 81] and our own experiment did not reveal any positive effects on chart reading speed like those observed with semantically resonant colors [112]. This may potentially be because icons can be distracting and thus increase reading difficulty. One visualization expert's approach to using the overlapping of icons to abstract them is highly insightful (see Figure 4.12), as it balances other expert strategies of retaining complete icons for their semantic association while simultaneously fading them into the background to prevent visual overload. This method reminded us of Escher's tessellations with recognizable figures and suggests that exploring a middle ground between iconic and geometric patterns may be a promising direction in pattern design.

Our observed equal or slightly better performance of unicolor charts compared to patterns may also be due to the fact that ***all*** charts we showed to participants were labeled. The associative quality of patterns [14, 15] may have enticed participants to use pattern or icon association for finding the right items, while for unicolor charts the lack of any pattern forced participants to read the labels. This was possible in a fast way, in particular for the short, one-word items we used and the lack of "distraction" from patterns. In situations where the labels are longer or where there is no possibility to have labels in the first

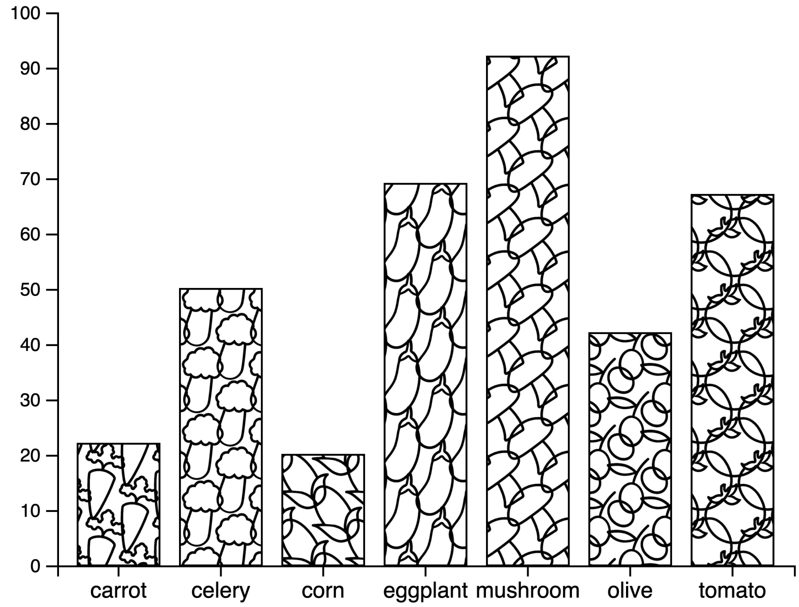


Figure 4.12: An iconic textured bar chart design (BI4) from Experiment 1, featuring overlapping icons.

place, the situation may thus be more favorable for textured charts.

Finally, we want to acknowledge some limitations of our work. Especially Experiments 2 and 3 are based on specific instantiations of iconic and geometric patterns and, as such, it is important not to make general claims for all possible patterns of these two types. We also only focused on three basic chart types as we already noted. Patterns have a much larger parameter space than color and are, as such, difficult to analyze comprehensively. We hope that our work will spark some interest in the community and that efforts in this space will continue.

4.6 . Conclusion

So, where does this leave us now? On the one hand, we could not show substantial benefits of patterns as a means of associating data representations to data items—akin to a null result. On the other hand, we also learned a lot and the patterns did not really fare worse than the baseline. So, in situations where color and/or labels are not available for some reason they are valid options for the design of visual representations. What particularly encourages us to continue is the enthusiasm expressed by some of the visualization experts we had approached. For example, one expert stated: “it’s been a fun morning for me. I wish all my mornings could start like this.” Another said, “nice to see someone doing work on patterns” and many expressed interest in the results. Some also saw the potential for visualization on alternative displays: "Please make e-ink visualization displays a thing! My tired eyes will thank you." So, ultimately, the use of patterns in visualization may be in the eye of the beholder—both patterns specifically and visualization in general are not "just" a science but also an art.

5 - BeauVis: A Validated Scale for Measuring the Aesthetic Pleasure of Visual Representations

In Chapter 4, we used an instrument called the BeauVis scale to empirically compare the aesthetics of patterns in visualizations. The BeauVis scale is a simple and validated instrument that we developed for researchers and practitioners to assess and compare the aesthetic pleasure of different visual data representations. It can be used independently for quick aesthetic comparisons or *together* with other approaches to provide an additional data point or to help formulate hypotheses that may explain other empirical results.

The development and validation of the BeauVis scale followed a standard scale development procedure that includes multiple steps [20, 62]. First, we conducted a systematic review of how aesthetic pleasure has been studied in the literature and extracted a set of terms used in the visualization literature. Next, we conducted surveys with 31 visualization experts, who we asked for additional terms. We narrowed our combined set of 209 terms to 37 terms and asked experts to rate them according to their relevance to the construct of aesthetic pleasure. We then derived a final set of 3–5 terms from a crowd-sourced experiment in which 1001 participants rated 15 different visualizations using a subset of the expert-rated terms. Finally, we conducted another confirmatory crowd-sourced analysis of 3 visualizations in which participants used our 5-item scale to rate the visual data representations' aesthetic pleasure. In this chapter, I present each step of this procedure in detail.

> This chapter is an updated version of my original article published at IEEE Transactions on Visualization and Computer Graphics [85]. The work was led by myself in collaboration with Petra Isenberg, Raimund Dachselt, and Tobias Isenberg.

5.1 . Related work

Aesthetics is an elusive concept that does not have a universally accepted definition. Generally speaking, aesthetics is related to beauty and its appreciation. In this section, we start by defining aesthetic pleasure and then summarize empirical aesthetic methods. Next, we present past work on the study of aesthetics in the field of visualization and finally, we review how researchers in related fields measured aesthetic pleasure.

5.1.1 . Definition of aesthetic pleasure

The debate about whether beauty is subjective or objective has persisted throughout history. Reber et al. [148] summarized that, in the philosophical tradition, there are three main ways of looking at beauty. According to the *objectivist view*, beauty is a characteristic of an object that causes a delightful experience in any appropriate perceiver. Several features of an object can contribute to its aesthetics, such as balance, symmetry, clarity, etc. According to the *subjectivist view*, in contrast, anything can be beautiful. Beauty depends on perceivers, and all attempts to discover the rules of beauty are futile. The most modern approach is an *interactionist view* that combines the previous two views and regards beauty as the function of both the characteristics of the object and the perceiver. We adopt this interactionist view in our work.

In the past, researchers have used "beauty" and "aesthetic pleasure" interchangeably. For instance, Reber et al. [148] defined beauty as "a pleasurable subjective experience that is directed toward an object and not mediated by intervening reasoning" and equate it to the concept of aesthetic pleasure, meaning essentially the same thing. This definition also fits well with how many researchers (e.g., [45, 47, 83, 173]) approached the concept in visualization, and we adopt this definition to describe the construct we want to measure in our scale. We can see similar definitions in other work, e.g., "the pleasure people derive from processing the object for its own sake, as a source of immediate experiential pleasure in itself, and not essentially for its utility in producing something else that is either useful or pleasurable" [65], but see this definition as largely equivalent to the first one, which we adopt.

Aesthetic pleasure is part of the concept of aesthetic experience as it is used in empirical aesthetics, which can be understood as the experience that arises from a unique combination of cognitive and emotional processes [110]. Aesthetic appreciation consists of three main modes [147]: aesthetic pleasure, emotions evoked by an artwork, and understanding of an artwork. Our work focuses on the aesthetic pleasure of visualizations, so it is to study the first modes of aesthetic appreciation. Graf and Landwehr [78, 79] proposed a comprehensive model of aesthetic pleasure called the Pleasure-Interest Model of Aesthetic Liking. This model shows that there are two forms of processing aesthetics, resulting in different forms of liking: *automatic processing* and *controlled processing*. Automatic processing is driven by a stimulus, which is a quick and instinctive judgment based on pleasure or displeasure as a response to the stimulus, and leads to *pleasure-based liking*. Controlled processing is driven by the perceivers, which leads to *interest-based liking*. This model involves both the stimuli and perceiver, so it is in line with our interactionist view on beauty.

5.1.2 . Empirical aesthetics

There are two main ways to study aesthetics [133]. *Philosophical aesthetics*, with a long tradition starting in ancient Greece, uses a top-down approach, examining general concepts and then applying them to specific cases. *Empirical aesthetics*, established by Gustav Theodor Fechner in the 19th century, works bottom-up, examining specific cases (e.g., what people like or dislike about something) and then deriving a set of principles from them. In our work, we mostly follow the approach of empirical aesthetics as we use empirical methodologies [133].

Experimental aesthetics is one of the most essential subfields of empirical aesthetics. It generally relies on the measurement of historical data, verbal ratings and judgments, measurement of nonverbal behavior, and measurement of psychophysiological changes. Among these methods, the one most relevant to our own work is the measurement of verbal responses. Researchers use this method to collect some aspect of the way participants experience a stimulus. Most commonly, participants are asked to provide "descriptive aspects of the stimuli (e.g., their complexity, regularity, or novelty), evaluative aspects of the hedonic value (e.g., degree of interest or pleasure, liking, beauty, or attractiveness), and internal states (e.g., evoked emotions or meanings)" [133]. Verbal ratings can, thus, be recorded and analyzed in several ways, but a common approach is to establish a scale that targets the construct described by the participants—which is what we do in this work.

5.1.3 . Aesthetic pleasure in visualization

The term *aesthetics* is often used in visualization to describe a property of a visual representation that is separated from how understandable, informative, or memorable it is; and that instead focuses on its beauty or visual appeal. In this way the concept aligns with the definition we adopted for *aesthetic pleasure*, and we set out to study it in more detail.

Chen [47] identified the exploration of "pretty or visually appealing" visualization designs as a key unsolved problem in information visualization in 2005. Since then, however, research dedicated to visualization aesthetics has been sparse, perhaps due to the challenges of describing, measuring, and quantifying aesthetics [173]. Lau and Vande Moere [108] proposed *information aesthetics* as a term that describes aesthetics in the context of visualization as a construct meant to augment "information value and task functionality." Vande Moere and Purchase [173], later, equate aesthetics with attractiveness in their work on the role of design in information visualization but describe aesthetics as a concept that is broad and includes aspects such as "originality, innovation, and novelty" [173]. The authors specifically call for research that aims to explain the reasons for aesthetic experiences. This is specifically not something our rating scale will accomplish. Our scale will allow researchers to compare the aesthetic pleasure of visual data representations as it is judged by participants, but it will not allow us to explain *why* participants rated the representation in a certain way. To derive reasons for aesthetically pleasurable experiences or to establish a comprehensive aesthetic measurement the scale can, however, be included in larger questionnaires or in qualitative studies (interviews, observations, etc.).

Aesthetics has also been regarded as an important factor in some subfields of visualization. For example, aesthetics has been identified as a heuristic for evaluating ambient visualization [121]. Also, within graph drawing, specific aesthetics heuristics have been defined as properties of a graph that not only describe attractiveness but impact readability and understanding [12, 145]. These include aesthetics related to symmetry, edge lengths, or the minimization of edge crossings. These heuristics have also been extended, e.g., to aesthetics heuristics for dynamic graph visualization [10] or the faithfulness criterion [136] based on readability.

Several studies have been conducted by previous researchers for *evaluating* the aesthetics of a visualization. Much of this work has borrowed from methods introduced many years ago in empirical aesthetics; e.g., the use of rating scales. Cawthon and Vande Moere [44] presented a conceptual model for assessing aesthetics as part of an information visualization's user experience. In another study[45], they asked participants to rate visualizations on a scale from "ugly" to "beautiful" to judge their aesthetics. Many other scales have been used in visualization. For example, Harrison et al. [83] used a rating scale from "not at all appealing" to "very appealing" in their study on infographics. Ajani et al. [3] used a rating scale from "very hideous" to "very beautiful" in their study on the aesthetics of three visualization designs. Chen et al. [49] used a rating scale from "nice" to "ugly" to study the aesthetic appearance of visualization technique. These examples target what we call aesthetic pleasure but are mostly based on intuition rather than a verified instrument that can ascertain that the terms indeed measure the aesthetic pleasure of visualizations reliably and validly. Also, compared with a multi-item scale, one item lacks enough information to calculate psychometric properties such as reliability [76] and leads to less accurate results due to item-specific measurement error [76, 20].

5.1.4 . Measuring aesthetic pleasure outside of visualization

In the field of HCI, researchers have developed several validated scales to measure the aesthetic appreciation of websites and interactive products. These scales were developed and validated broadly following a standard process which we outline in Section 5.2.

To measure the aesthetic pleasure of websites, Lavie and Tractinsky [109] proposed a scale with two dimensions, which they termed *classical aesthetics* and *expressive aesthetics*. The *classical aesthetics* dimension comprises the five items "clean," "clear," "pleasant," "symmetrical," and "aesthetic." The *expressive aesthetics* dimension, in contrast, includes the five items "original," "sophisticated," "fascinating," "creative," and "uses special effects." Moshagen and Thielsch [131], however, pointed out that Lavie and Tractinsky's scale has the following problems: the items "symmetrical" and "uses special effects" are not necessarily aesthetic judgments, it is hard to explain why the term "aesthetic" only relates to the classic aesthetic dimension, and their items are too abstract to be used for improving the design. Based on Lavie and Tractinsky's scale, Moshagen and Thielsch thus proposed a scale with the four dimensions of simplicity, diversity, colorfulness, and craftsmanship, with items such as "the layout appears well structured," "the design appears uninspired," "the color composition is attractive," and "the layout appears professionally designed."

To measure aesthetic pleasure for designed artifacts, Blijlevens et al.[18] pointed out that previous scales do not measure aesthetic pleasure separately from its determinants. Hence, they proposed the Aesthetic Pleasure in Design Scale in which they distinguish between both. Their scale includes five items: "beautiful," "attractive," "pleasing to see," "nice to see," and "like to look at." In addition, they also pointed out some dimensions suitable for measuring prominent determinants of aesthetic pleasure such as typicality, novelty, unity, and variety.

In addition to scales specific to aesthetics, some scales for user experience also include dimensions related to aesthetics. The widely used AttrakDiff questionnaire [84], e.g., includes *hedonic quality* and *overall attractiveness*, which are related to aesthetic pleasure and include items such as "pleasant," "attractive," and "creative." The User Experience Questionnaire (UEQ) [157] has a dimension *attractiveness* to capture the overall impression of a product, with items such as "enjoyable," "good," and "friendly." The meCUE questionnaire [128] has a dimension *visual aesthetics*, with items such as "creatively designed," "attractive," and "stylish." These questionnaires, however, should be administered after full exposure to a product to measure people's experience—different from our goal of capturing viewers' first impressions.

To the best of our knowledge, there exists no targeted scale yet for measuring the aesthetic pleasure of visual data representations. Until now, visualization researchers can only use scales that are designed for interactive products in general; for example, the AttrakDiff questionnaire has been used in several visualization studies (e.g., [34, 186]).

5.2 . The BeauVis scale: Methodology overview

We largely followed the process described by DeVellis and Thorpe [62] and Boateng et al. [20] to establish a validated scale of *aesthetic pleasure* for future use in the visualization field. This process contains four steps: (1) generating a pool of possible terms, (2) item review, (3) item evaluation, and (4) scale validation.

At the start of our work, we decided to target a Likert scale [111] response format, with equally weighted items. We also pre-determined to use a 7-point Likert scale throughout our work with the same categories for each item, from 1 = strongly disagree to 7 = strongly agree—except for Survey 2 in which we ask about the relevance of terms, for which a lower number is encouraged [62]. We chose an odd number of response categories to offer participants a neutral rating and the number 7 to strike a balance between discriminability and usability; in addition, the related literature on aesthetic pleasure scales also uses 7-point Likert scales facilitating comparison. However, our final scale could certainly be used with a larger or smaller number of response categories.

We began our research by investigating past visualization publications for their use of terms relating to some form of aesthetic ratings, such as in evaluations of techniques or tools. We also checked the literature for terms used in aesthetics-related scale development in other related fields as additional input. As a final source of candidate terms we conducted a survey among visualization experts for terms they would suggest to use. We then narrowed down the aggregated list of terms based on several objective criteria, and again asked visualization experts to rate how important each of the remaining terms was for studying aesthetic pleasure in visualization. This gave us a list of 31 terms, which we then used in a crowd-sourced experiment that asked participants to rate 15 diverse visual data representations with respect to each of the final terms. We then conducted an exploratory factor analysis and calculated the reliability of scales with a smaller number of items. Based on these analyses, we arrived at our final five-item BeauVis scale. Finally, we conducted another crowd-sourced experiment to validate our final scale using a confirmatory factor analysis, calculated Cronbach's alpha, convergent validity and discriminant validity. We will discuss our detailed approach next.

5.3 . Generating a pool of possible terms

The first step in our process was the generation of a pool of terms that could describe the construct of *aesthetic pleasure*. We drew these possible items from the literature and experts.

5.3.1 . Literature review

Our literature review involved two sources: the VIS literature as a source of terms used in the past by the community as well as related work on scales in other domains as a source of terms considered and used for measuring the same construct (i.e., aesthetic pleasure).

Collecting terms from the visualization literature

To determine which terms the community had used in the past to study aesthetics, we reviewed IEEE VIS papers (1991–2020) and TVCG and CG&A journal papers presented at IEEE VIS (2011–2021)—3 189 paper PDF files in total. We extracted the text of these files and searched for the occurrence of "aesthetic," "likert," "questionnaire," and "interview." We retrieved 1 061 articles with at least one of our four search terms, and then summarized the results in a spreadsheet (recording publication year, journal, paper title, DOI link, found search term, and PDF filename). I then opened each of these PDFs and checked whether the authors had indeed conducted a study that recorded participants' subjective feelings about the aesthetics of a visual data representation. We focused on collecting terms used as part of rating scales. We found terms in 68 papers, but many did not relate to aesthetic pleasure. For example, we did not include terms that were used to judge interaction, usability, or task-related aspects (e.g., how confident a participant felt in their answers). We included, however, terms that described an aesthetic-related subjective feeling such as "clarity" or "understandability." With this initially rather broad spectrum of terms, we accounted for the complexity of the aesthetic construct and ensured that we would not miss any potentially relevant terms.

Term grouping, adjective forming, and counting. To be able to better analyze the use of terms by the visualization community, we wanted to count terms which in turn required extensive cleaning and rechecking of the literature. We turned all terms into adjectives and merged different forms of the same word. For example, we merged "understandable," "understandability," and "ease of understanding" all into "understandable." In addition, we went back to the 68 papers to verify the counts and checked the context of each term to determine what these terms measured (e.g., visual encoding, design, interface, etc.). Based on the latter analysis, we kept all terms that measured a visual encoding (e.g., visualization technique, representation, design etc.) but discussed among the authors cases that measured interface, tool, or layout. We could not completely disregard this last group because many of the tools described in the visualization literature are visual analysis tools, which, in turn, naturally comprise visual representations as a major component; so an aesthetic-related assessment of such a tool may also largely be an evaluation of the visual representation(s) included within. We thus based our decision on our impression if the evaluation related to the visual representation (included), as opposed to the interaction or usability (excluded). After completing this step, we retained a final list of 41 adjective terms. The most common terms were aesthetic (20×), understandable (12×), and intuitive (9×).

Term categorization. Next, we tagged the 41 terms with the types of judgments they target: aesthetic, emotion-oriented, cognitive-oriented, data-aesthetic, or other. Terms could receive more than one tag. We considered a term to make an *aesthetic judgment* if it clearly applied to the aesthetic pleasure caused by a visual representation. The most common terms in this category were "aesthetic" (20×), "well-designed" (5×), and "cluttered" (5×, cross-tagged with cognitive-oriented). *Emotion-oriented judgments* describe broad emotional or affective reactions to visuals. The most common terms in this category were "pleasing" (7×), "engaging," "enjoyable," and "likable" (all 4×). We categorized terms as targeting *cognitive-oriented judgments* when they seemed to primarily assess the cognitive process of understanding or analyzing data with the visualization. The most common terms in this category were "understandable" (12×), "intuitive" (9×), and "clear" (7×). Fourth, terms targeting *data-aesthetic judgments* are those whose aesthetic judgment hinged largely on the combination of data and design. We tagged only three terms in this category "expressive" (4×, cross-tagged with aesthetic), "informative" (4×, cross-tagged with cognitive-oriented), and "suitable" (1×). Four terms seemed to target *another judgment*, such as being related to quality ("high-quality," 1×), innovation ("innovative," 2×), or established practice ("conventional," 2×). The most common word with more than one tag was "cluttered" (5×), which can be considered to make both an aesthetic and a cognitive-oriented judgment. We show the final list and classification in Table B.1 in the appendix.

Term input from related fields

In addition to reviewing visualization literature, we also consulted literature from related fields about aesthetic pleasure scales. We found four scales for assessing the aesthetics of websites and interactive products that are most aligned with our own goals or had high citation counts. These include: two scales for websites by Lavie and Tractinsky [109] and Moshagen and Thielsch [131]; one scale for designed artifacts by Blijlevens et al. [18]; and one questionnaire (AttrakDiff) for interactive products by Hassenzahl et al. [84]. We extracted the terms studied in these four papers to compare them to the ones we had collected. For Lavie and Tractinsky's paper [109] and Blijlevens et al.'s paper [18], we were able to extract all terms that the authors had considered in the development of their scale from the papers. For Moshagen and Thielsch's paper [131], the authors kindly e-mailed us their early list of considered terms (not included in their final paper) and we translated these German terms into

English. From Hassenzahl et al.'s paper [84] we could only use the terms the authors selected as their final scale. For all terms from these four papers we followed the same cleaning and tagging process as before for the visualization literature and then combined them with our list. The total list from our literature review thus included 176 terms (Table B.2 in the appendix).

5.3.2 . Expert suggestion—Survey 1

To supplement our literature review, next we conducted a pre-registered (osf.io/wvehs) and IRB-approved (Inria COERLE, avis № 2022-12) survey to ask for expert input on words we had not yet considered.

Participants. We invited 57 visualization experts among a wide spread of topic expertise to participate in our survey by direct e-mail. We selected participants based on our knowledge of their work and their reputation in the visualization community. Participants were not compensated for taking part in the study. After sending the invitation e-mails, we waited for one week and, during this time, received 31 complete responses (9 female, 21 male, 1 gender not disclosed; past experience in visualization research: mean = 19.7 years). All responses were valid and we included them in our analysis.

Procedure. We first asked participants to complete the informed consent form and to answer background questions about their gender and expertise. We then explained the study scenario and task which involved wanting to investigate people's subjective opinions about the aesthetics of a visualization they had created, using a 7-point Likert scale with the question: "To what extent do you agree or disagree with the following statement: This visualization is [...]." We then asked each of our expert participants to provide us with at least three words they would want to use or could envision to use for filling the blank in the question. We gave them the opportunity to leave additional comments after providing us with their term suggestions.

Results. From the 31 completed surveys we collected 113 different words. We cleaned these words by removing duplicates, fixing typos, as well as merging them and forming adjectives as before. Through this process we received 77 unique adjectives (Table B.3 in the appendix) and counted their frequencies. The most common terms were: "beautiful" (18×), "pleasing" (16×), and "aesthetic" (15×). We then combined these terms with the terms we collected from the literature and categorized them as before. Through this process our list of terms added 33 new terms and grew to a total of 209 terms (Table B.4 in the appendix).

5.4 . Term filtering

As a next step we needed to select a meaningful subset of the 206 terms we had identified, so that we would have a manageable number to administer to a development sample (Section 5.5). We thus first removed less relevant terms based on several considerations (Section 5.4.1), followed by an expert review via a second survey (Section 5.4.2).

5.4.1 . Filtering on occurrence and semantics

After several rounds of discussions among the author team and consulting the literature on scale development [20, 62], we settled on the following criteria to decide whether we should retain a term or not.

1. The terms needed to be **related to *aesthetic pleasure*** rather than *understanding* or *comprehension* of a visual representation or its data (e.g., we excluded "informative," "clear," or "confusing").

2. The terms had to have **appeared at least twice** in one of the three resources we used for our item generation: visualization papers, other relevant aesthetics scale papers, or expert suggestions.

3. The terms should be **usable in a rating scale** and have a **clearly good or bad connotation** (e.g., we excluded "complex" because a complex aesthetic could be seen as positive or as negative).

4. The terms should be **easy to understand** (e.g., we excluded "consistent" because it would be unclear according to what aspect a visual appearance would be consistent) and their **interpretation should be clear** (e.g., we excluded "novel" because it would require people to know what "old" visualizations look like; we also excluded "drab" as a rare term that is not easily understood by many non-native speakers of English).

5. The terms had to **clearly apply to an assessment of a visual representation** (e.g., we excluded "dynamic" because, within visualization, the term may be read as referring to the property of being animated or interactive, rather than a dynamic aesthetic).

6. The terms should **not be pairs of opposite adjectives**. We only retained negative terms that did not have a clear positive opposite (e.g., we excluded "ugly" as the opposite of "beautiful").

Based on the first criterion, we excluded terms that made a cognitive judgment because, for such a judgment, one needs to understand the data and we aimed to assess the visuals only. We had an intensive deliberation about terms that made an emotional judgment. We finally decided to include them because such a judgment can be closely related to the aesthetic *pleasure* generated by a visual representation and it can be difficult to separate those terms from emotion-only expressions. In the Pleasure-Interest Model of Aesthetic Liking [78, 79], the interest could be considered as an aesthetic emotion

[147]. Thus, the boundary between aesthetic pleasure and aesthetic emotion is not always clear. Ultimately, we thus arrived at a shortlist of 37 terms (see Table B.5 in the appendix) that we categorized as making an aesthetic, emotional, and other judgment, that served as the input for an expert review.

5.4.2 . Expert review—Survey 2

Next, we conducted a second pre-registered (`osf.io/5gmut`) and IRB-approved (Inria COERLE, avis № 2022-12) survey to elicit expert feedback on the relevance of the 37 terms for measuring the aesthetic pleasure of a visual data representation.

Participants. We e-mailed the same experts (excluding one who had participated in a pilot, for a total of 56 experts), and received 25 complete responses after three days (8 female, 16 male, 1 gender not disclosed; past experience in visualization research: mean = 20.1 years). All responses were valid and we included them in our analysis.

Procedure. We first asked the participants to provide their informed consent and background information. We then introduced them to our definition of aesthetic pleasure and asked them to rate "how relevant do you think the following terms are for judging or describing the aesthetic pleasure of a visualization?". The rating scale included 5 points from 1 being 'not at all relevant' to 5 being 'very relevant.' Finally, we again allowed them to leave additional comments.

Results. For each term, we calculated the median and mode of all participants' answers. From the 37 total terms, 32 terms received a mode of 3 or above or a median of 3 or above. Among these 32 terms, we removed the term "aesthetic" based on our own discussion and the recommendation of one expert, as we feared the term to be too abstract and elusive to rate reliably. We thus arrived at a final list of 31 terms (Table B.6 in the appendix) that we used in our exploratory phase.

5.5 . Exploratory phase: Exploratory factor analysis

During scale development, it is important to establish how a set of items actually studies the targeted construct, aesthetic pleasure in our case. Specifically, it is important to establish whether the ratings for the terms we collected are all caused by the same property of aesthetic pleasure or perhaps multiple identifiable factors of aesthetic pleasure such as symmetry, clarity, or familiarity. So we needed to identify the minimum number of these hypothetical factors as a next step of our analysis [185]. In addition, 31 terms are too many for the easy-to-administer research instrument we were targeting. We thus needed to identify the terms that performed best and exclude terms that did not perform well. Exploratory factor analysis (EFA) [185] has specifically been developed as an analytic tool to help researchers with these challenges. To generate data for an EFA we conducted a third pre-registered (osf.io/az8sm) and IRB-approved (Inria COERLE, avis № 2022-12) survey, in which participants used our 31 terms to rate a set of visualizations.

5.5.1 . Exploratory survey—Survey 3

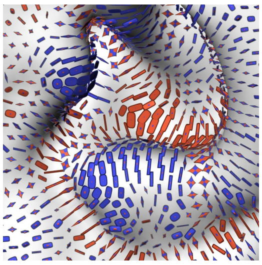
Stimuli. In total, we selected 15 representative images that showed a variety of different visualization techniques that participants would rate. For our selection of specific visual representations (Figure 5.1) we used different criteria that may affect aesthetic pleasure judgments. We wanted to cover a wide variety of areas of visualization work and different approaches to visualizations designs, such as 2D/3D, black vs. white backgrounds, abstract vs. physical content, hand-crafted vs. computer-generated aesthetic, and black and white vs. colorful. All images came from scientific publications, because our scale targets research evaluations such as surveys.

Participants. There is no consensus about sample size for factor analysis but general recommendations say that the more items to test, the more participants are required. In line with two suggestions [13, 20] we targeted a sample size of 200 participants per visualization. We recruited participants through Prolific, who had to be fluent English speakers and to be of legal age (18 years in most countries). Participants received a compensation of 10.20 euros per hour.

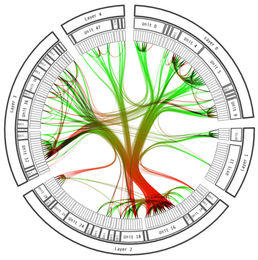
Procedure. We first asked the participants to provide their consent and collected demographics. Then we asked them to rate 3 visualizations, randomly selected from the 15 visualizations. They rated each visualization according to the question "To what extent do you agree or disagree with the following statement: The visualization is ...." For each of the 31 terms, we asked participants to choose an answer on a 7-point Likert item ranging from "strongly disagree" to "strongly agree." We showed the terms and visualizations in a random order, because we could not counter-balance the order due to the limitations of the Limesurvey system we used. We showed the images without captions so that participants would focus on the visuals. We also included one attention check question for each visualization. We asked participants to answer the online survey on a computer or laptop due to the high number of items to rate and the visual length of the scale.

5.5.2 . Results

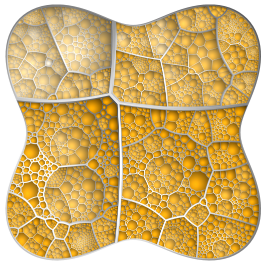
We recruited a total number of 1001 participants, who all provided their informed consent. We excluded 2 participants who each answered our survey twice due to a technical error. We also excluded 10 participants who answered two or three of our attention check questions incorrectly. We used the remaining 989 responses for our analysis (ages: mean = 28.3, SD = 9.4; 389 female, 589 male, 11 gender not disclosed; education: 618 Bachelor's or



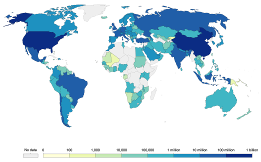
(a) Image 1, from [159].



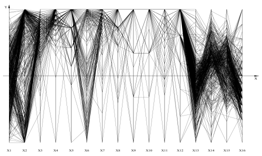
(b) Image 4, from [58].



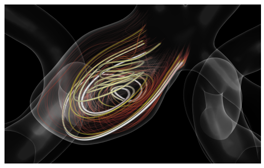
(c) Image 7, from [6].



(d) Image 2, from [124].

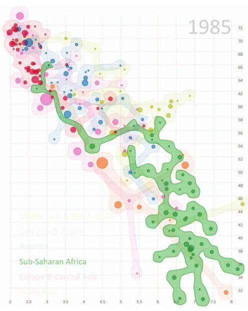


(e) Image 10, from [96].

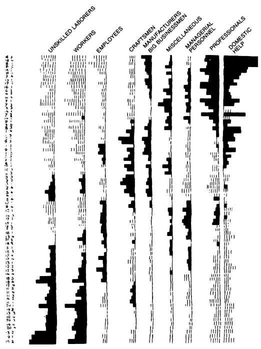


(f) Image 15, from [11].

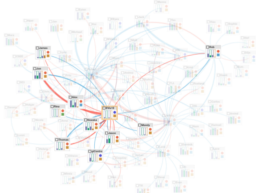
(g) Image 3, from [167].



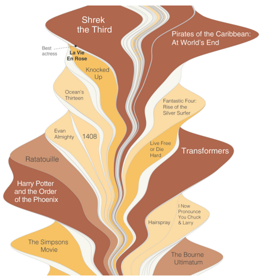
(h) Image 6, from [56].



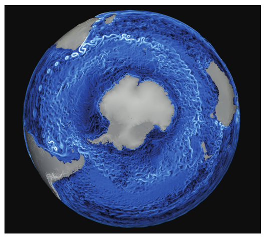
(i) Image 9, from [15, 14].



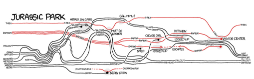
(j) Image 5, from [137].



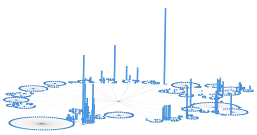
(k) Image 11, from [36].



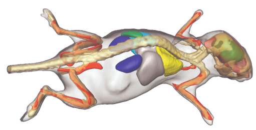
(l) Image 12, from [189].



(m) Image 8, from [114].



(n) Image 13, from [122].



(o) Image 14, from [103].

Figure 5.1: The 15 visual representations that we used as examples from the visualization literature in our analysis. Image permissions: (a–c, e, h, k–l, o) © IEEE; (d) © Springer-Nature; (f) © Wiley; (g) © C. Tominski and H. Schumann; (i) © EHESS [14, p. 230, #3]; (j) © ACM/Nobre et al. [137]; (n) by Marai et al. [122], CC-BY 4.0; (m) by R. Munroe (originally XKCD # 657), CC-BY-NC 2.5. All images are used with permission from the respective copyright holders.

equivalent, 138 Master's or equivalent, 22 PhD or equivalent, 211 other) and reversed their scores for the negative term "cluttered." Due to our random assignment of participants to images, each image was rated by approx. 200 people (mean = 197.7, SD = 19.5, min = 178, max = 218).

5.5.3 . Exploratory factor analysis (EFA)

We followed Watkins' systematic guide to EFA [185] and implemented all tests using the `psych` R package [150], applying them separately for each visual representation.

Appropriateness of EFA. Before conducting the EFA, we needed to confirm whether our data was suitable for EFA. First, we calculated a correlation matrix of all terms for each of the 15 visualizations. Only "provoking" and "cluttered" had a low correlation (< 0.3) with other terms, for all 15 visualizations. The other correlations were outside the interval $[-0.3, .3]$, which meant that the data was suitable for EFA. We then conducted Bartlett's test of sphericity [8]. The results showed that $p < .001$ for all 15 visualizations, which indicates that there is a large-enough correlation between terms. We also conducted a Kaiser-Meyer-Olkin (KMO) test [101]. All individual terms' KMO values were above 0.7. Based on all these tests, we confirmed that our data's correlation matrices were factorable and then submitted them to EFA.

Extracting Factors. We conducted an exploratory factor analysis of the 989 responses to the 31 terms for each image. We chose a common factor analysis model rather than PCA (principal component analysis) as it is recommended for the creation of measurement instruments such as rating scales [71, 185]. Roughly speaking, common factor analysis targets to find hypothetical factors that *caused* the ratings of participants, while PCA components are *defined* by the ratings.

We used *scree plots* and *parallel analysis* (for details on both see DeVellis and Thorpe's book [62]) to determine the potential factors of our scale. Parallel analysis, which uses purely statistical criteria to determine the number of factors, indicated that there was more than one factor for all 15 visualizations (Table 5.1). We complemented this objective finding with a more subjective analysis using scree plots. Here, we inspected the scree plots for all images such as the one shown in Figure 5.2. We noted that, in all plots, the eigenvalues of the second factor were close to 1, similar to the pattern seen in Figure 5.2 (we show all plots in Section B.2). The eigenvalues represent how much information is captured by a factor. If a factor's eigenvalue is 1, it captures the same proportion of information as a single item [62]. As we were after the compression of our item pool, we decided that factors that captured only little more information than single items would not be retained. We thus conducted our EFA for all images using one factor only. However, to not overlook a potentially prominent factor, we also conducted an exploratory analysis us-

Table 5.1: Number of factors as output by the parallel analysis.

Image	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Factors	2	2	3	3	2	2	3	2	3	2	2	3	2	2	2

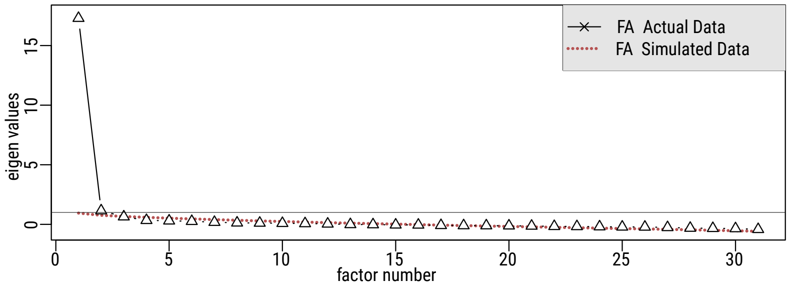


Figure 5.2: Scree plot for Image 1 (3D surface glyphs).

ing an EFA for two factors using a Varimax (orthogonal) and Promax (oblique) rotation and analyzed the data (we provide the data of this analysis in Section B.7). For a few images, we analyzed how the terms were split into two factors but were unable to extract meaningful factor descriptions. Therefore, we confirmed that our items indeed measured one factor (aesthetic pleasure) and based our further analysis on the results of the EFA with one factor only.

Reducing Terms. The next step in scale development is to find an acceptable number of final terms to use. One of the important outputs of an EFA is a table with factor loadings per term. The higher a factor loading, the more the term defines the factor or, in our case, the better it is able to describe aesthetic pleasure. Based on their factor loadings, the terms the least descriptive for aesthetic pleasure in our data were "provoking" and "cluttered" with factor loadings below 0.5 for all of the 15 visualizations, see Figure 5.3. Twelve terms had a factor loading of > 0.7 for all of 15 visualizations, which are considered high values [80]. In decreasing order of their average factor loadings these were: "likable, pleasing, enjoyable, appealing, nice, attractive, delightful, satisfying, pretty, beautiful, lovely, and inviting." We removed all other terms and did not further consider them in the creation of our final scale.

At this point we had 12 terms left, which we could combine into even smaller scales. For each possible scale one can compute a reliability statistic that indicates whether a scale would perform in consistent and predictable ways. A perfectly reliable scale would always consistently measure the true aesthetic pleasure of a visual representation. Reliability measures approximate this "true" value by computing the proportion of a "true" score to the observed score. We used Cronbach's alpha as our reliability measure, which looks at the scale's total variance attributable to a common source and which is the most commonly used measure of reliability in scale development [62].

Because we were aiming for a lightweight instrument, we tested the reliability of final scales of size 3–5. Three items is the minimum number for the

terms / image	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Average
likable	0.91	0.79	0.88	0.87	0.86	0.84	0.90	0.88	0.84	0.86	0.85	0.89	0.87	0.87	0.89	0.87
pleasing	0.85	0.80	0.84	0.88	0.89	0.87	0.90	0.84	0.80	0.88	0.87	0.88	0.87	0.84	0.88	0.86
enjoyable	0.87	0.78	0.83	0.86	0.86	0.84	0.88	0.87	0.84	0.87	0.85	0.88	0.83	0.85	0.89	0.86
appealing	0.85	0.80	0.80	0.84	0.87	0.83	0.88	0.85	0.85	0.88	0.85	0.88	0.88	0.83	0.90	0.85
nice	0.90	0.81	0.81	0.82	0.87	0.83	0.87	0.87	0.81	0.85	0.84	0.82	0.89	0.82	0.89	0.85
attractive	0.84	0.78	0.81	0.81	0.86	0.87	0.89	0.84	0.84	0.86	0.85	0.87	0.86	0.84	0.85	0.84
delightful	0.86	0.74	0.78	0.85	0.83	0.81	0.89	0.82	0.79	0.82	0.86	0.88	0.89	0.84	0.88	0.83
satisfying	0.77	0.73	0.77	0.83	0.85	0.80	0.90	0.80	0.82	0.85	0.86	0.87	0.85	0.81	0.84	0.83
pretty	0.85	0.76	0.77	0.78	0.81	0.81	0.88	0.79	0.76	0.80	0.84	0.85	0.83	0.86	0.85	0.82
beautiful	0.84	0.77	0.76	0.79	0.84	0.78	0.87	0.81	0.76	0.82	0.85	0.85	0.78	0.82	0.84	0.81
lovely	0.85	0.75	0.78	0.82	0.80	0.77	0.83	0.81	0.74	0.81	0.86	0.86	0.83	0.79	0.83	0.81
inviting	0.83	0.74	0.71	0.73	0.82	0.80	0.84	0.85	0.78	0.78	0.83	0.78	0.84	0.76	0.83	0.79
engaging	0.79	0.70	0.76	0.74	0.78	0.78	0.82	0.83	0.74	0.76	0.79	0.77	0.80	0.73	0.80	0.77
tasteful	0.78	0.64	0.68	0.72	0.77	0.78	0.80	0.81	0.81	0.80	0.82	0.76	0.81	0.77	0.83	0.77
exciting	0.79	0.66	0.72	0.76	0.81	0.76	0.81	0.77	0.70	0.77	0.82	0.77	0.79	0.75	0.79	0.77
motivating	0.74	0.65	0.71	0.77	0.83	0.78	0.84	0.75	0.75	0.77	0.78	0.71	0.83	0.76	0.77	0.76
elegant	0.83	0.76	0.71	0.78	0.74	0.68	0.83	0.69	0.71	0.84	0.76	0.80	0.78	0.74	0.80	0.76
harmonious	0.79	0.69	0.76	0.75	0.82	0.74	0.74	0.74	0.69	0.80	0.77	0.80	0.76	0.75	0.81	0.76
well designed	0.76	0.71	0.67	0.77	0.81	0.73	0.69	0.71	0.73	0.74	0.76	0.81	0.81	0.66	0.76	0.74
fascinating	0.68	0.64	0.73	0.77	0.70	0.72	0.80	0.71	0.72	0.66	0.73	0.77	0.76	0.70	0.71	0.72
interesting	0.70	0.70	0.71	0.74	0.76	0.71	0.73	0.74	0.61	0.64	0.70	0.73	0.74	0.59	0.74	0.70
balanced	0.69	0.63	0.61	0.73	0.71	0.69	0.59	0.70	0.65	0.77	0.74	0.66	0.68	0.71	0.74	0.69
clean	0.73	0.70	0.71	0.64	0.70	0.60	0.66	0.70	0.60	0.68	0.71	0.71	0.63	0.73	0.67	0.68
sophisticated	0.68	0.63	0.62	0.63	0.61	0.62	0.73	0.65	0.66	0.63	0.63	0.75	0.71	0.71	0.71	0.66
organized	0.59	0.61	0.62	0.74	0.67	0.59	0.55	0.60	0.59	0.66	0.64	0.66	0.65	0.62	0.65	0.63
creative	0.53	0.49	0.55	0.60	0.67	0.62	0.66	0.70	0.62	0.68	0.65	0.64	0.58	0.54	0.65	0.61
artistic	0.52	0.49	0.51	0.59	0.66	0.63	0.69	0.61	0.56	0.66	0.64	0.69	0.55	0.58	0.67	0.60
professional	0.63	0.67	0.52	0.61	0.62	0.53	0.60	0.46	0.50	0.61	0.52	0.67	0.67	0.62	0.60	0.59
color harmonious	0.65	0.59	0.63	0.63	0.64	0.63	0.48	0.55	0.43	0.62	0.51	0.62	0.43	0.64	0.64	0.58
provoking	0.17	0.20	0.22	0.28	0.28	0.33	0.19	0.37	0.32	0.27	0.40	0.32	0.22	0.22	0.35	0.28
cluttered	0.30	-0.33	0.03	0.15	0.39	0.18	0.27	0.34	0.41	0.45	0.21	-0.05	0.12	0.05	0.24	0.18

Figure 5.3: Factor loadings for all 31 terms and images using diverging red–blue color scale centered at 0.7, which is mapped to white.

statistical identification of a factor and four to six items per factor have been recommended [72]. Here, choosing the right size is a tradeoff between usability and reliability. Cronbach's alpha increases with the number of items, but more items require participants to spend more time to answer and rate visual representations. We calculated Cronbach's alpha for all potential 3-item, 4-item and 5-item combinations of these 12 high factor loading terms, for all 15 visual representations that we started to use in Section 5.5.1 (i.e., those in Figure 5.1).

Final Scale. The reliability of scales constructed through the combinations of the highest factor-loading terms was high overall (Figure 5.4) and multiple word combinations are possible.

The best 3-item subset (enjoyable, likable, pleasing) had an alpha of 0.91 (range of 0.86–0.93 for the images tested), the 4-item subset (enjoyable, likable, pleasing, nice) had a reliability of 0.93 (range of 0.9–0.95), and the 5-item subset (enjoyable, likable, pleasing, nice, appealing) a reliability of 0.94 (range of 0.92–0.96). In Figure 5.4 we see that alpha generally rises with more items. To further understand the effect of a 3-, 4-, or 5-item subset we conducted an exploratory analysis in which we calculated the average aesthetic ratings for each image as if participants had only used those items. These calculations

terms / image	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	avg
3-item scale																
enjoyable-likable-pleasing	0.92	0.86	0.89	0.91	0.91	0.90	0.94	0.92	0.88	0.92	0.91	0.93	0.91	0.92	0.93	0.91
enjoyable-likable-nice	0.93	0.87	0.90	0.90	0.91	0.89	0.93	0.92	0.88	0.91	0.91	0.92	0.91	0.92	0.93	0.91
likable-nice-pleasing	0.93	0.87	0.88	0.90	0.92	0.90	0.93	0.91	0.86	0.91	0.91	0.92	0.91	0.91	0.92	0.91
4-item scale																
enjoyable-likable-pleasing -nice	0.94	0.90	0.91	0.92	0.93	0.92	0.95	0.94	0.90	0.93	0.93	0.94	0.93	0.93	0.95	0.93
enjoyable-likable-appealing -pleasing	0.94	0.89	0.91	0.93	0.93	0.92	0.95	0.94	0.91	0.94	0.92	0.94	0.93	0.93	0.94	0.93
enjoyable-likable-appealing -nice	0.94	0.90	0.91	0.92	0.93	0.92	0.95	0.94	0.91	0.93	0.92	0.94	0.93	0.93	0.95	0.93
5-item scale																
enjoyable-likable-nice -pleasing-appealing	0.95	0.92	0.92	0.94	0.94	0.94	0.96	0.95	0.92	0.94	0.94	0.95	0.95	0.94	0.96	0.94
appealing-attractive -enjoyable-likable-pleasing	0.94	0.91	0.92	0.94	0.94	0.93	0.96	0.94	0.92	0.95	0.94	0.95	0.94	0.94	0.95	0.94
attractive-enjoyable-likable -nice-pleasing	0.95	0.91	0.92	0.93	0.94	0.94	0.96	0.94	0.92	0.94	0.94	0.95	0.94	0.94	0.95	0.94

alpha 0.7 0.9 1.0

Figure 5.4: Cronbach's alpha for each image on the most reliable 3-, 4-, and 5-item subsets of the remaining 12 terms with factor loading > 0.7.

are exploratory because we cannot guarantee that the presence of additional items did not influence the ratings of our participants (yet to exclude these possible effects we conducted a confirmatory factor analysis in the next step described in Section 5.6). Figure 5.5 shows, for two images, that there were only small variations in the average ratings. The average rating of all 15 images (see Figure B.35–B.49 in the appendix) also reflects the balance of the aesthetic quality of the images we selected: the number of images scoring above and below the middle score were almost equal.

We thus conclude that a combination of 3, 4, and 5 items would produce reliable results. Scales with Cronbach's alpha > 0.7 are considered reliable [20], so even our minimum 3-item scale was reliable. Nonetheless, we recommend using the 5-item scale for its even higher reliability and because it can still be completed quickly by participants.

5.6 . Validation phase

The final scale development step is to validate the developed scale. Broadly speaking, a validated scale should actually measure the construct (aesthetic pleasure) and should do so reliably. We conducted a confirmatory factor analysis (CFA) to test the scale's dimensionality, verifying the scale measures only one factor of aesthetic pleasure as planned during the exploratory phase (Section 5.5) [20]. Then we tested the reliability of the results on new data we collected. Finally, we determined several measures of the construct validity of our scale that target how well the scale measured aesthetic pleasure.

(a) Average Likert ratings for Image 2 for the highest ranked 5, 4, and 3 items subsets.

(b) Average Likert ratings for Image 9 for the highest ranked 5, 4, and 3 items subsets.

Figure 5.5: Comparison of ratings from subsets of the rating items for Image 2 and Image 9 that had the lowest and highest average ratings in our image set. We show the plots for the other images in the appendix.

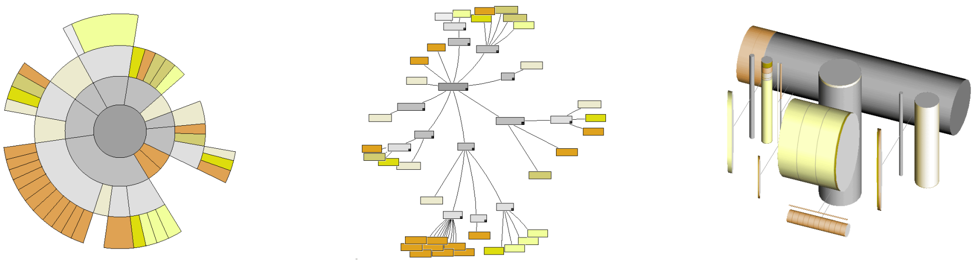


Figure 5.6: The visual representations SunBurst, StarTree, and BeamTree from Cawthon and Vande Moere's [45] study of perceived aesthetics that we used in our validation. SunBurst (left) was ranked as most beautiful, StarTree (middle) as neutral, and BeamTree (right) as most ugly in the experiment [45]. All images are © IEEE, used with permission.

5.6.1 . Validation survey—Survey 4

For this phase we conducted a fourth pre-registered (osf.io/gsq6p) and IRB-approved (Inria COERLE, avis № 2022-12) survey, like the last one also using crowd-sourcing. Again, participants rated visualization but this time using the 5-item scale proposed in the previous section. To validate our results we had participants rate 3 visualizations that had been previously assessed for aesthetic pleasure by other researchers (and participants) using a different measuring instrument [45].

Stimuli. We chose to partially reproduce findings from Cawthon and Vande Moere's experiment on the effect of aesthetics on visualization usability [45]. They had asked participants to assess the aesthetic pleasure of 11 visualizations using a one-item 100-point scale from "ugly" to "beautiful." To achieve a broader range of aesthetic experience, we selected three (SunBurst, StarTree, and BeamTree, see Figure 5.6) out of the 11 visualization techniques that were rated to be the most "beautiful" (Sunburst), most "ugly" (BeamTree), and somewhat neutral (StarTree).

Cawthon and Vande Moere kindly provided their stimuli images to us, and we used them as stimuli in our validation survey. We hypothesized that our BeauVis scale would rank these visualizations similarly from high to low as follows: SunBurst, StarTree, and BeamTree.

Participants. We targeted to recruit 200 participants from the general public on Prolific, using the same approach as in Survey 3 (Section 5.5.1).

Procedure. We also followed the same procedure as we did in Survey 3, which we described in Section 5.5.1, with the following exceptions: We used a clear within-subjects design where all participants rated all three visual representations (SunBurst, StarTree, BeamTree) with the five terms in our scale (enjoyable, likable, pleasing, nice, appealing) as well as with Lavie and Tractinsky's [109] 5-item scale for measuring classic aesthetics of websites (aesthetic, pleasant, clear, clean, symmetric) (see Section 5.1.4). We used this additional five-item scale for validating convergent validity, which we explain below. We only used one attention check question in this survey.

5.6.2 . Results

We recruited a total number of 201 participants. All participates provided their informed consent. We excluded 4 participants who answered the attention check questions incorrectly. We used the remaining 197 responses for our analysis (ages: mean = 25.1, SD = 6.4; 69 female, 126 male, 1 gender not disclosed; education: 125 Bachelor's or equivalent, 22 Master's or equivalent, 2 PhD or equivalent, 48 other). Participants received a compensation of 10.20 euros per hour.

Confirmatory factor analysis (CFA)

Confirmatory Factor Analysis (CFA) is a statistical technique that allows us to make inferences about the constructs that were measured. As aesthetic pleasure was the single construct we targeted during the exploratory phase, we used CFA to examine the construct structure as well as to verify the number of constructs measured and the item-construct relationships via factor loadings, similar to the earlier EFA. We used the methods based on structural equation modeling (SEM), which is the most commonly used CFA method [62]. We evaluated model fit by means of a series of statistical tests in CFA, including χ^2, Tucker Lewis Index (TLI), Comparative Fit Index (CFI), Standardized Root Mean Square Residual (SRMR), and Root Mean Square Error of Approximation (RMSEA). We implemented all tests using the `lavaan` R package [152], applying them separately for each image.

Table 5.2: Goodness of fit indices (TLI = Tucker Lewis Index; CFI = Comparative Fit Index; SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error of Approximation).

	SunBurst	StarTree	BeamTree
p-value (χ^2)	0.290	0.222	0.016
TLI	0.998	0.996	0.982
CFI	0.999	0.998	0.991
SRMR	0.009	0.011	0.014
RMSEA	0.034	0.045	0.095

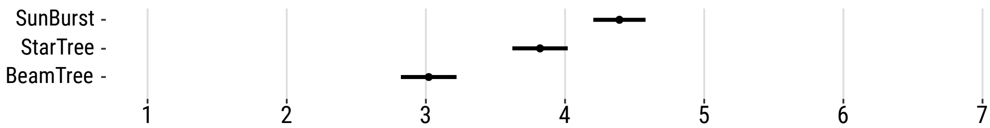


Figure 5.7: Average results with our scale of the three visualization.

Goodness of Fit. To calculate how well the scale items describe the aesthetic pleasure construct we needed to define a model that describes our only factor (aesthetic pleasure) defined as the sum of the five items of our scale. In Table 5.2 we can see that almost all indices show a good fit of this model to the data. For the three visual representations, virtually all of the following criteria are met that are indicative of a good fit [20]: χ^2 is not significant, TLI $\geq$ 0.95, CFI $\geq$ 0.95, SRMR $\leq$ 0.08. The only value that does not meet these criteria is the p-value of the χ^2 test for BeamTree, but this statistical test can be sensitive to the size of the sample and should not be used as the basis for accepting or rejecting a scale [156, 174]. For a robust assessment using this test one would have needed participant pools of N $\geq$ 400 [21] or even N $\geq$ 2 000 [192]. The RMSEA values of SunBurst and StarTree are $\leq$ 0.06—also indicative of a good fit [20]. The RMSEA value of BeamTree is 0.095, which is considered to be sufficient as RMSEA values $\in [.05, .10]$ suggest "acceptable" fits [107]. Based on the above results, we can say the CFA results validated our one-factor model of the BeauVis scale.

Factor Loadings. Factor loadings describe the correlation between the items and the aesthetic pleasure factor. Values close to 1 indicate that the construct of aesthetic pleasure strongly influences the item ratings. In the SEM approach of CFA, standardized factor loading values of $\geq$ 0.7 indicate a well-defined model [80]. As we show in Table 5.3, the values for all 5 items in our scale are well above 0.7.

In summary, the CFA confirmed the one-factor structure of our scale and that the items in the scale are well able to measure the construct.

Table 5.3: Standardized factor loading for five items, for each image.

Item	Factor Loading		
	SunBurst	StarTree	BeamTree
enjoyable	0.893	0.878	0.911
likable	0.914	0.925	0.874
pleasing	0.889	0.895	0.893
nice	0.845	0.877	0.888
appealing	0.910	0.842	0.889

Table 5.4: Cronbach's alpha for each visualization.

	SunBurst	StarTree	BeamTree
Cronbach's Alpha	0.95	0.946	0.95

Reliability

As before, we assessed the reliability of the scale using Cronbach's alpha for each image. As we show in Table 5.4, all alpha scores are well above 0.7 and thus our scale can be considered reliable.

Validity

A scale is considered to be valid if it can be established that it indeed measures the construct it was developed for [20]. The validity of a scale should not only be ensured at the end of the scale development phase, but also throughout the earlier phases of the process [20]. According to scale development theory [20, 62], the validity of our scale can be determined according to three main aspects:

Content validity is the degree to which aesthetic pleasure is indeed reflected by the terms we chose for the scale. To establish content validity, the main method is to ask experts who are familiar with the aesthetic pleasure of visualizations to review the initial item lists. We did so early in the process as explained in Section 5.4.2.

Criterion validity looks at whether the scale can explain or predict another criterion related to the "performance" of a visualization. For example, we could theoretically assess connections between a visualization's aesthetic pleasure and its usability or memorability. Practically, however, establishing whether such a connection exists would require established and validated ways to measure the usability or memorability of visualizations and much more complex research setups. We, therefore, did not test for criterion validity.

Table 5.5: Pearson correlation.

	SunBurst	StarTree	BeamTree
Classic Aesthetic	0.84	0.88	0.87
Age	0.07	0.12	0.14

Construct validity describes how well a scale is related to and measures the concept it promises to assess. To assess it, we focused on three indices of construct validity: *convergent validity*, *discriminant validity*, and *differentiation by known group*.

The first, *convergent validity*, refers to whether different methods of measuring the same construct produce similar results. It can be demonstrated by a high correlation between a newly developed scale with other scales that promise to measure the same or a closely related construct [20]. To assess convergent validity, we had participants rate visualizations also using Lavie and Tractinsky's [109] scale for assessing the aesthetic of websites. We chose their scale's *classic aesthetic factor* because its items ("aesthetic," "pleasant," "clear," "clean," and "symmetric") are more suitable for assessing visual representations than the items of their *expressive aesthetic factor*. The latter includes the term "uses special effects," e.g., which is hard to interpret for our static images. For a high convergent validity our scale's results should be correlated with those of Lavie and Tractinsky's classic aesthetics scale. As we show in Table 5.5, we found that, indeed, the Pearson correlations between both scales were high (i.e., > 0.5), for all three visualizations.

Second, *discriminant validity* allows us to understand to which degree a new scale measures a unique concept and that it is not related to other variables to which it should not be related. We can check for this validity by testing the correlations between the newly developed scale and other, existing measures.[1] In our case there is no reason to assume that the participant's age would be related to aesthetic pleasure and we thus use age for establishing discriminant validity, in line with Lavie and Tractinsky's [109] work. As shown in Table 5.5, the Pearson correlation factors between our scale and age for the three visual representations were low (i.e., well below 0.3), so we can conclude that our scale has at least discriminant validity concerning age.

Finally, in our last analysis of validity we look at the *differentiation by known groups*. Here, our "groups" are the three visualizations from Cawthon and Vande Moere (Figure 5.6) [45] for which we have empirically established aesthetic measures. To contribute to the validity of the construct, we then compared the results of our scale with their previous scores to check if the scores

[1] Note that, essentially, we would need to check for this lack of correlation to an infinite amount of other measures, yet here we follow the established procedure [20] and the examples from the literature (e.g., [109]).

were as expected and if the new scale could discriminate between the aesthetic pleasure of the three visualizations [20]. In Figure 5.7 we show the average results for these three visual representations for the five items of our scale, with a 95% confidence interval. The scores, from highest to lowest, are SunBurst, StarTree, and BeamTree, which fully align with Cawthon and Vande Moere's results. In Cawthon and Vande Moere's original study the individual aesthetic ranking result for SunBurst was 58%, StarTree was 49% (estimated from Fig. 4 in [45]), and BeamTree was 36%. We translated these results into our 7-point Likert scale through a linear mapping, the result for SunBurst was 4.48 ($= 1 + (7 - 1) \cdot 0.58$), the result for StarTree was 3.94 ($= 1 + (7 - 1) \cdot 0.49$), and the result for BeamTree was 3.16 ($= 1 + (7 - 1) \cdot 0.36$). As one can see in Figure 5.7, these results are sufficiently close to the actual scores in our survey such that we can also conclude validity w.r.t. differentiation by known groups.

5.7 . Discussion and limitations

In this section we discuss the use of our BeauVis scale, reflect on the terms they include, and discuss limitations and future work.

5.7.1 . Guidelines for and limits of Using the scale

The BeauVis scale provides a simple instrument to *compare* the aesthetic pleasure of different visual representations. The mean of all items can be used to obtain a single value [138]. This value, however, should be seen in comparison and not be interpreted as an absolute measurement of how beautiful an image is or whether it is "sufficiently" beautiful.

The scale cannot be used for measuring people's impressions of the visual representation that relate to data—such as memorability, intuitiveness, informativeness, or understandability or context-of-use related aspects such as appropriateness. We validated our scale to capture first impressions, without interactivity and context.

The scale does not establish an exhaustive or final measurement of the broad concept of aesthetics, and we do not mean to replace in-depth qualitative analyses of aesthetic experience or other methods of empirical analysis. Some experts in our two expert surveys mentioned that aesthetics cannot be measured. This is a valid opinion representing subjectivist views of aesthetics that attributes the experience entirely to the viewer (Section 5.1.1). We address this view somewhat by narrowing our scale toward "aesthetic pleasure" or "beauty," rather than the full concept of aesthetics. Our scale can be used alone to quickly compare the aesthetic pleasure of two representations or together with other test results and be interpreted carefully in context. Cawthon and Vande Moere [45], for example, used an aesthetic pleasure rating in their larger study on aesthetic pleasure and user experience. Xu et al. [190] studied the effectiveness (in terms of time and error) of representations but also asked people for their aesthetic preferences to compare techniques. Stusak et al. [164] conducted a primarily qualitative study on data physicalizations but also asked participants to rate their aesthetics on a Likert scale to accompany the wealth of other data collected.

When the BeauVis scale should be administered in a study, however, requires careful consideration. We validated the scale by asking participants to rate visualizations without having interacted with them and without having read the data; that is, we asked for their first impressions. As such, we recommend to use our scale at the beginning of an empirical study similar to how we did in our own experiment. Administering a visualization rating scale after an experiment, however, is common practice and here results need to be interpreted in light of usage experiences or the data content. We addressed the concern of a possible difference between pre- and post-study administration somewhat by excluding terms related to comprehension of the visualized data. Yet, further formal validation should establish potential differences.

5.7.2 . The rating question

In setting up the scale we had to decide on a rating question and settled on "To what extent do you agree that this visual representations is...?" We debated the wording of this question deeply and decided to use one that would not require clear opposing terms to be established, such as "ugly" vs. "beautiful," because we found it difficult to find suitable opposites for many terms (e.g., "likable," "pleasing," etc.). Our chosen rating question also required all terms to be adjectives, which is not always easy to achieve. When we first asked experts to suggest terms, some experts criticized our statement as they found the question to constrain suitable terms. Changes in the question might certainly make other terms possible but would also require some of our terms to be changed and the scale to be re-evaluated. Nevertheless, we expect small changes in the question not to have a great effect on the results. The term "visual representation," which we used to focus on the visual artifact and not the process of its creation [176, 175], could be exchanged by the name of the actual technique being studied, for example.

5.7.3 . Terms in our scale

All terms of our final scale are related and similar to one-another. In a unidimensional, one-factor scale like ours all items measure the same construct. Their similarity stems from the reliability calculation that determines correlations. Having some similarity is useful: by having five terms in our final scale, we address variations of people's understanding of the individual terms and reduce noise. Other terms that we originally tested, in the end, turned out not to be descriptive of the concept of aesthetic pleasure and were removed.

Apart from "nice," all other terms came from what we had labeled the "emotion" category, despite the fact that there was a larger number of terms we tested in the "aesthetic" category. Clear outliers in our term exploration were "provoking" and "cluttered," but the terms "color-harmonious, professional, artistic, creative, and organized" also generally had low factor loadings for all images. In retrospect, this makes sense as many of these terms require viewers to assess the visual representation according to something else that may or may not be known. To assess whether a visual representation looks professional or artistic, e.g., one needs to know what an amateur version of it would look like. Such comparisons are not needed for terms like "pleasing" or "enjoyable," which can be answered through purely personal experience.

The terms in our scale relate to other scales of aesthetic pleasure, but have small differences. The Aesthetic Pleasure in Design scale [18], for instance, also contains the terms "pleasing to see, like to look at, and nice to see" in addition to "beautiful", and "attractive." And Lavie and Tactinsky's scale for websites [109] includes "pleasant design" under the factor classic aesthetics. Our items are specific to visualization in that they avoid terms that require a cognitive assessment of the visual representation and how understandable the data was. We purposefully avoided, for example, terms such as "clear" that are included in Lavie and Tactinsky's scale. In addition, we avoided terms that may be important for aesthetic product ratings but less important for the aesthetic pleasure of visual representations. "Innovative," for example, may be important for products and is a term in the AttrakDiff scale [84], but it is difficult to judge in a visualization context where participants would need to know a "standard" visual representation to rate the innovation of a new one.

We debated for a long time but finally eliminated terms that were not clearly positive or negative when applied to visual representations such as "simple" or "complex." These terms can certainly describe what a visual representation looks like but would not be able to clearly measure aesthetic pleasure because there are certainly both beautiful and ugly "simple" data representations. By avoiding terms that can describe aesthetic pleasure in two different ways the combined result of all items in the scale is more comparable.

6 - Discussion and Conclusion

In this thesis, we explore how to use the visual variable *pattern* for data visualization. Patterns have long been a powerful visual variable in data visualization from the time before the affordable color printing. Today, patterns remain valuable, particularly in contexts where devices have limited color display capabilities, such as e-ink displays or black-and-white printing. They are also useful for improving accessibility for viewers with color vision deficiencies or visual impairments. Despite their potential, *pattern* visual variable remain largely unexplored compared to other visual variables with respect to modern visualization use. This thesis addresses these issues by contributing to understanding patterns as a visual variable through design and evaluation.

In this chapter, I summarize the work and contributions of my thesis to both patterns and visualization evaluation. I also discuss my reflections on related research topics and potential future work.

6.1 . Summary and contribution of my thesis

In this section, I summarize the key contributions of my thesis. Corresponding to our four research questions, the contributions are threefold: theoretically, we contribute to the conceptualization of the visual variable pattern and the development of a design space for pattern variations (**RQ1** and **RQ2**); empirically, we provide findings on the use of patterns for categorical data visualization (**RQ3**); and, in terms of evaluation methodology, we present the development and validation of a measurement instrument for assessing aesthetic pleasure of visualizations (**RQ4**).

RQ1: What is the visual variable "pattern"? To understand the use of patterns in visualization, we first clarified the ambiguous terminology and recommended the term *pattern* over *texture* for the visual variable featuring repetitive elements in maps and charts. *Texture* has broader meanings and varies in interpretation across visualization and related fields, making the term *pattern* more suitable for describing this visual variable. Inspired by previous research on pattern variations and inconsistencies in Bertin's use of visual variables, we conceptualized *pattern* as a composite visual variable with graphical primitives as sub-marks.

RQ2: What pattern variations can we use for data encoding?

Based on the concept of *pattern*, we developed a design space systematically describing pattern variations for data encoding. The design space includes three attribute sets: (1) spatial relationships between primitives, (2) appearance relationships between primitives, and (3) individual appearance characteristics of primitives. In addition, we discussed encoding geographical information into sub-marks and connect the concept of *pattern* to the map-reading process.

RQ3: How can we better use black-and-white patterns for categorical visualization?

We then needed to know how to use the parameters in the design space to produce good patterns for visualizations. We started our empirical study on the use of black-and-white patterns for the visualization of categorical data. We contributed the results of three experiments that elicited design strategies as well as aesthetic and effectiveness measures. We specifically studied how to use what we call geometric and iconic patterns. Geometric patterns use patterns of repeated abstract geometric shapes, while iconic patterns use repeated icons that may stand for data categories. We parameterized both types of patterns and developed a tool for designers to create patterns on simple charts by adjusting pattern parameters. 30 visualization experts used our tool and designed 66 textured bar charts, pie charts, and maps. We then had 150 participants rate these designs for aesthetics. Finally, with the top-rated geometric and iconic patterns, our perceptual assessment experiment with 150 participants revealed that charts filled with patterns perform about equally well as unicolor charts, and that there are some differences depending on the type of chart.

RQ4: How can we compare the aesthetic pleasure of visual data representations?

To compare the aesthetic pleasure of different pattern designs, we developed and validated a rating scale to assess the *aesthetic pleasure* (or *beauty*) of a visual data representation: the BeauVis scale. With our work we offer researchers and practitioners a simple instrument to compare the visual appearance of different visualizations, regardless of the data or context of use. Our rating scale can, for example, be used to accompany results from controlled experiments or be used as informative data points during in-depth qualitative studies. Given the lack of an aesthetic pleasure scale dedicated to visualizations, researchers have mostly chosen their own terms to study or compare the aesthetic pleasure of visualizations. Yet, many terms are possible, and no clear guidance exists on their effectiveness regarding the judgment of aesthetic pleasure. To solve this problem, we engaged in a multi-step research process to develop the first validated rating scale specifically for judging the aesthetic pleasure of a visualization. Our final BeauVis scale consists of five items, “enjoyable,” “likable,” “pleasing,” “nice,” and “appealing.” Beyond this scale itself, we also present the methodology of scale development to the visualization community, providing future researchers with a framework they can adopt.

In summary, we first defined the visual variable pattern and described the attributes of patterns, then collected effective pattern designs and evaluated them for aesthetics and effectiveness. Finally, we presented the development and validation process of the measurement tool for the aesthetics of visualization.

6.2 . Using pattern in visualization

This thesis establishes a theoretical foundation and provides some empirical results to tackle the issues related to the use of patterns in data visualization. Pattern, as a visual variable, has significant potential for encoding data. However, it is currently not commonly used and has not been fully explored. To unlock the full potential of patterns and enable their easy and appropriate application in visualization, it is essential to provide users with design guidelines and user-friendly tools for implementing patterns. Despite the progress made in this thesis, there is still more work to be done. In this section, I discuss the future work necessary to address these challenges, as well as a specific scenario that merits investigation: the use of patterns in data physicalization.

6.2.1 . Implementation of patterns

Current visualization tools and graphical drawing libraries offer limited support for patterns. Most tools provide only a few options to vary patterns, so users cannot fully use all pattern attributes. Achieving complex patterns often requires programming skills, making their implementation challenging, especially for designers with limited technical backgrounds.

For example, one of the most popular visualization tools, Tableau, does not officially support pattern fills so far. Although there have been requests for this feature in the forums since ten years ago[1] , this feature has not yet been integrated. Users can use workarounds [2] , but these operations are far more complicated than using other visual variables such as color, size, or shape. Some graphical drawing libraries offer pattern fills, but users can only select from default patterns or create repetitive tiling of shapes on a grid. Examples include Matplotlib [93] and Plotly [142] for Python, and ggpattern [73] for R.

If we want to create patterns in charts, one of the most flexible options is using the SVG <pattern> element, which offers a high degree of customiza-

[1]For example, two posts in the Tableau Community Forums about this issue: Pattern fill (community.tableau.com/s/question/0D54T00000C5nGlSAJ/pattern-fill), Fill Patterns (Dots and Stripes) (community.tableau.com/s/question/0D54T00000C5nGlSAJ/pattern-fill).

[2]For example, A. McCann shares two tutorials in 2018: Multiple pattern fill bar charts. (duelingdata.blogspot.com/2018/06/multiple-pattern-fill-bar-charts.html), Pattern fill bar chart in tableau. duelingdata.blogspot.com/2018/06/pattern-fill-bar-chart-in-tableau.html

tion. However, it is described as "arguably one of the more confusing fill types to use in SVG" [57]. It is based on, and thus confined to, the repetitive tiling of shapes in vertical and horizontal directions. Therefore, even creating the most commonly seen diagonal line pattern does not follow the native logic of SVG `<pattern>` and can confuse people[3]. There exists a library, Texture.js [155], that aims to make SVG `<pattern>` easier to use, but it still requires extensive manual coding and does not fully break the constraint of repetitive tiling shapes. In addition, its options are limited. For example, although it supports line patterns, the lines cannot fully rotate 180 degrees and have only several predefined rotation options, such as 3/8.

To facilitate better pattern design, we developed a technology probe[4] based on d3.js and SVG `<pattern>` (as described in Section 4.2). This tool allows users to adjust most pattern attributes using sliders. It offers greater freedom and ease of use compared to existing libraries and tools. However, it has some limitations: since we developed this tool earlier than we proposed our pattern design space, the tool does not cover all possible pattern variations. In addition, the tool is currently a web design interface with limited usage scenarios. Extending it into a JavaScript library would allow more people to use patterns in their chart or map designs. It could even be integrated into tools like Tableau for easy pattern application. Developing a more comprehensive and flexible pattern library for visualization based on our design space is a promising direction for future work.

6.2.2 . Empirical studies on patterns

Establishing general design guidelines for patterns would be extremely useful but will require more empirical studies in the community. One important and fundamental direction is pattern discrimination. For using patterns to encode categorical data, it would be interesting to study how many different categories patterns can support. It is challenge because this relies a lot on pattern design. In addition, we can use patterns with color to enhance discrimination and represent more categories that people can perceive. For example, Chan et al. [46] employed this approach to create sufficient variations for differentiation in their design, as shown in Figure 6.1. They also emphasized that further empirical studies are necessary to thoroughly understand the perceptual scalability of using color and patterns together and to develop an optimized pattern design. For using patterns to encode ordered data, it is necessary to define the range and steps of each pattern attribute that people can

[3] For example, a question on Stack Overflow about this issue: Simple fill pattern in SVG: diagonal hatching (`stackoverflow.com/questions/13069446/simple-fill-pattern-in-svg-diagonal-hatching`)

[4] The implementation details can be found in this GitHub repository: github.com/tingying-he/design-characterization-for-black-and-white-textures-in-visualization/tree/main/texture-design-interface

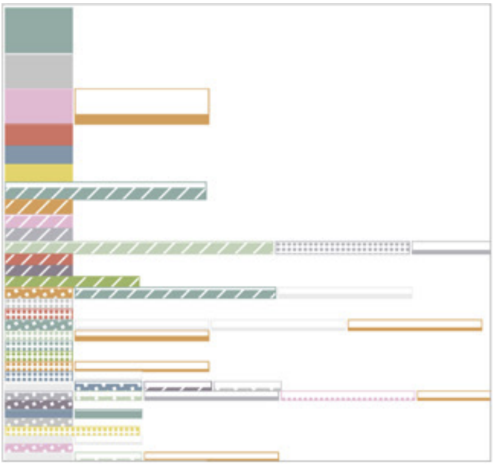


Figure 6.1: An example of using color and patterns together by Chan et al. [46]. © IEEE; used with permission.

perceive by measuring Just Noticeable Difference (JND). These empirical results on pattern discrimination can also improve design tool development. An automated tool that warns users when their visualization design is incompatible with their data—especially when patterns are indistinguishable—would be particularly beneficial.

Different context

Our experiments also suggest that the effect of patterns is influenced by the context in which they are used, indicating several directions for future research. The use of patterns seems to depend, to a large degree, on the type of representation to which they are applied, as noted by some of our participating experts. Bertin, for instance, provided numerous patterns examples for maps, but maps with textures were less successful in our experiment in Section 4.3, receiving below-average BeauVis ratings. Consequently, exploring dedicated patterns for different chart types, particularly maps, is a promising direction for future research. In addition, we only tested the effect of patterns in a simple chart reading task of comparing two values. The effect of patterns on a broader range of tasks, including those involving long-term memory or multiple-category differentiation, should be analyzed.

Visual style

The visual style of patterns may also affect their use in data mapping and is worth investigating. When patterns are used in old news graphics [30, 31], they often feature beautifully hand-crafted representations. Recreating this aesthetic is still a benefit of using black-and-white patterns today. This style may alleviate the vibratory effect to some extent because it avoids strict duplication of elements, thereby improving aesthetics and chart reading effectiveness. Previous work [5] also hypothesizes that a hand-drawn style can be more engaging than a neutral style, as it indicates to viewers that the visualization author has invested considerable time and effort in contemplating and creating it. Consequently, a viewer may be more inclined to spend ample time investigating the details and appreciating both the artistry and the data. In future work, we should conduct experiments to investigate the effects of hand-crafted patterns on viewer engagement, comprehension, and aesthetic appreciation.

Semantic association

In Chapter 4, we invited designers to create black-and-white pattern sets for categorical visualization, focusing on two types: geometric patterns, based on simple lines or dots, and iconic patterns, which use figurative icons (like a banana icon for bananas). Although iconic patterns are clearly semantically resonant, we found they did not enhance chart reading speed as anticipated. On the other hand, geometric patterns showed promise, as they improved the reading speed in pie charts. An interesting observation, as we discussed in Section 4.2.3, is that five designers followed specific strategies in creating patterns with semantic associations. Notably, four of them attempted to establish a semantic association with the abstract geometric patterns. Figure 6.2 shows a very good example. When discussing their design strategies, the designer mentioned:

"I also wanted to elicit visual associations with the geometric texture where possible: olives are small and circular, tomatoes are large and circular; black olives are dark; ripe tomatoes are a deep red; carrots, celery, and stalks of corn are elongated, so line textures seemed appropriate, though the line thickness and foreground / background choice seemed less deliberate or coherent (some carrots are larger than some celery stalks, and vice versa, while individual corn kernels are quite small, hence the finer texture for corn); eggplants are neither round nor long, but they are dark in color, so the rotated grid pattern with a dark background seemed appropriate; lastly, mushrooms are small and white, but are not circular or elongated, so once again a grid pattern with a white background seemed appropriate, though one that is finer than the eggplant grid."

We can notice that this designer made good use of rich pattern attributes to connect the patterns to the corresponding concepts. This design got highest BeauVis score in our experiment, as show in Table 4.2. This insight prompted a direction to explore further in general: How can semantic meaning effectively be embedded in abstract patterns, and can this approach improve the aesthetics and the chart reading effectiveness?

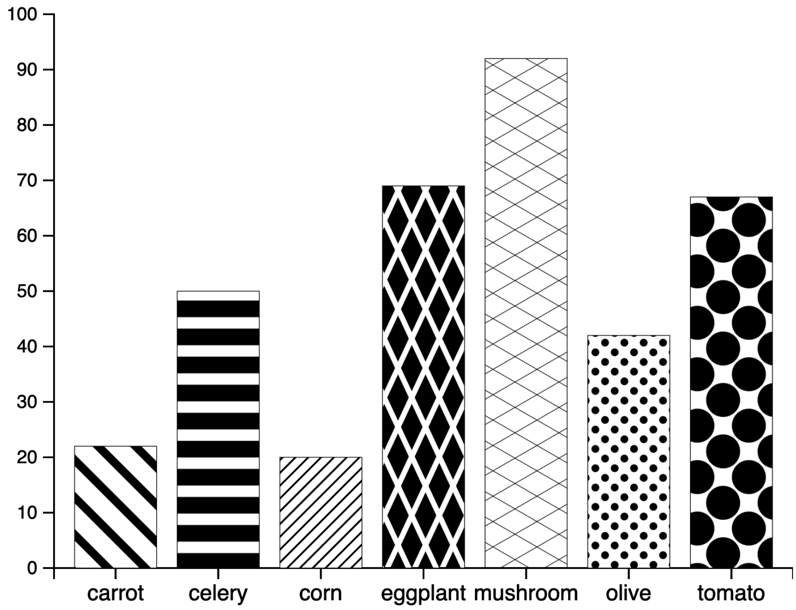


Figure 6.2: A bar chart design with gemeotric patterns (BG1) collected in our Experiment 1.

6.2.3 . Data physicalization with patterns

Black-and-white patterns are very suitable as visual variables for encoding data in data physicalization. The monochromatic nature of these patterns often simplifies the process of physical production. In this section, we primarily discuss two potential future research directions for data physicalization with patterns: personal visualization through data embroidery and accessible visualization with tactile patterns.

> The content in Section 6.2.3 is based on my original workshop paper published in the proceedings of the alt.VIS Workshop at IEEE VIS 2023 [86]. The work was led by myself in collaboration with Petra Isenberg and Tobias Isenberg.

Personal visualization through data embroidery

A promising yet so far unexplored avenue within data embroidery involves the use of black-and-white patterns. Data embroidery [178] is an innovative technique for data physicalization [98]. Machine embroidery as a computer-numerically controlled (CNC) technology makes it possible to produce complex data embroideries (relatively) quickly and integrate them into fabric-based personal belongings [178]. Data embroidery of personal data has potential because a less conventional approach to visualization may stimulate people to explore their own data more intensively [177]. It can also serve as an ambient visualization within a home setting, thereby initiating dialogues with curious visitors [143]. Data embroidery can, like in our case, be accessible to a broad set of the population through local Fablabs.

Owing to their monochromatic characteristics, black-and-white patterns promise to be easy to employ in machine embroidery. Their inherent simplicity facilitates the conversion of images to embroidery files, overcoming challenges associated with the lower color resolution of embroidery machines compared to color screens. Moreover, they eliminate the need for multiple color changes during the embroidery process, enhancing efficiency.

We preliminary explored data embroidery using black-and-white patterns. Our experiments involved different textured visualizations designed by experts. We detail our workflow and evaluate the performance and suitability of various patterns (see Figure 6.3). In addition, we conducted a survey on vegetable preferences within a family and created a canvas bag as a case study (see Figure 6.4). This bag featured the embroidered family data to demonstrate how embroidered data can be applied in practice. By integrating family data into an everyday item used for grocery shopping, data embroidery can act as a daily reminder of the family's preferences.

Our study represents the first step in exploring this technique and we provide our experiences for future embroidery work. Such future work could focus more systematically on evaluating the impact of data embroidery with black-and-white patterns in terms of both efficiency and aesthetics [85].

Accessible visualization with tactile patterns

Pattern itself is closely linked to the accessibility of charts. To ensure that individuals with color vision deficiencies can read charts, accessibility guidelines often recommend using patterns alongside colors to encode data. Beyond this benefit, black-and-white patterns also offer a unique and promising avenue for accessible visualization due to their ease of physical reproduction. We can create tactile through various methods such as 3D printing, laser engraving, vinyl cutting, or embossing.

Leveraging the pattern designs collected from previous work, we experimented with 3D printing of textured visualizations and produced two charts; one with geometric patterns and another with iconic patterns (see Figure 6.5). Compared to embroidery, setting up a 3D printer is simpler and less prone to errors. The process follows basic 3D printing steps: converting the image file (`PNG` or `SVG`) to `STL` using stand-alone or online converters, slicing the STL model to `GCODE` using a slicer, and, ultimately, importing the `GCODE` to the 3D printer for printing. The printing process was error-free—textured pieces are

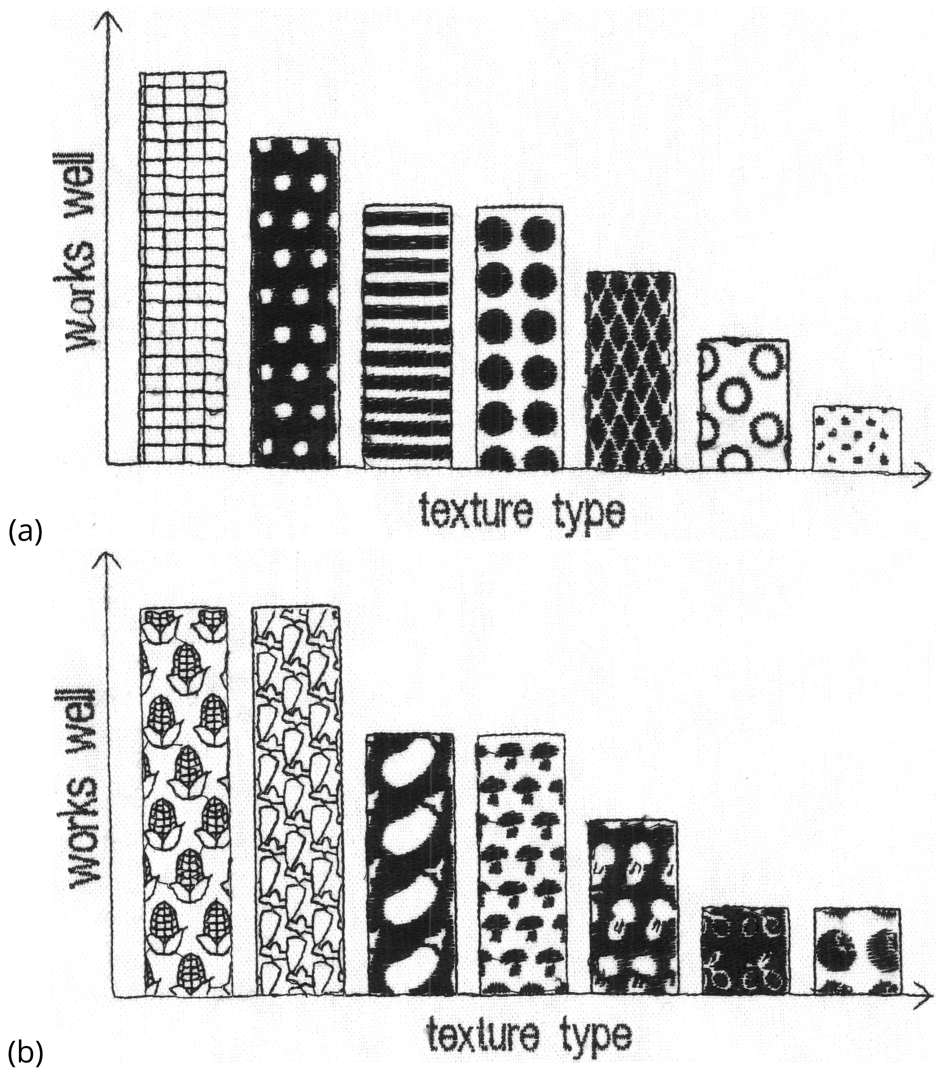


Figure 6.3: Two embroidered charts showing the performance of different patterns in machine embroidery: (a) for geometric patterns, and (b) for iconic patterns.

Figure 6.4: (a): An embroidered chart with black-and-white patterns displaying the results of a survey within a family. (b): A canvas bag featuring the embroidered chart on the left. (c) and (d): the bag being used within the family.

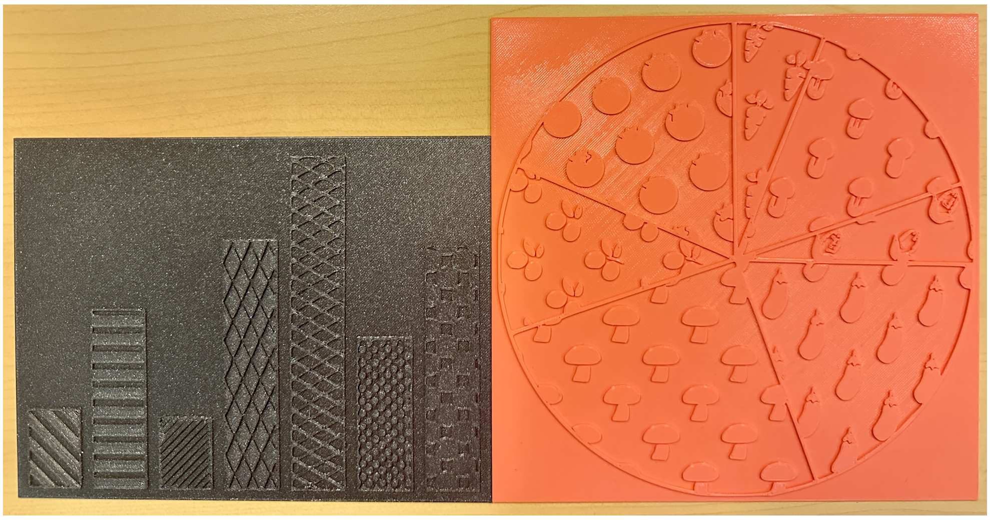


Figure 6.5: Two 3D printed textured charts, one with geometric patterns, and another with iconic patterns.

not different from any other 3D print.

For future investigations, we could explore the potential use of patterns in tactile charts for blind or low-vision (BLV) individuals. Existing guidelines on tactile graphics [26, 158, 144] recommend using patterns to differentiate areas within these graphics, and suggest that patterns should be distinct and limited in number to ensure discriminability for tactile readers. Future research could build on these guidelines and current studies on accessible tactile charts (e.g., [67, 68, 69, 70, 140, 191]) and maps (e.g., [91, 92]) to further identify best practices for tactile pattern encoding across different contexts, such as everyday use, research, education, or art. Such studies should include empirical evaluations conducted in collaboration with BLV individuals and accessibility experts to assess how effectively these patterns can be perceived tactually and

◆ **Understand subscale**

`understand1` It is **obvious** for me how to read this visualization
`understand2` I can easily understand **how the data is represented** in this visualization
`understand3` I can **easily understand** this visualization

◆ **Layout subscale**

`layout1` I **don't** find this visualization **messy**
`layout2` I **don't** find this visualization **crowded**
`layout3` I **don't** find **distracting parts** in this visualization

◆ **DataFeat subscale**

`dataFeat1` I find data features (for example, a minimum, or an outlier, or a trend) **visible** in this visualization
`dataFeat2` I can **clearly see** data features (for example, a minimum, or an outlier, or a trend) in this visualization

◆ **DataRead subscale**

`dataRead1` I can easily **find specific elements** in this visualization
`dataRead2` I can easily **identify relevant information** in this visualization
`dataRead3` I can easily **retrieve information** from this visualization

Figure 6.6: PREVis [37] with its 4 subscales and 11 items. CC BY; used with permission.

whether they enhance accessibility for BLV users [116].

6.3 . Development of measurement instruments for visualization

From the pattern design strategies collected from experts in our experiments, it is evident that the two most important quality metrics of visualizations for experts are aesthetic pleasure and readability. Therefore, as a follow-up to the BeauVis scale, we also developed and validated another instrument for comparing the perceived readability of visualizations, called the PREVis (Perceived Readability Evaluation for Visualizations) [37]. PREVis instrument consists of 11 items across 4 dimensions: understandability, layout clarity, readability of data values, and readability of data patterns. Figure 6.6 shows the complete instrument. The details of the development and validation process of the PREVis instrument can be found in our paper [37]. We provide the questionnaire as a PDF file, along with its implementation guidelines, on osf.io/bdavt in the OSF repository of this project osf.io/9cg8j.

The PREVis instrument was introduced in our original article published in IEEE Transactions on Visualization and Computer Graphics [37]. The work was led by Anne-Flore Cabouat, in collaboration with myself, Petra Isenberg, and Tobias Isenberg.

There is currently a significant lack of rigorously validated scales targeted specifically for visualization. Therefore, researchers in our community have to often construct their own scales. South et al. [163] systematically reviewed the use of Likert scales in 134 visualization papers published between 2009 and 2019. They found that most of the papers (123 papers, 92%) in this survey constructed their own custom Likert questionnaires rather than using validated scales. Without validation, however, we cannot ensure the validity and reliability of these custom scales. Therefore, in the future, we should develop more targeted scales to measure the qualities needed in the field of visualization. Our current work lays the methodological foundation for the future development of such visualization-specific scales.

6.4 . Conclusion

In summary, this thesis contributes to the understanding of the visual variable *pattern* from theoretical, empirical, and evaluative perspectives. Specifically, we conceptualized *pattern* as a composite variable consisting of submarks and developed a design space that outlines potential pattern variations for data encoding. In addition, we presented initial empirical findings demonstrating that patterns are a viable option for encoding categorical data based on both aesthetic appeal and effectiveness. We also developed and validated an instrument to measure the aesthetic pleasure of visualizations. Our work highlights the potential of the visual variable *pattern* and establishes a theoretical foundation for future exploration and application of patterns in visualization. Furthermore, this thesis exemplifies the interdisciplinary nature of the visualization domain: we used psychological methods to construct a design space applicable to the field of computer science.

A - Appendix for Chapter 4

In this appendix we provide additional tables, plots, and charts that show data beyond the material that we could include in the Chapter 4 due to space limitations or because it was not essential for explaining our approach.

Images/graphs/plots/tables/data license/copyright

A.1 . Original analysis in Experiment 3

Initially, we included all 150 responses in the analysis of response time, readability, and aesthetics, as pre-registered on the OSF platform. Later, in addition to our pre-registered analysis plan, we examined the individual accuracy rate per participant. We found 64 participants whose overall accuracy rate was below 90%. We decided to adjust our approach by excluding these low-accuracy participants to minimize the influence of chance performance (i.e., random guessing), because these low-accuracy participants may have largely guessed randomly. This is an additional exclusion criterion, in addition to the exclusion criteria outlined in our pre-registration. We now only counted the 86 participants who achieved a 90% overall accuracy threshold (45$\times$ bar, 41$\times$ pie). Note that there are two trials in our data where we recorded that the participants gave the correct answers, but their recorded response times were slightly above 5 seconds. The times for these two trials were 5.002 and 5.006 seconds, respectively, which should be timed out. We speculate that this situation occurred because, due to network latency, the page did not redirect in time, allowing the participants the opportunity to input their answers, which were then recorded. Given that we know that these two trials are correct, and that the differences between their duration and the 5-second threshold were minimal, we still counted them as correct trials when calculating the accuracy rate.

In addition, we note that in our pre-registration we decided to remove "incomplete responses" from our analysis in Experiment 3. With this wording we intended to refer to those participants who did not complete our experiment; i.e., those who quit the experiment midway and did not reach the last page (and we indeed excluded those participants). Another interpretation of our wording could have been to refer to participants with missing trials due to the log file issue (we lost 12 trials out of 9,000 trials), which is what we did not intend to mean. So ultimately we did not remove the 6 participants with missing trials (4 missed 1 trial, 1 missed 2 trials, and 1 missed 6 trials), because these comparatively few missing trials do not affect other trials.

Below we present Figure A.1–A.3, which show the results of our original analysis (i.e., as pre-registered). We also discuss the difference observed in the refined analysis as compared to the original analysis.

A.1.1 . Response time

We initially included all participants and counted both their correct and incorrect trials. We removed the few timed-out trials ($<$ 1.5%) as we could not estimate whether a person was distracted or how much more time they would have needed. Figure A.1 presents mean response times and pairwise comparisons for all fill types in bar and pie charts from the original analysis (as pre-registered). The pairwise differences indicate that, for bar charts, we have evidence that iconic patterns have a longer response time than the other two fill types. For pie charts, we have evidence that geometric patterns have shorter response times than the other two fill types. No other combination of fill types showed an evident difference. In addition, all these differences were minimal, within a range of $<$ 230 ms.

Later, we improved our analysis approach, as previously mentioned. In addition, for response time analysis specifically, we only counted the correct trials. This exclusion is necessary due to the difficulty in interpreting the speed of incorrect responses, and because averaging the response times of both correct and incorrect trials does not logically make sense. So, in our adjusted approach we now analyze the response times of correct trials from the 86 high-accuracy participants, excluding both incorrect and timed-out trials.

Figure 4.9 presents the mean response times and pairwise comparisons for all fill types, as represented in both bar and pie charts, from our refined analysis. A detailed explanation of these results can be found in Figure 4.4.6 in the main paper. In summary, the only change in our findings is the observed evidence of longer response times for geometric patterns compared to unicolor fill in bar charts, a difference that was not evident in our original analysis. All other results remained consistent, and the outcomes for both of our hypotheses were unaffected. The differences in response times across the three fill types remained minimal, within a range of $<$ 255 ms, thereby also maintaining our overall conclusion.

A.1.2 . Readability

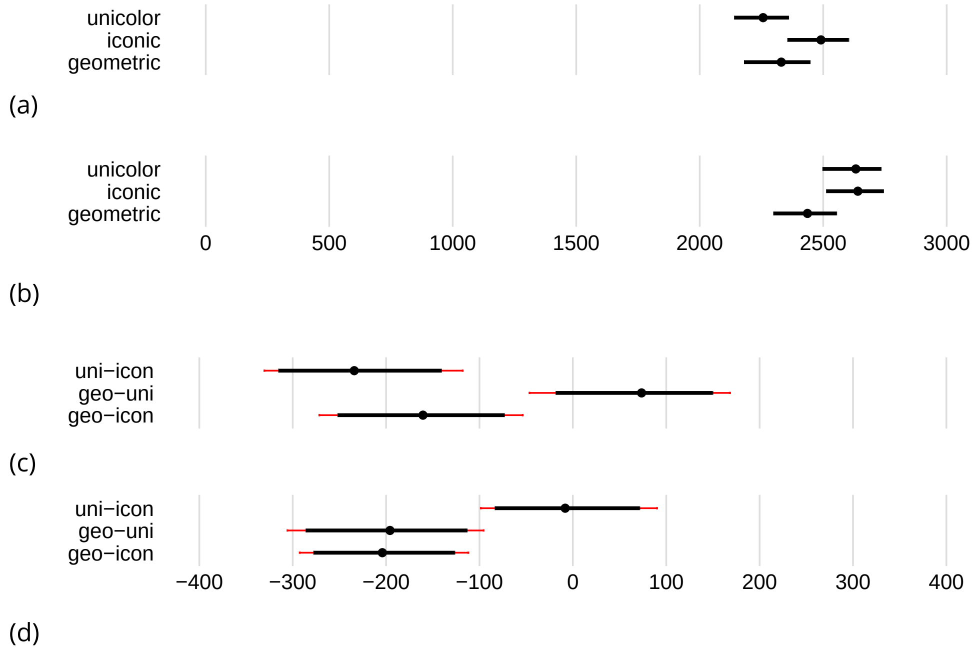


Figure A.1: Results of our original analysis for response times (as pre-registered). Response times in ms for (a) bar and (b) pie charts; (c), (d) corresponding pairwise comparisons between the fill types. Error bars: 95% CIs. Red bars: CIs for Bonferroni-corrected pairwise comparison.

In Figure A.2 we present the mean readability scores, along with pairwise comparisons, for all fill types in both bar and pie charts from the original analysis (as pre-registered). There is no change in the results between the original (pre-registered) and the refined analysis.

A.1.3 . Aesthetics

Figure A.3 presents mean BeauVis scores and pairwise comparisons for all fill types in bar and pie charts from the original analysis (as pre-registered). The only difference in the results is that in the original analysis, from pairwise differences (Figure A.3(c)), we see evidence suggesting that geometric patterns are considered to be less aesthetically pleasing than unicolor fill for bar charts. Pairwise differences of bar charts from the refined analysis (Figure 4.11(c)), however, reveal no evidence of difference between geometric patterns and unicolor fill with respect to whether they are considered to be aesthetically pleasing or not. Because geometric patterns are still considered by participants to be less aesthetically pleasing than iconic patterns for bar charts, however, the refined analysis does not change our result of the related hypothesis (H2), nor does it affect our overall conclusion.

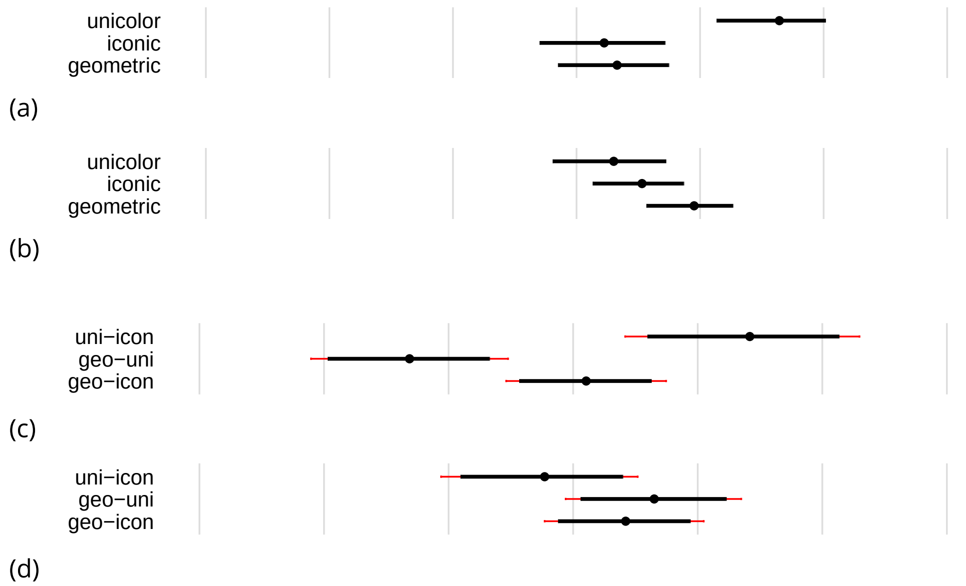


Figure A.2: Results of our original analysis for readability scores (as pre-registered). Readability scores for (a) bar and (b) pie charts; (c), (d) corresponding pairwise comparisons between the fill types. Error bars: 95% CIs. Red bars: CIs for Bonferroni-corrected pairwise comparison.

A.2 . All designs generated by the visualization experts in Experiment 1

In Figure A.4(a)–A.9(k) we show the 66 designs we collected from 30 visualization designers in Experiment 1. The collection comprises 14 bar charts (Figure A.4(a)–A.5(g)), 30 pie charts (Figure A.6(a)–A.7(o)), and 22 maps (Figure A.9(a)–A.9(k)).

We include all these images here and Tables 4.2–4.7) as pixel images on purpose because the SVG vector version relies on tiled pattern samples, which—when converted to PDF for the inclusion in the paper—lead to unfortunate errors in the display in all PDF readers we tested. Likely this effect is due to numeric issues that affect the exact positions where the pattern tiles meet. Nonetheless, you can find the original SVG images in our OSF repository at osf.io/n5zut and you can look at them with a browser such as Chrome, Microsoft Edge, or Firefox.

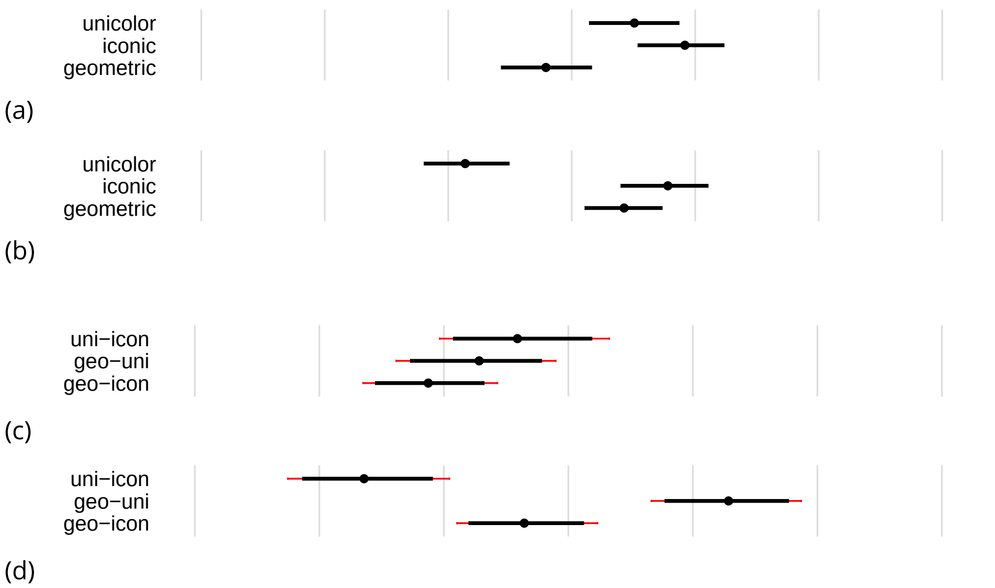
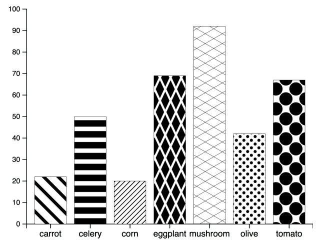
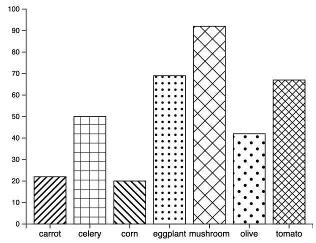


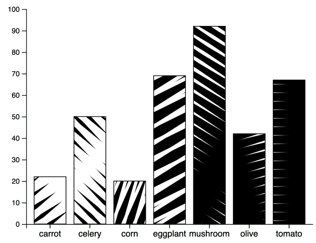
Figure A.3: Results of our original analysis for BeauVis scores (as preregistered). BeauVis scores for (a) bar and (b) pie charts; (c), (d) corresponding pairwise comparisons between the fill types. Error bars: 95% CIs. Red bars: CIs for Bonferroni-corrected pairwise comparison.



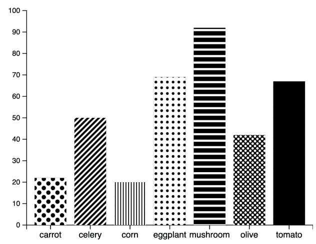
(a) BG1



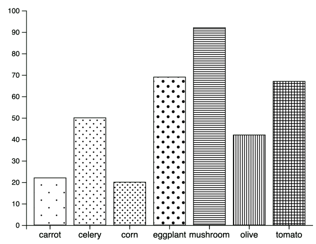
(b) BG2



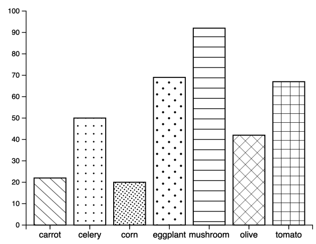
(c) BG3



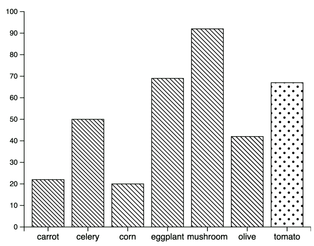
(d) BG4



(e) BG5

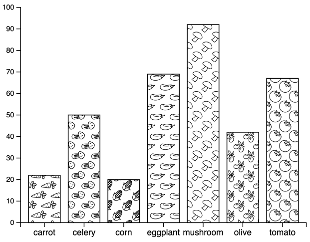


(f) BG6

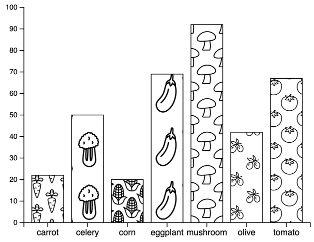


(g) BG7

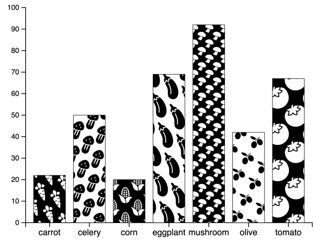
Figure A.4: Geometric textured bar chart designs collected in our Experiment 1.



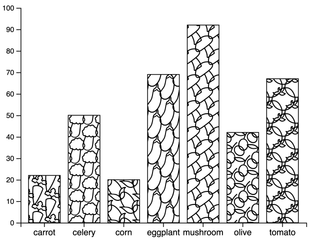
(a) BI1



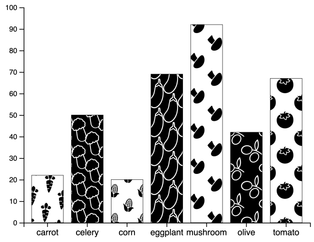
(b) BI2



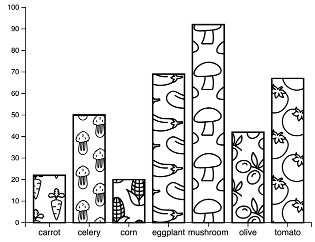
(c) BI3



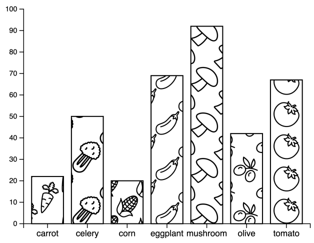
(d) BI4



(e) BI5

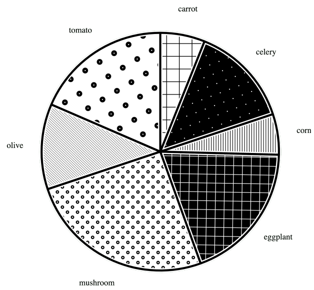


(f) BI6

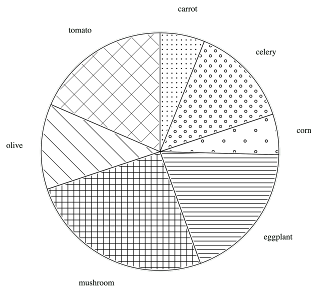


(g) BI7

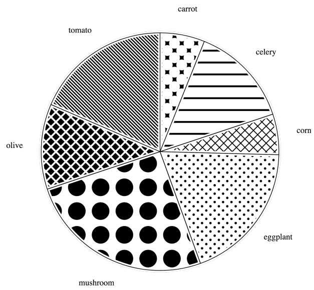
Figure A.5: Iconic textured bar chart designs collected in our Experiment 1.



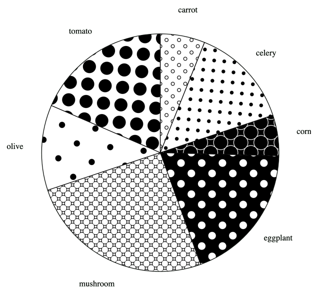
(a) PG1



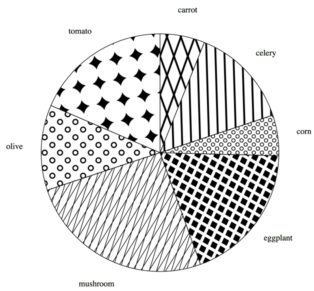
(b) PG2



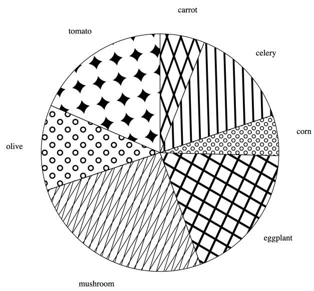
(c) PG3



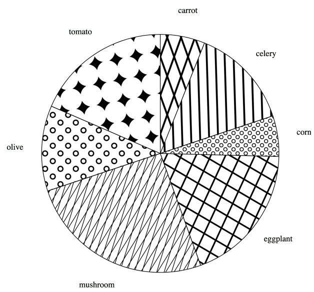
(d) PG4



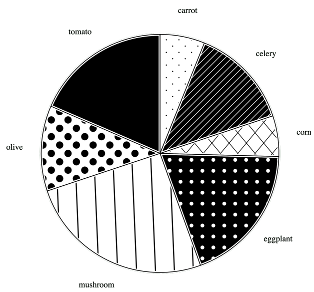
(e) PG5



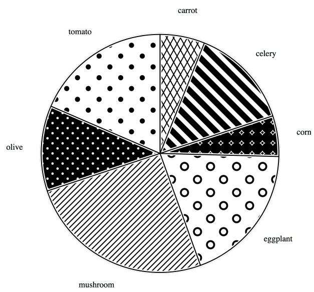
(f) PG6



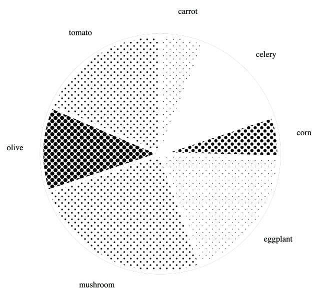
(g) PG7



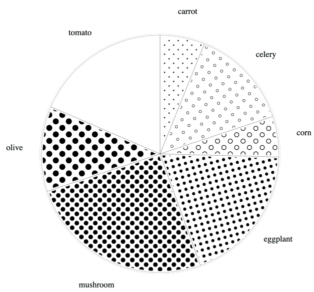
(h) PG8



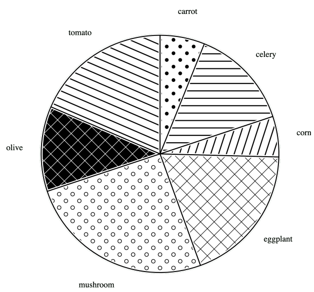
(i) PG9



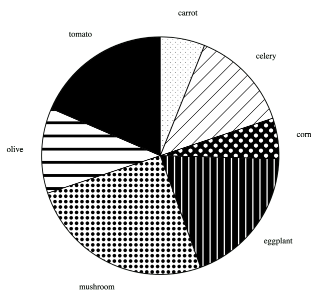
(j) PG10



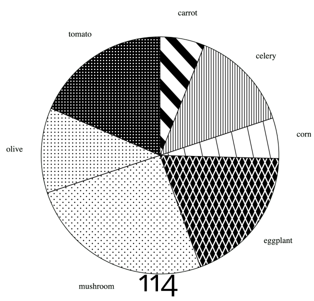
(k) PG11



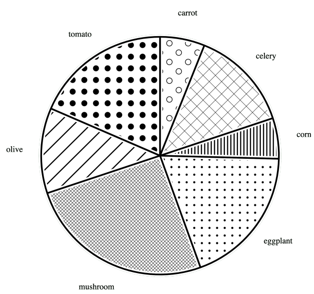
(l) PG12



(m) PG13

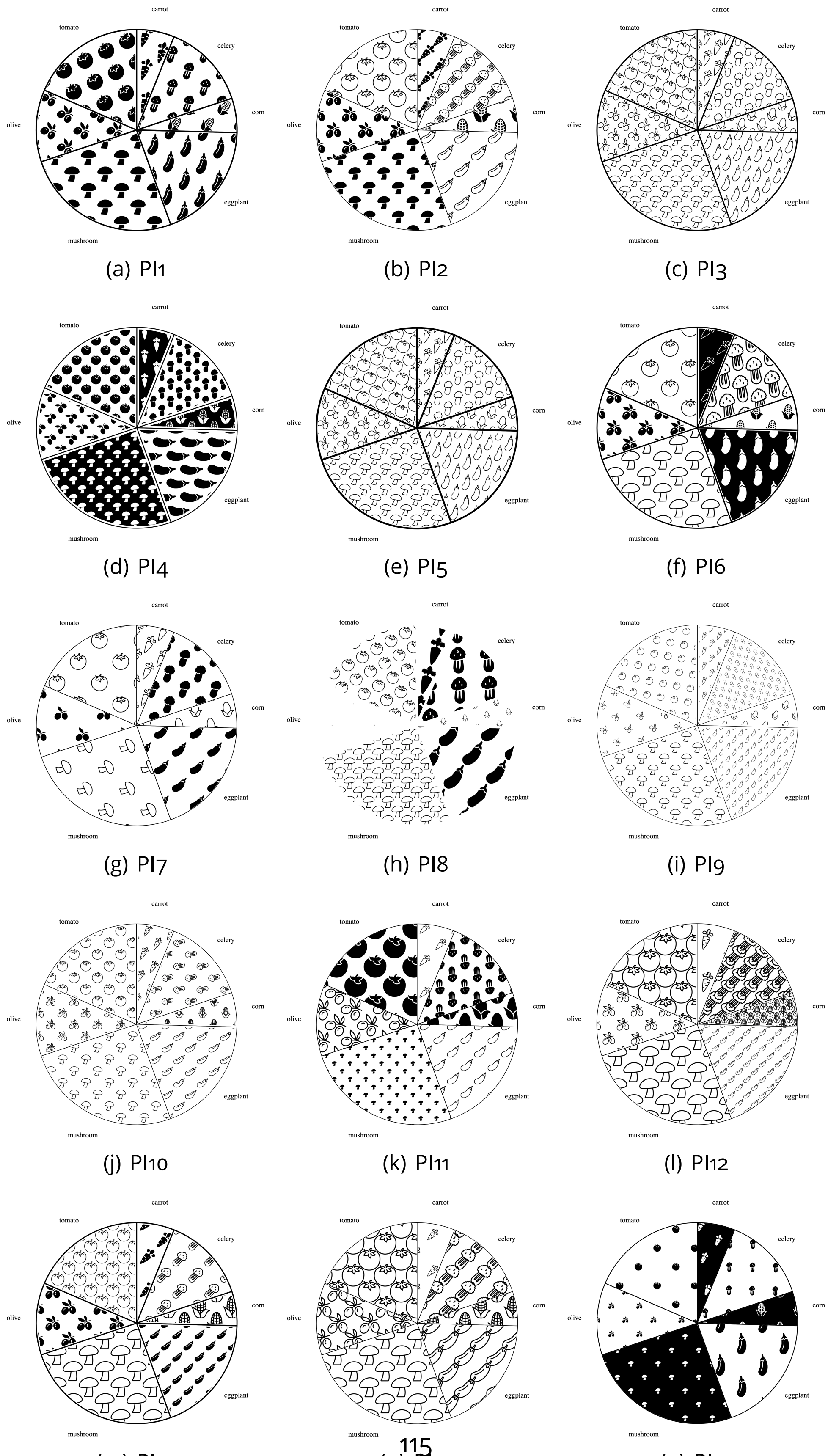


(n) PG14



(o) PG15

Figure A.6: Geometric textured pie chart designs collected in our Experiment 1.



(a) PI1 (b) PI2 (c) PI3

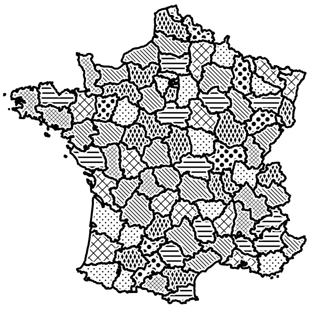
(d) PI4 (e) PI5 (f) PI6

(g) PI7 (h) PI8 (i) PI9

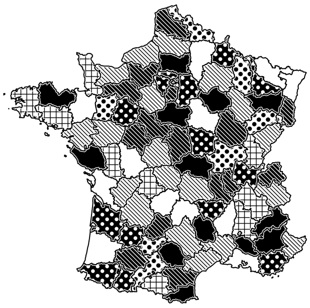
(j) PI10 (k) PI11 (l) PI12

(m) PI13 (n) PI14 (o) PI15

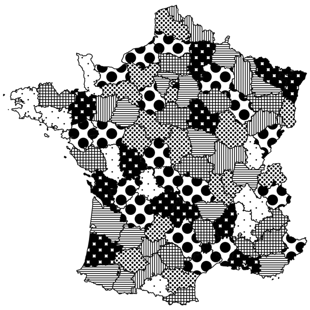
Figure A.7: Iconic textured pie chart designs collected in our Experiment 1.



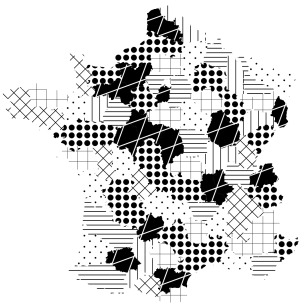
(a) MG1



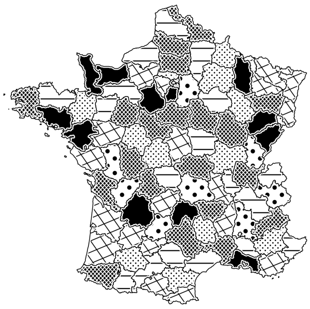
(b) MG2



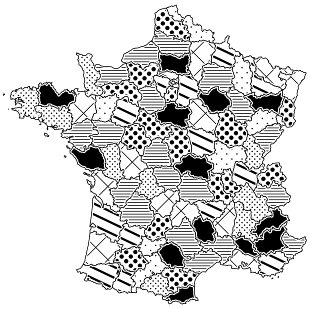
(c) MG3



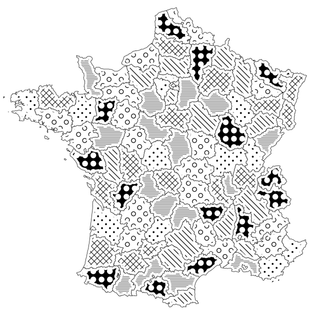
(d) MG4



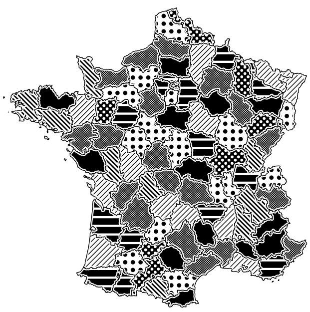
(e) MG5



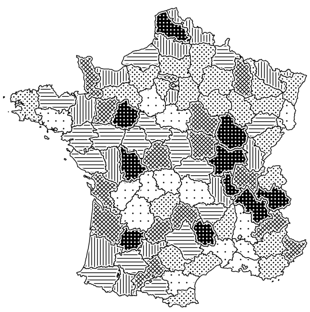
(f) MG6



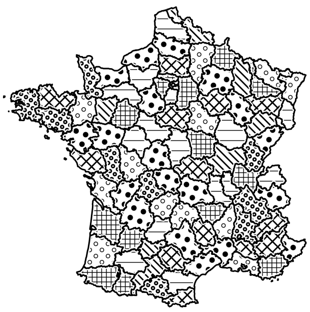
(g) MG7



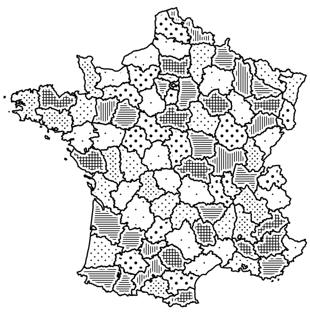
(h) MG8



(i) MG9

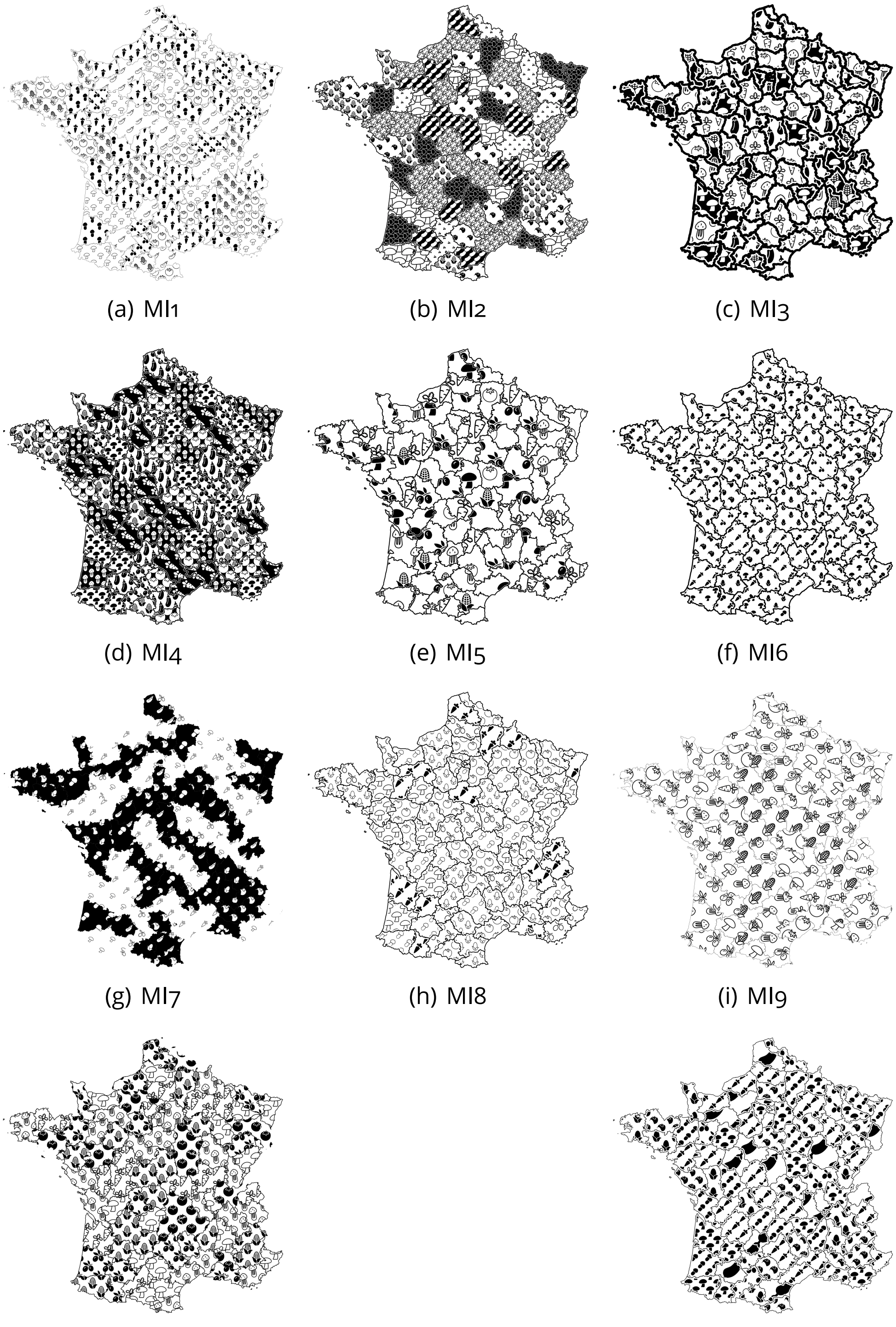


(j) MG10



(k) MG11

Figure A.8: Geometric textured map designs collected in our Experiment 1.



(a) MI1 (b) MI2 (c) MI3

(d) MI4 (e) MI5 (f) MI6

(g) MI7 (h) MI8 (i) MI9

(j) MI10 (k) MI11

Figure A.9: Iconic textured map designs collected in our Experiment 1.

B - Appendix for Chapter 5

In this appendix we provide additional tables, plots, and charts that show data beyond the material that we could include in the Chapter 5 due to space limitations or because it was not essential for explaining our approach.

Images/graphs/plots/tables/data license/copyright

B.1 . Term development

Here we list the various states of term lists that we generated throughout our scale development process. Table B.1 lists the terms we had initially extracted from the visualization literature. Next, Table B.2 lists terms we generated from our literature review (visualization literature and 4 papers from related fields about aesthetic pleasure scale). Table B.3 lists terms we generated from the experts' suggestions, and Table B.4 lists terms we generated from both literature review and the experts' suggestions. Table B.5 lists terms used as input for expert review. Finally, Table B.6 lists terms that we used as input for our exploratory phase.

B.2 . Scree plots

In Figure B.1–B.15 we show the scree plots for all 15 images, as a complement for Figure 5.2 in the paper, which only showed the scree plot for Image 1.

B.3 . Term combination comparisons

In Figure B.16–B.19 we show Cronbach's alpha for additional combinations of terms over all 15 test images, including for 2-item combinations. They serve as a complement for Figure 5.4 in the paper, which only showed the data for the top three combinations for 3-, 4-, and 5-item subsets.

B.4 . Term correlation matrices

Table B.1: 41 terms generated from VIS Literature. Terms in italics are repeated in different categories. The numbers in brackets denote how frequently we observed each term.

aesthetic	**emotion**	**cognitive**	**data-aesthetic**
aesthetic (20×)	*appealing* (2×)	clear (7×)	*expressive* (4×)
appealing (2×)	boring (3×)	*cluttered* (5×)	*informative* (4×)
attractive (4×)	*calm* (1×)	comprehensible (1×)	suitable (1×)
beautiful (3×)	cool (1×)	confusing (3×)	
calm (1×)	engaging (4×)	interpretable (6×)	***other***
cluttered (5×)	enjoyable (4×)	intuitive (9×)	*conventional* (2×)
conventional (2×)	entertaining (2×)	readable (7×)	*high-quality* (1×)
drab (1×)	exciting (2×)	understandable (12×)	*innovative* (2×)
elegant (2×)	fun (1×)		
expressive (4×)	happy (1×)		
high-quality (1×)	hideous (1×)		
innovative (2×)	interesting (1×)		
inviting (1×)	likable (4×)		
nice (1×)	motivating (1×)		
pretty (1×)	pleasing (7×)		
ugly (2×)	satisfying (2×)		
well-designed (5×)	stimulating (1×)		

In Figure B.20–B.34 we provide an additional analysis by image that checks for correlation between the final 31 terms of Table B.6, which we computed with R's `cor()` function based on the participants' ratings per image from Survey 3.

B.5 . Term subset ratings

In Figure B.35–B.49 we show the comparison of ratings from subsets of the rating items for all images, for 3, 4, 5, and for all 31 terms of Table B.6. Essentially, these figures are a complement for Figure 5.5 in the paper which only showed the data for Image 2 and Image 9.

B.6 . Factor loading for one factor

Tables B.7–B.21 show the factor loading for the final 31 terms of Table B.6, for each visualization, using an EFA using one factor. In the tables, PA1 is the factor loading, h2 is the communality, u2 is the uniqueness, and com is the complexity of the factor loadings. Osborne et al. [139] suggest that items with communalities > 0.4 are acceptable, while Child [51] suggests that items with communalities < 0.2 should be removed.

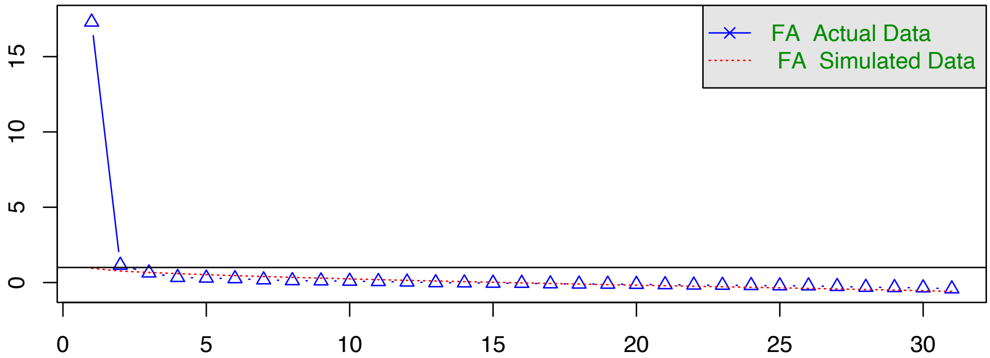


Figure B.1: Scree plot for Image 1, eigen values of principal factors on the y-axis over factor number on the x-axis.

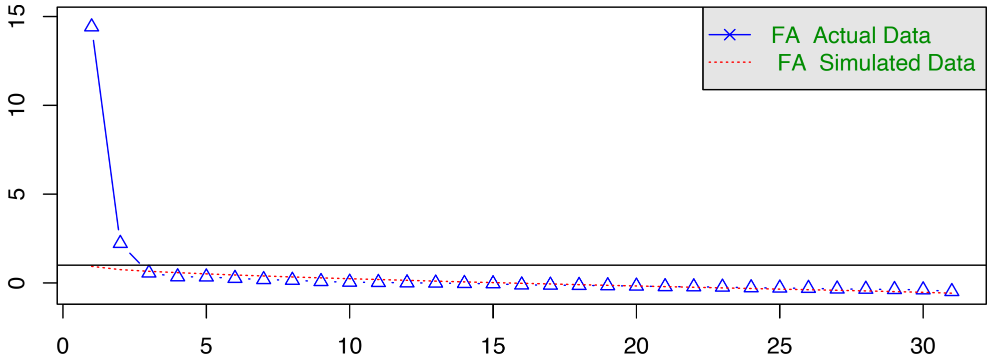


Figure B.2: Scree plot for Image 2, eigen values of principal factors on the y-axis over factor number on the x-axis.

B.7 . Factor loading for two factors

Tables B.22–B.51 show the factor loading for the final 31 terms of Table B.6, for each visualization, using an EFA using two factors with Varimax rotation or Promax rotation. In the tables, PA1 is the factor loading on the first factor, PA2 is the factor loading on the second factor, the remaining values have the same meaning as described in Section B.6.

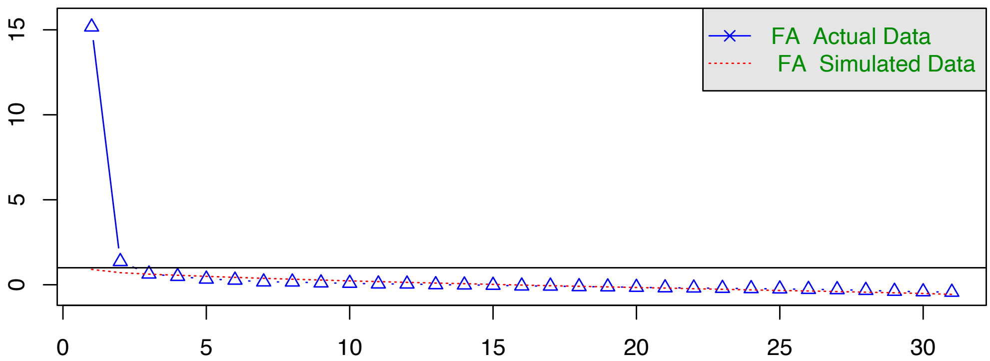


Figure B.3: Scree plot for Image 3, eigen values of principal factors on the y-axis over factor number on the x-axis.

Table B.2: 176 terms generated from literature review (visualization literature and 4 papers from related fields about aesthetic pleasure scale). Terms in italics are repeated in different categories. We do not list frequencies here as the terms come from dissimilar sources.

aesthetic	**emotion**	**cognitive**	**data-aesthetic**
a poor visual focus	alienating	*a poor visual focus*	*expressive*
aesthetic	*appealing*	appropriate	*informative*
appealing	appreciating	attention-catching	suitable
artistic	averageness	categorizable	
asymmetrical	awe	challenging	
attractive	boring	clear	**other**
balanced	bring me closer to people/separates me from people	*cluttered*	a printing effect
beautiful	*calm*	comprehensible	admirable
bold	comfortable	conceptless	alive
calm	connective	confusing	amateurish
captivating	cool	cumbersome	bad
cautious	delightful	easy to grasp	botched
clean	disgreeable	elicits associations	cheap
cluttered	dynamic	*informative*	consistent
colorful	elation	inspiring	convenient
complex	emotive	interpretable	convenient
conservative	energetic	intuitive	*conventional*
conventional	engaging	meaningful	easy orientation
creative	enjoyable	memorable	easy to navigate
crowded	entertaining	practical	easy to use
discouraging	exciting	readable	fit together
distinctive	fascinating	straightforward	fluent to process
drab	favorable	structured	good
elegant	fun	undemanding	hectic
expressive	gratifying	understandable	*high-quality*
familiar	happy	*use of color is successful*	human
harmonious	hideous		*innovative*
has enough free space	integrating		it is possible to discover new things even when looking at the page for a longer time.
high-quality	intense		manageable
innovative	interesting		noisy
inventive	intriguing		one-sided
inviting	intrusive		pleasantly animated
lack imagination	isolating		premium
made with care	likable		professional
modern	motivating		restless
nice	moved		some elements seem out of place
novel	perfection		sophisticated
old-fashioned	pleasing		static
orderly	positive		stucco
ordinary	powerful		technology
organized	predictable		the control instructions are too static
original	preferable		the number of images is adequate
overloaded	relaxed		the page contains too much text
patchy	satisfying		too little happens on the page
presentable	stimulating		unique
pretty	sublime		unruly
realistic appearance	the page changes too little due to user actions		uses special effects
rejecting	thrills or chills		varied
simple	touched		versatile
stylish	warm feeling		well-combined
symmetrical			well-finished
tacky			wretched
tasteful			
thrown together			
ugly			
unimaginative			
up-to-date			
use of color is successful			
vulgar			
well-designed			
well-proportioned			

Table B.3: 77 terms generated from the experts' suggestions. Terms in italics are repeated in different categories. The numbers in brackets denote how frequently each term was mentioned by the experts.

aesthetic	**emotion**	**cognitive**	**data-aesthetic**
aesthetic (15×)	*appealing* (11×)	attention-catching (1×)	*expressive* (1×)
appealing (11×)	comfortable (1×)	challenging (1×)	
artistic (5×)	delightful (2×)	clear (3×)	
attractive (7×)	desirable (1×)	*cluttered* (1×)	**other**
awesome (1×)	disturbing (1×)	compelling (2×)	colorblind-safe (1×)
balanced (4×)	emotive (1×)	contemplative (1×)	consistent (1×)
beautiful (18×)	engaging (5×)	legible (1×)	easy on eyes (1×)
captivating (1×)	enjoyable (1×)	meaningful (2×)	fauvist (1×)
clean (4×)	evocative (1×)	memorable (2×)	flowing (1×)
cluttered (1×)	evoking feelings (1×)	slick (1×)	good (1×)
color-harmonious (2×)	fun (1×)	stimulating creativity (1×)	romantic (1×)
colorful (1×)	interesting (2×)	stimulating curiosity (1×)	shows complete ignorance of human visual perception (1×)
contrast (1×)	intriguing (1×)	understandable (1×)	sophisticated (1×)
crisp (1×)	likeable (1×)		unprofessional (1×)
elegant (5×)	motivating (1×)		
expressive (1×)	pleasing (16×)		
eye-catching (2×)	preferable (1×)		
geometric (1×)	provoking (5×)		
harmonious (5×)	satisfying (1×)		
illuminating (1×)	striking (1×)		
just eye-candy (1×)			
looks great, but does not enable to get insight (1×)			
lovely (2×)			
nice (5×)			
painterly (1×)			
pretty (3×)			
simple (2×)			
streamlined (1×)			
stunning (1×)			
stylish (1×)			
tasteful (2×)			
thoughtful (1×)			
ugly (2×)			
unique (1×)			
well-crafted (1×)			
well-designed (4×)			

Table B.4: 209 terms generated from both literature review and experts' suggestion. Terms in italics are repeated in different categories.

aesthetic	**emotion**	**cognitive**	**data-aesthetic**
a poor visual focus	alienating	*a poor visual focus*	*expressive*
aesthetic	*appealing*	appropriate	*informative*
appealing	appreciating	attention-catching	suitable
artistic	averageness	categorizable	
asymmetrical	awe	challenging	
attractive	boring	clear	**other**
awesome	bring me closer to people/separates me from people	*cluttered*	a printing effect
balanced	*calm*	compelling	admirable
beautiful	comfortable	comprehensible	alive
bold	connective	conceptless	amateurish
calm	cool	confusing	bad
captivating	delightful	contemplative	botched
cautious	desirable	cumbersome	cheap
clean	disgreeable	easy to grasp	colorblind-safe
cluttered	disturbing	elicits associations	consistent
color-harmonious	dynamic	*informative*	convenient
colorful	elation	inspiring	convenient
complex	emotive	interpretable	*conventional*
conservative	energetic	intuitive	easy on eyes
contrastful	engaging	meaningful	easy orientation
conventional	enjoyable	memorable	easy to navigate
creative	entertaining	practical	easy to use
crisp	evocative	readable	fauvist
crowded	evoking feelings	slick	fit together
discouraging	exciting	stimulating creativity	flowing
distinctive	fascinating	stimulating curiosity	fluent to process
drab	favorable	straightforward	good
elegant	fun	structured	hectic
expressive	gratifying	undemanding	*high-quality*
eye-catching	happy	understandable	human
familiar	hideous	*use of color is successful*	*innovative*
geometric	integrating		it is possible to discover new things even when looking at the page for a longer time.
harmonious	intense		manageable
has enough free space	interesting		noisy
high-quality	intriguing		one-sided
illuminating	intrusive		pleasantly animated
innovative	isolating		premium
inventive	likable		professional
inviting	motivating		restless
just eye-candy	moved		romantic
lack imagination	perfection		shows complete ignorance of human visual perception
looks great, but does not enable to get insight	pleasing		some elements seem out of place
lovely	positive		sophisticated
made with care	powerful		static
modern	predictable		stucco
nice	preferable		technology
novel	provoking		the control instructions are too static
old-fashioned	relaxed		the number of images is adequate
orderly	satisfying		the page contains too much text
ordinary	stimulating		too little happens on the page
organized	striking		unique
original	sublime		unruly
overloaded	the page changes too little due to user actions		uses special effects
painterly	thrills or chills		varied
patchy	touched		versatile
presentable	warm feeling		well-combined
pretty			well-finished
realistic appearance			wretched
rejecting			
simple			
streamlined			
stunning			
stylish			
symmetrical			
tacky			
tasteful			
thoughtful			
thrown together			
ugly			
unimaginative			
unique			
up-to-date			
use of color is successful			
vulgar			
well-crafted			
well-designed			
well-proportioned			

Table B.5: 37 terms used as input for expert review. Terms in italics are repeated in different categories.

aesthetic	**emotion**	**cognitive**	**data-aesthetic**
aesthetic	*appealing*	*cluttered*	/
appealing	boring		
artistic	delightful		
attractive	engaging		**other**
balanced	enjoyable		good
beautiful	entertaining		professional
clean	exciting		sophisticated
cluttered	fascinating		
color-harmonious	interesting		
creative	likable		
elegant	motivating		
harmonious	pleasing		
inviting	provoking		
lovely	satisfying		
modern			
nice			
organized			
overloaded			
pretty			
tasteful			
well-designed			

Table B.6: 31 terms used as input for our exploratory phase. Terms in italics are repeated in different categories.

aesthetic	**emotion**	**cognitive**	**other**
appealing	*appealing*	*cluttered*	professional
artistic	delightful		sophisticated
attractive	engaging		
balanced	enjoyable		
beautiful	exciting		
clean	fascinating		
cluttered	interesting		
color-harmonious	likable		
creative	motivating		
elegant	pleasing		
harmonious	provoking		
inviting	satisfying		
lovely			
nice			
organized			
pretty			
tasteful			
well-designed			

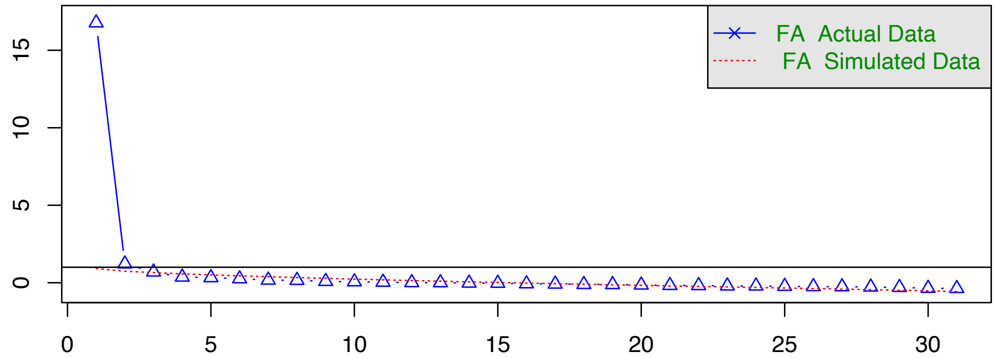


Figure B.4: Scree plot for Image 4, eigen values of principal factors on the y-axis over factor number on the x-axis.

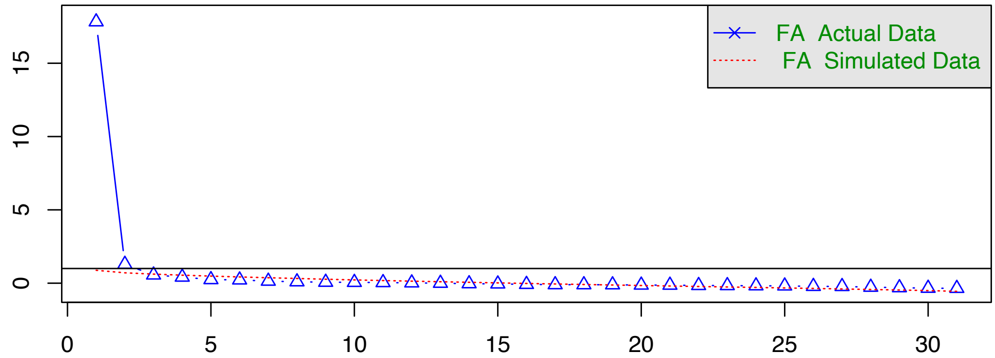


Figure B.5: Scree plot for Image 5, eigen values of principal factors on the y-axis over factor number on the x-axis.

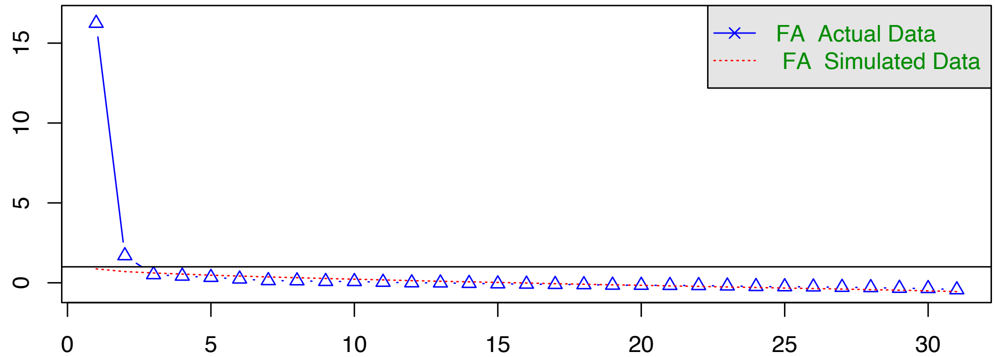


Figure B.6: Scree plot for Image 6, eigen values of principal factors on the y-axis over factor number on the x-axis.

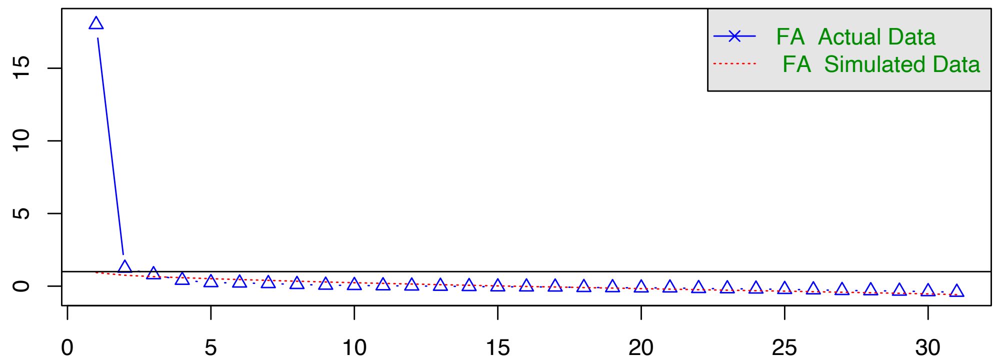


Figure B.7: Scree plot for Image 7, eigen values of principal factors on the y-axis over factor number on the x-axis.

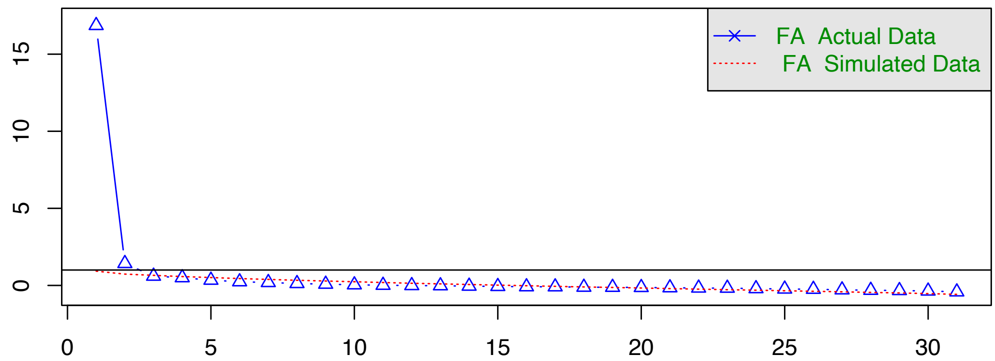


Figure B.8: Scree plot for Image 8, eigen values of principal factors on the y-axis over factor number on the x-axis.

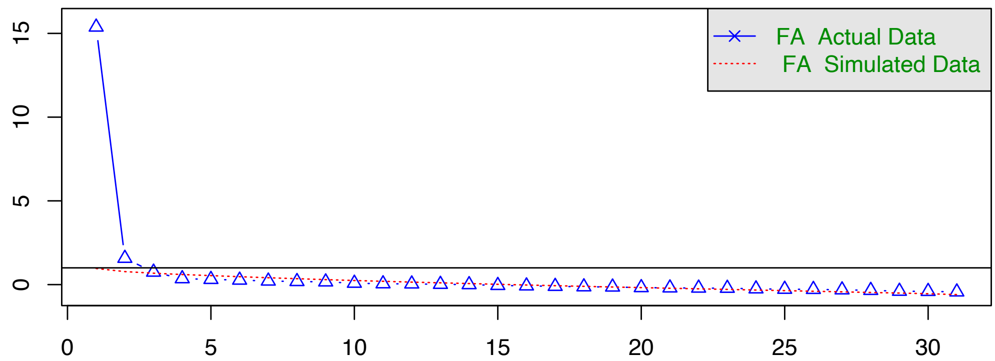


Figure B.9: Scree plot for Image 9, eigen values of principal factors on the y-axis over factor number on the x-axis.

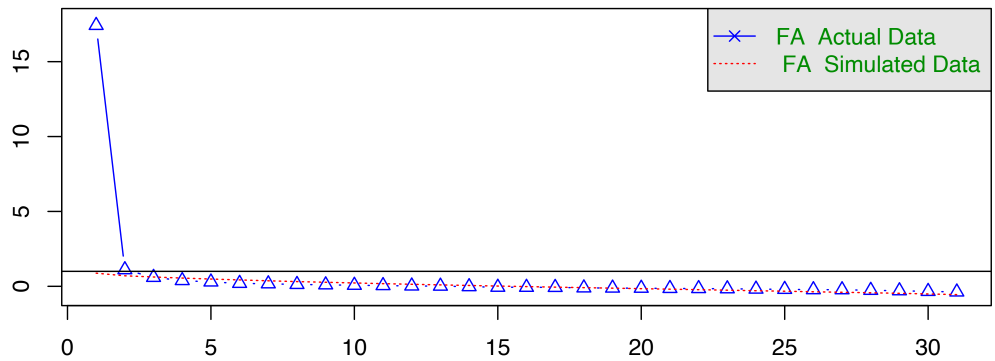


Figure B.10: Scree plot for Image 10, eigen values of principal factors on the y-axis over factor number on the x-axis.

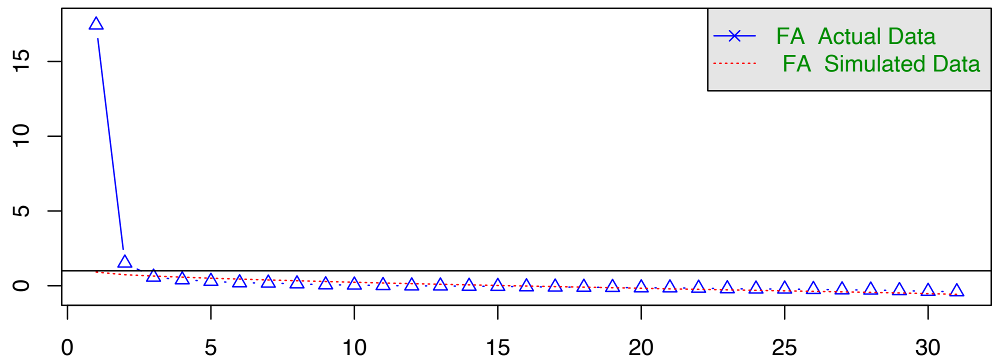


Figure B.11: Scree plot for Image 11, eigen values of principal factors on the y-axis over factor number on the x-axis.

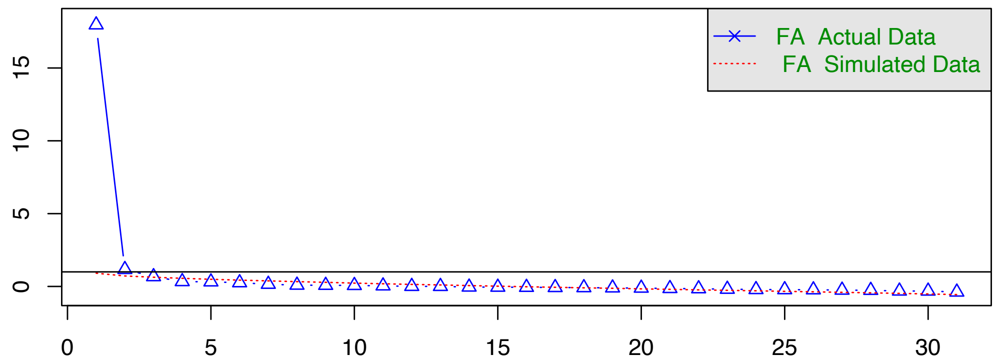


Figure B.12: Scree plot for Image 12, eigen values of principal factors on the y-axis over factor number on the x-axis.

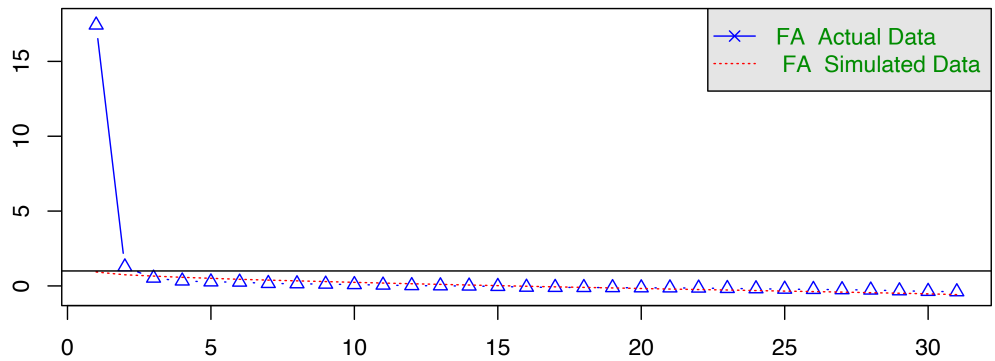


Figure B.13: Scree plot for Image 13, eigen values of principal factors on the y-axis over factor number on the x-axis.

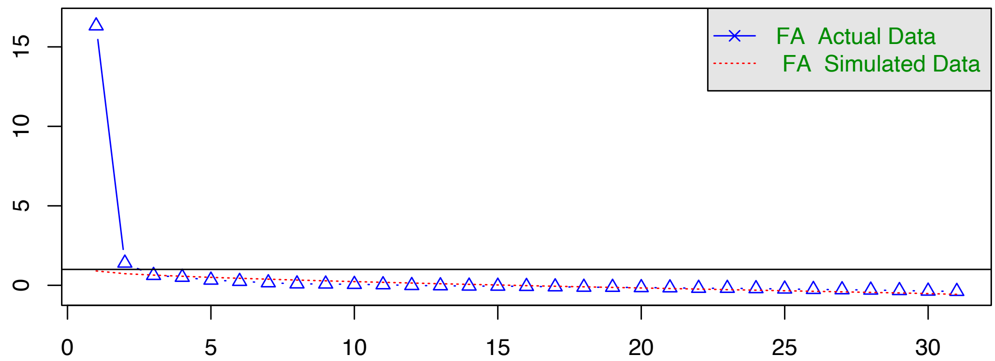


Figure B.14: Scree plot for Image 14, eigen values of principal factors on the y-axis over factor number on the x-axis.

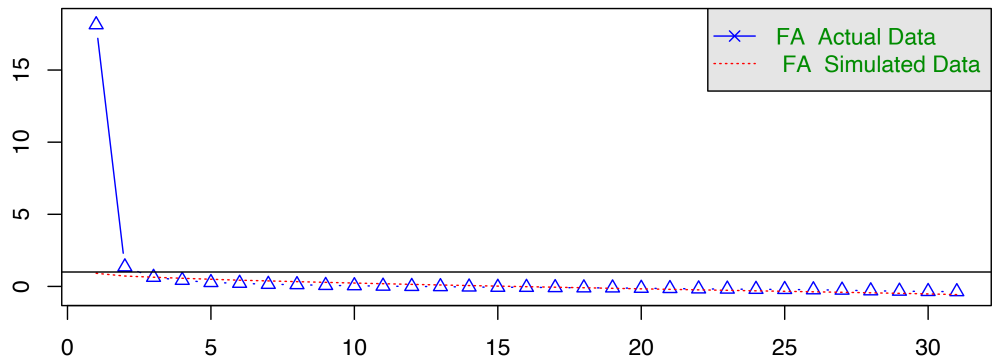


Figure B.15: Scree plot for Image 15, eigen values of principal factors on the y-axis over factor number on the x-axis.

Terms	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Grand ..
enjoyable-likable	0.90	0.80	0.88	0.87	0.87	0.83	0.90	0.90	0.86	0.89	0.87	0.91	0.86	0.90	0.91	0.88
beautiful-pretty	0.87	0.82	0.84	0.88	0.90	0.87	0.90	0.84	0.85	0.86	0.87	0.90	0.90	0.91	0.91	0.87
likable-nice	0.91	0.84	0.84	0.85	0.88	0.85	0.90	0.88	0.81	0.86	0.88	0.89	0.90	0.89	0.90	0.87
likable-pleasing	0.89	0.79	0.83	0.86	0.88	0.86	0.92	0.87	0.81	0.89	0.89	0.89	0.87	0.88	0.87	0.87
enjoyable-pleasing	0.88	0.83	0.83	0.86	0.87	0.86	0.90	0.89	0.81	0.89	0.85	0.89	0.87	0.87	0.91	0.87
appealing-likable	0.91	0.82	0.81	0.86	0.87	0.84	0.90	0.87	0.84	0.87	0.82	0.88	0.87	0.87	0.88	0.86
appealing-pleasing	0.86	0.80	0.83	0.87	0.87	0.87	0.89	0.85	0.79	0.89	0.88	0.88	0.90	0.85	0.90	0.86
nice-pleasing	0.89	0.83	0.82	0.88	0.89	0.88	0.89	0.88	0.80	0.85	0.85	0.87	0.86	0.85	0.88	0.86
enjoyable-nice	0.90	0.81	0.84	0.84	0.87	0.86	0.91	0.88	0.82	0.85	0.85	0.87	0.87	0.85	0.91	0.86
appealing-enjoyable	0.85	0.79	0.80	0.87	0.86	0.83	0.89	0.90	0.85	0.88	0.84	0.88	0.88	0.87	0.88	0.86

Max. Alpha: 0.7907, 0.8200, 0.8400, 0.8600, 0.8800, 0.9180
Avg. Alpha: 0.7000 1.0000

Figure B.16: Cronbach's alpha broken down by image vs. term combinations for the most reliable 2-item subsets of the remaining 12 terms. The diverging red-blue color scale is centered at alpha = 0.9.

Terms	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Grand ..
enjoyable-likable-pleasing	0.92	0.86	0.89	0.91	0.91	0.90	0.94	0.92	0.88	0.92	0.91	0.93	0.91	0.92	0.93	0.91
enjoyable-likable-nice	0.93	0.87	0.90	0.90	0.91	0.89	0.93	0.92	0.88	0.91	0.91	0.92	0.91	0.92	0.93	0.91
likable-nice-pleasing	0.93	0.87	0.88	0.90	0.92	0.90	0.93	0.91	0.86	0.91	0.91	0.92	0.91	0.91	0.92	0.91
appealing-enjoyable-likable	0.92	0.86	0.88	0.91	0.91	0.88	0.93	0.92	0.90	0.92	0.89	0.93	0.91	0.92	0.92	0.91
appealing-likable-pleasing	0.92	0.86	0.88	0.91	0.91	0.90	0.93	0.90	0.87	0.92	0.90	0.92	0.92	0.90	0.92	0.90
attractive-enjoyable-likable	0.91	0.85	0.89	0.90	0.90	0.89	0.94	0.90	0.90	0.92	0.90	0.93	0.90	0.92	0.92	0.90
enjoyable-nice-pleasing	0.92	0.87	0.88	0.90	0.91	0.91	0.93	0.92	0.86	0.90	0.89	0.92	0.91	0.90	0.93	0.90
appealing-enjoyable-pleasing	0.90	0.86	0.87	0.91	0.91	0.90	0.93	0.91	0.87	0.92	0.90	0.92	0.92	0.90	0.93	0.90
appealing-likable-nice	0.93	0.87	0.88	0.89	0.91	0.89	0.93	0.91	0.87	0.90	0.89	0.91	0.92	0.91	0.93	0.90
appealing-attractive-enjoyable	0.90	0.85	0.85	0.90	0.91	0.89	0.93	0.90	0.89	0.92	0.90	0.92	0.91	0.90	0.92	0.90

Avg. Alpha: 0.84859, 0.86000, 0.88000, 0.90000, 0.92000, 0.93659
Avg. Alpha: 0.7000 1.0000

Figure B.17: Cronbach's alpha broken down by image vs. term combinations for the most reliable 3-item subsets of the remaining 12 terms. The diverging red-blue color scale is centered at alpha = 0.9.

Terms	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Grand ..
enjoyable-likable-nice-pleasing	0.94	0.90	0.91	0.92	0.93	0.92	0.95	0.94	0.90	0.93	0.93	0.94	0.93	0.93	0.95	0.93
appealing-enjoyable-likable-pleasi..	0.94	0.89	0.91	0.93	0.93	0.92	0.95	0.94	0.91	0.94	0.92	0.94	0.93	0.93	0.94	0.93
appealing-enjoyable-likable-nice	0.94	0.90	0.91	0.92	0.93	0.92	0.95	0.94	0.91	0.93	0.92	0.94	0.93	0.93	0.95	0.93
appealing-likable-nice-pleasing	0.94	0.90	0.90	0.92	0.93	0.92	0.95	0.93	0.90	0.93	0.92	0.93	0.94	0.93	0.94	0.93
appealing-attractive-enjoyable-lika..	0.93	0.89	0.90	0.92	0.93	0.91	0.95	0.93	0.92	0.94	0.92	0.94	0.93	0.93	0.94	0.93
attractive-enjoyable-likable-pleasi..	0.93	0.88	0.91	0.92	0.93	0.92	0.95	0.93	0.90	0.94	0.92	0.94	0.92	0.93	0.94	0.93
attractive-enjoyable-likable-nice	0.94	0.88	0.91	0.91	0.93	0.92	0.95	0.93	0.91	0.93	0.92	0.94	0.93	0.93	0.94	0.92
appealing-enjoyable-nice-pleasing	0.93	0.90	0.90	0.92	0.93	0.92	0.94	0.93	0.90	0.93	0.92	0.93	0.93	0.92	0.95	0.92
delightful-enjoyable-likable-pleasi..	0.93	0.86	0.91	0.93	0.92	0.91	0.95	0.93	0.90	0.93	0.93	0.94	0.93	0.93	0.94	0.92
enjoyable-likable-pleasing-satisfyi..	0.93	0.87	0.90	0.93	0.93	0.91	0.95	0.92	0.91	0.93	0.93	0.94	0.93	0.92	0.94	0.92

Avg. Alpha: 0.85841, 0.88000, 0.90000, 0.92000, 0.94000, 0.95258
Avg. Alpha: 0.7000 1.0000

Figure B.18: Cronbach's alpha broken down by image vs. term combinations for the most reliable 4-item subsets of the remaining 12 terms. The diverging red-blue color scale is centered at alpha = 0.9.

Terms	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Grand ..
appealing-enjoyable-likable-nice-pleasing	0.95	0.92	0.92	0.94	0.94	0.94	0.96	0.95	0.92	0.94	0.94	0.95	0.95	0.94	0.96	0.94
appealing-attractive-enjoyable-likable-plea..	0.94	0.91	0.92	0.94	0.94	0.93	0.96	0.94	0.92	0.95	0.94	0.95	0.94	0.94	0.95	0.94
attractive-enjoyable-likable-nice-pleasing	0.95	0.91	0.92	0.93	0.94	0.94	0.96	0.94	0.92	0.94	0.94	0.95	0.94	0.94	0.95	0.94
appealing-attractive-enjoyable-likable-nice	0.95	0.91	0.92	0.93	0.94	0.93	0.96	0.94	0.93	0.94	0.93	0.95	0.95	0.94	0.95	0.94
enjoyable-likable-nice-pleasing-satisfying	0.95	0.90	0.92	0.94	0.94	0.93	0.96	0.94	0.92	0.94	0.94	0.95	0.94	0.94	0.95	0.94
delightful-enjoyable-likable-nice-pleasing	0.95	0.89	0.92	0.94	0.94	0.93	0.96	0.94	0.91	0.94	0.94	0.95	0.95	0.94	0.96	0.94
appealing-attractive-likable-nice-pleasing	0.95	0.91	0.92	0.93	0.94	0.94	0.96	0.94	0.92	0.94	0.94	0.94	0.95	0.94	0.95	0.94
appealing-delightful-enjoyable-likable-plea..	0.94	0.89	0.92	0.94	0.94	0.93	0.96	0.94	0.92	0.94	0.94	0.95	0.95	0.94	0.95	0.94
appealing-attractive-enjoyable-nice-pleasing	0.94	0.91	0.92	0.93	0.94	0.94	0.96	0.94	0.92	0.94	0.93	0.95	0.94	0.94	0.95	0.94
appealing-enjoyable-likable-pleasing-satisf..	0.94	0.90	0.92	0.94	0.94	0.93	0.96	0.94	0.92	0.94	0.94	0.95	0.94	0.94	0.95	0.94

Alpha: 0.89080, 0.92000, 0.94000, 0.95869
Alpha: 0.7000 1.0000

Figure B.19: Cronbach's alpha broken down by image vs. term combinations for the most reliable 5-item subsets of the remaining 12 terms. The diverging red-blue color scale is centered at alpha = 0.9.

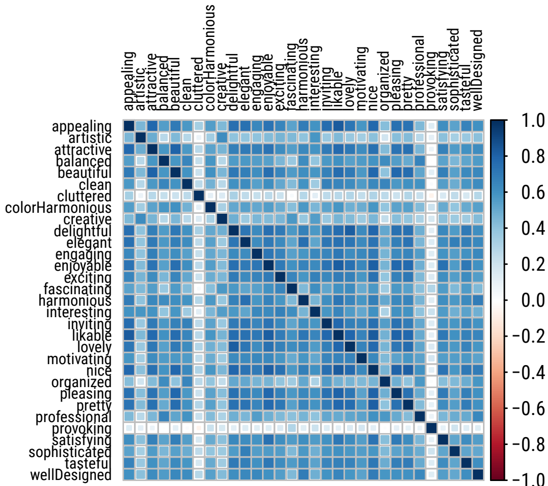


Figure B.20: Term correlation matrix for Image 1.

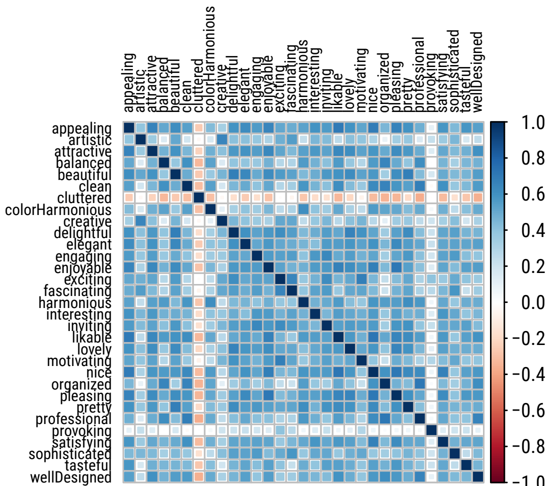


Figure B.21: Correlation matrix for Image 2.

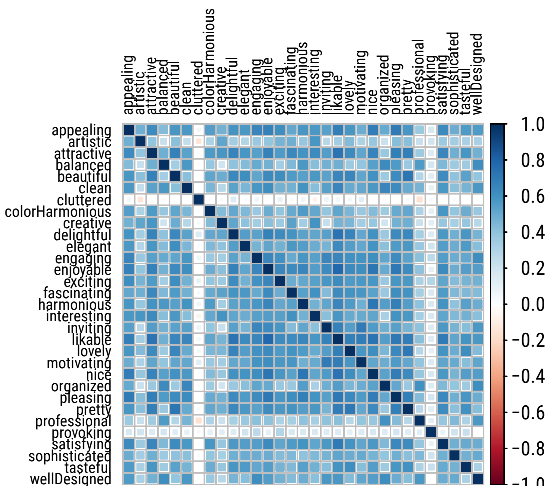


Figure B.22: Correlation matrix for Image 3.

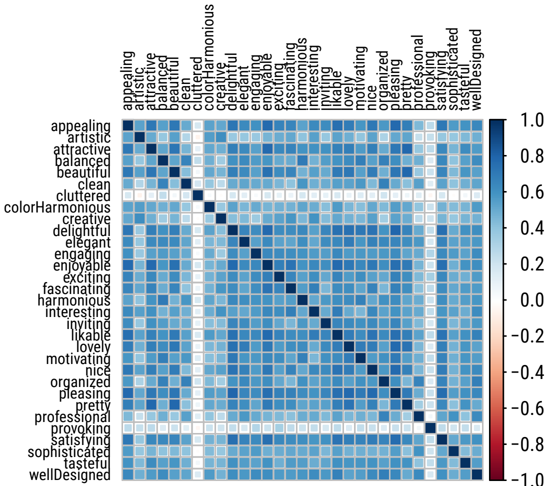


Figure B.23: Correlation matrix for Image 4.

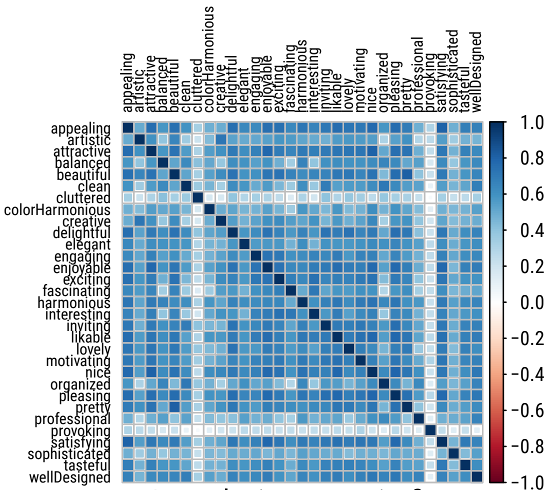


Figure B.24: Correlation matrix for Image 5.

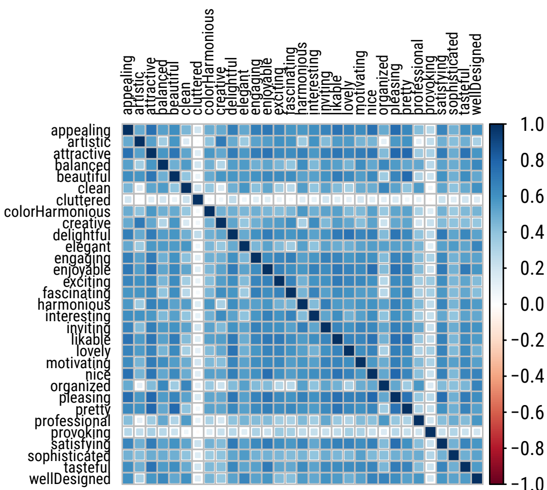


Figure B.25: Correlation matrix for Image 6.

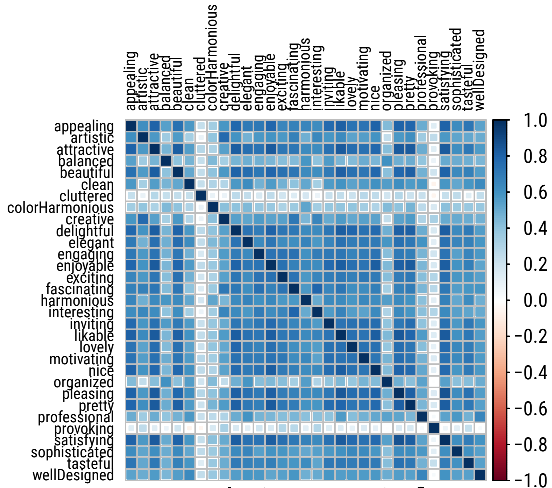


Figure B.26: Correlation matrix for Image 7.

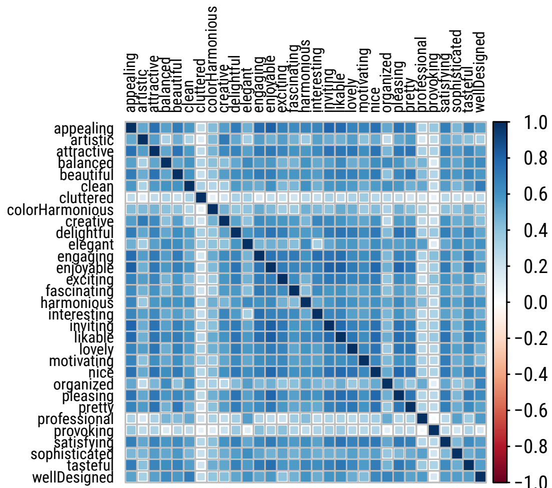


Figure B.27: Correlation matrix for Image 8.

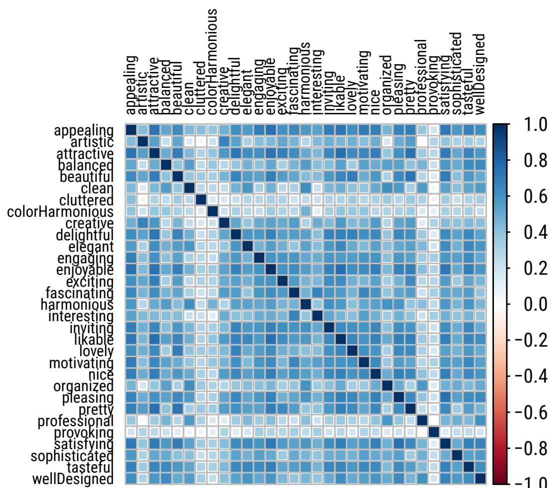


Figure B.28: Correlation matrix for Image 9.

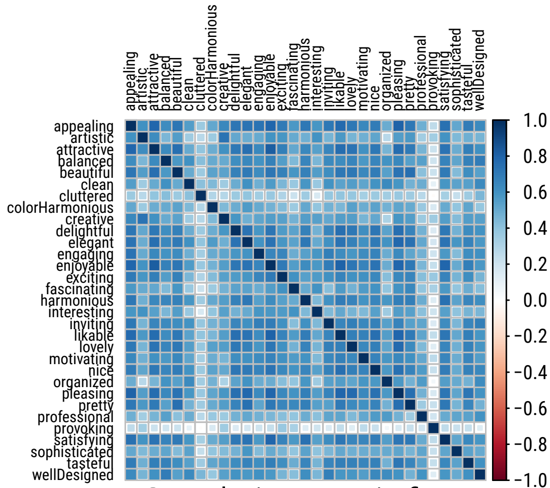


Figure B.29: Correlation matrix for Image 10.

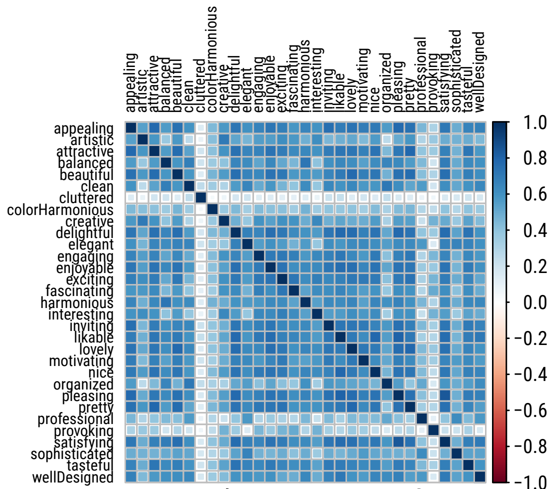


Figure B.30: Correlation matrix for Image 11.

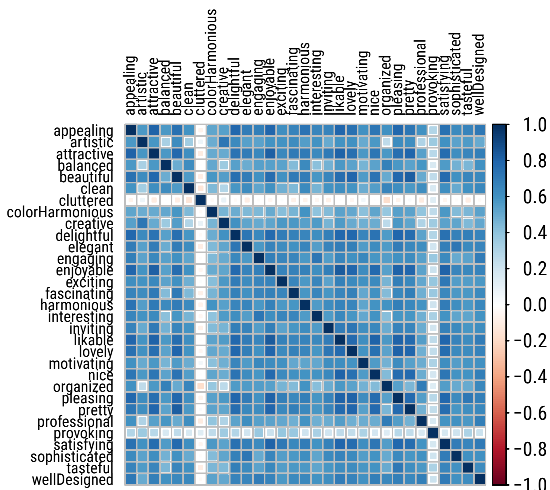


Figure B.31: Correlation matrix for Image 12.

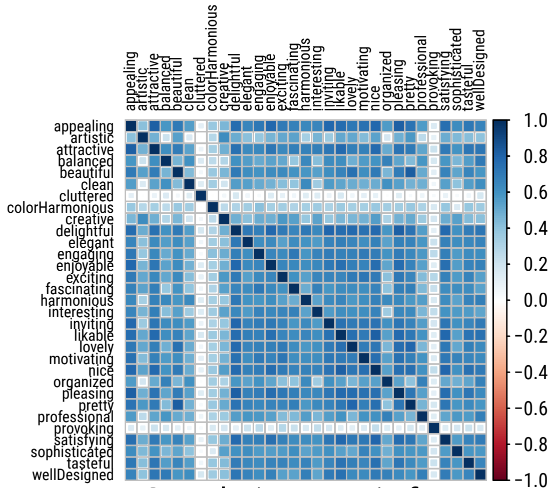


Figure B.32: Correlation matrix for Image 13.

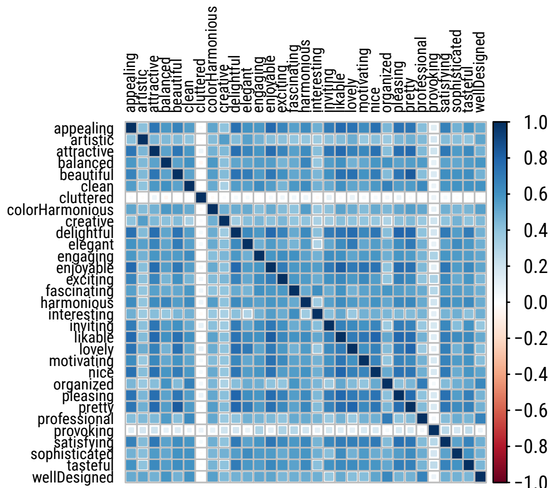


Figure B.33: Correlation matrix for Image 14.

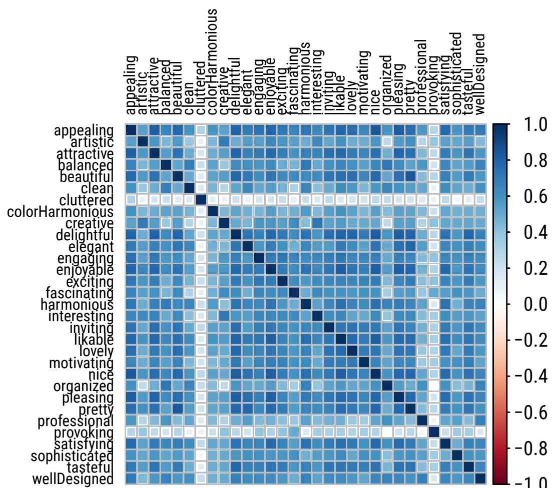


Figure B.34: Correlation matrix for Image 15.

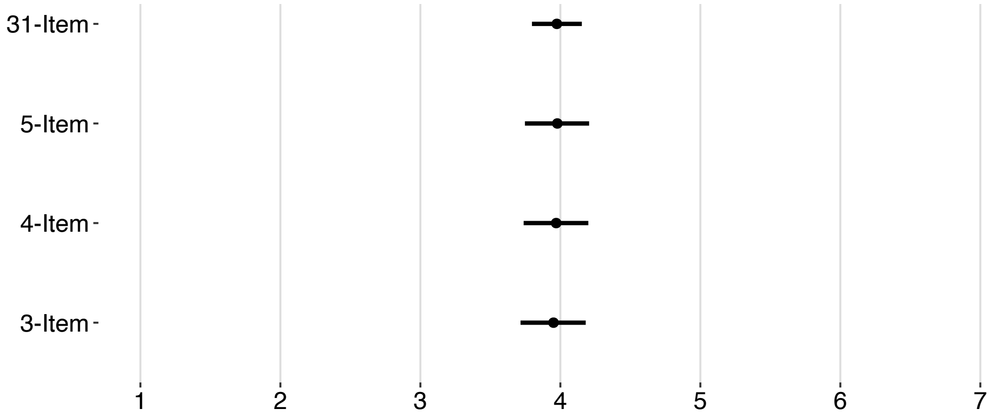


Figure B.35: Comparison of ratings from subsets of the rating items for Image 1.

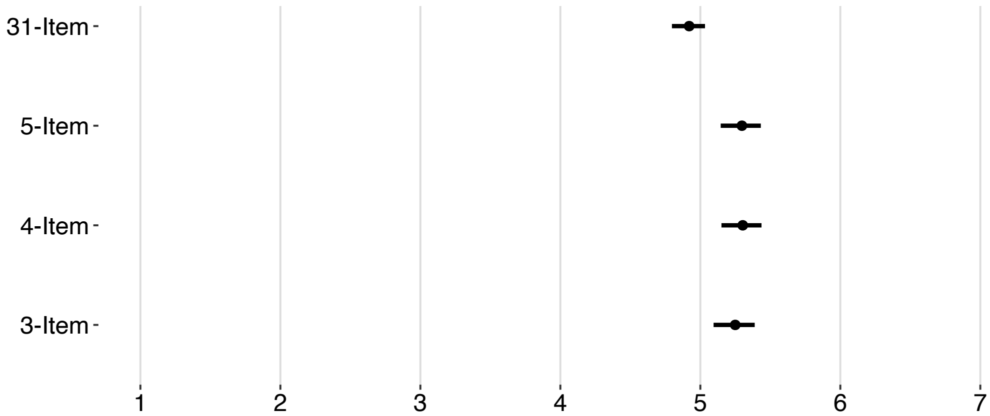


Figure B.36: Comparison of ratings from subsets of the rating items for Image 2.

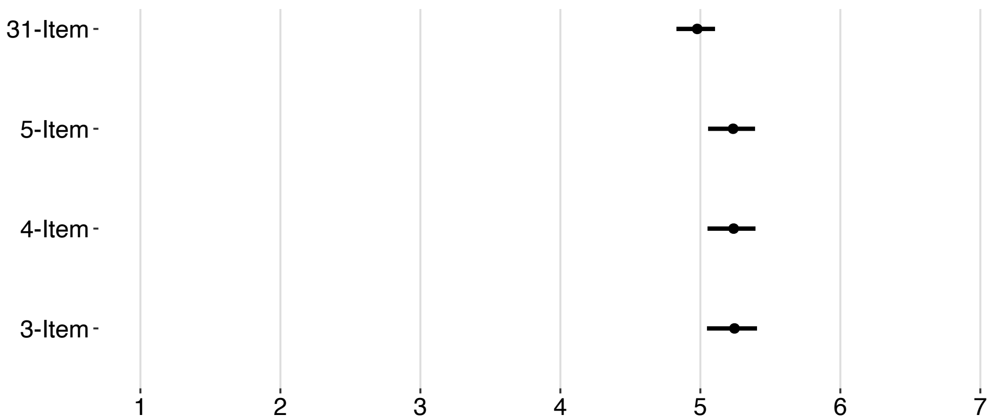


Figure B.37: Comparison of ratings from subsets of the rating items for Image 3.

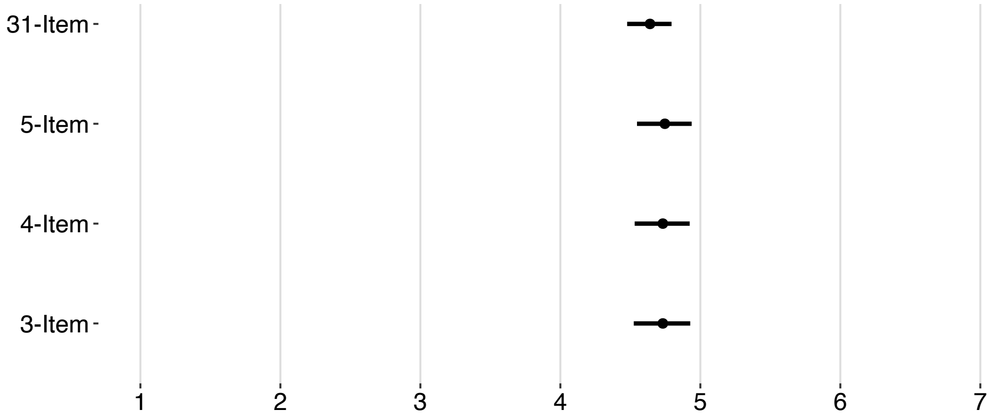


Figure B.38: Comparison of ratings from subsets of the rating items for Image 4.

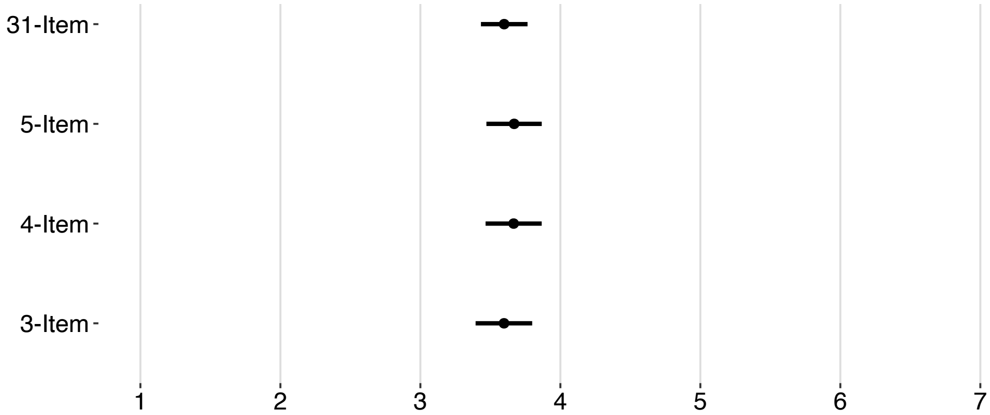


Figure B.39: Comparison of ratings from subsets of the rating items for Image 5.

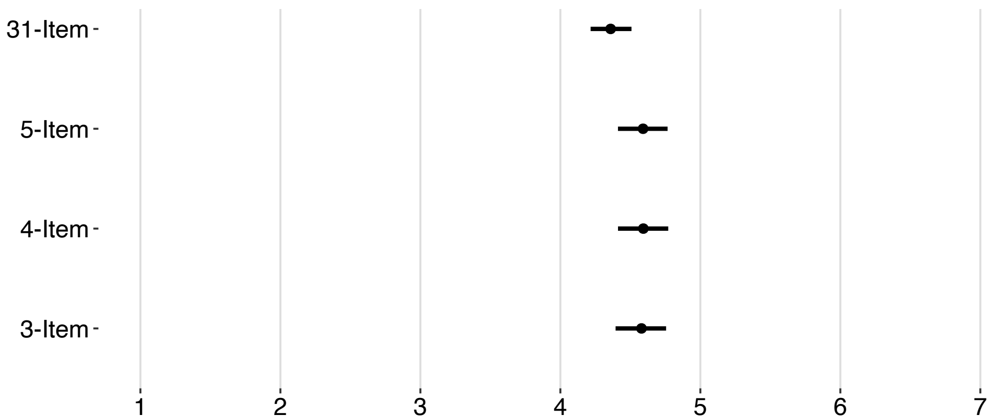


Figure B.40: Comparison of ratings from subsets of the rating items for Image 6.

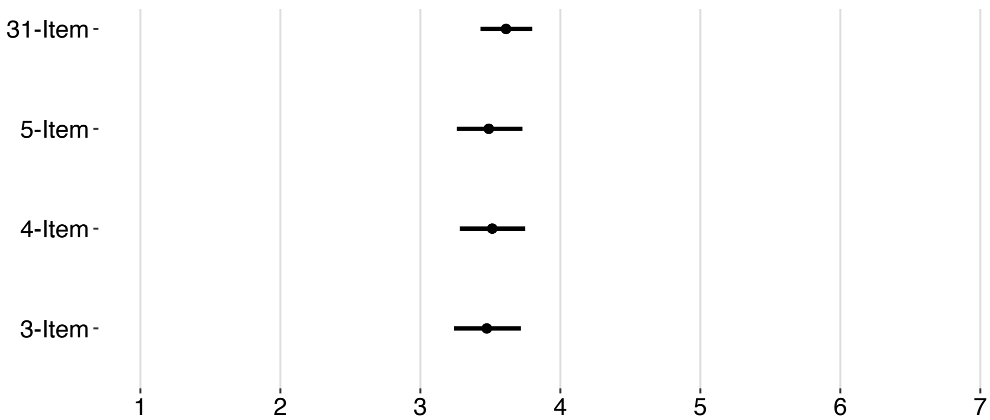


Figure B.41: Comparison of ratings from subsets of the rating items for Image 7.

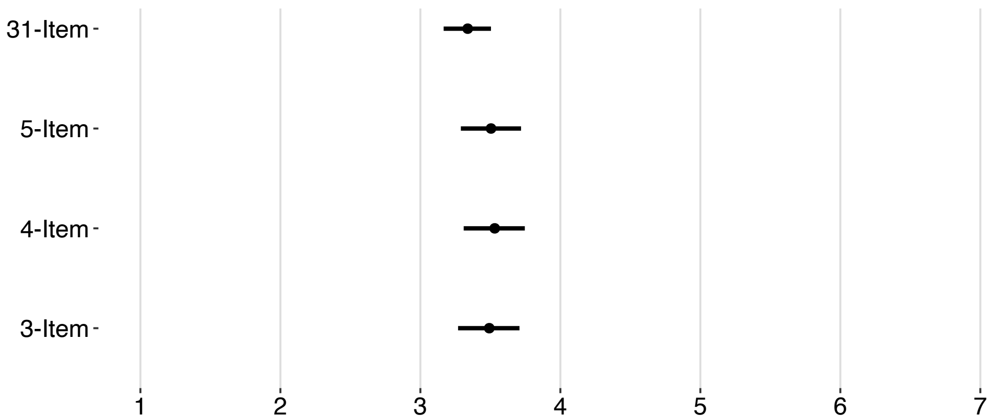


Figure B.42: Comparison of ratings from subsets of the rating items for Image 8.

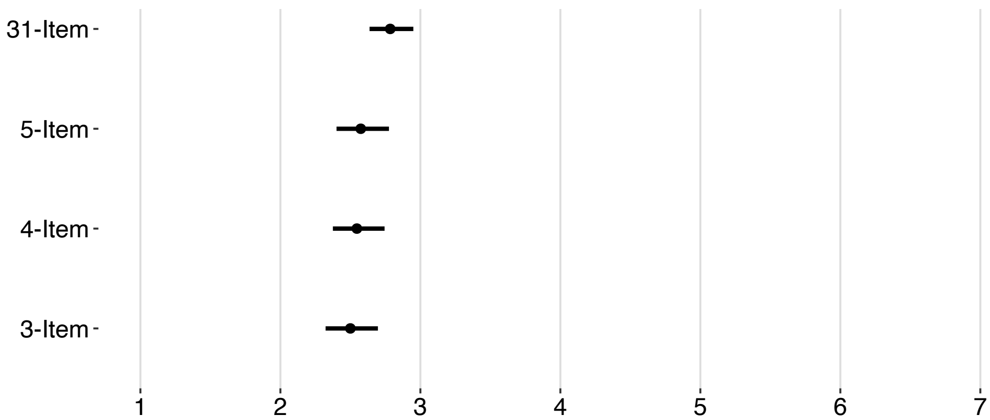


Figure B.43: Comparison of ratings from subsets of the rating items for Image 9.

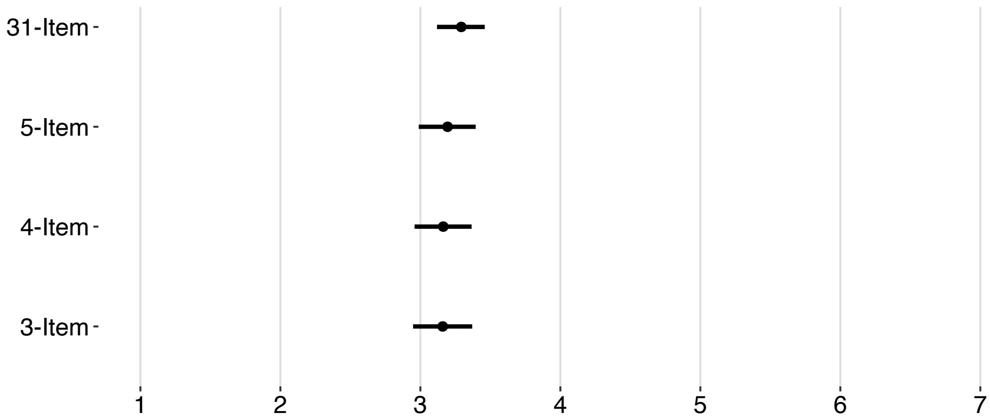


Figure B.44: Comparison of ratings from subsets of the rating items for Image 10.

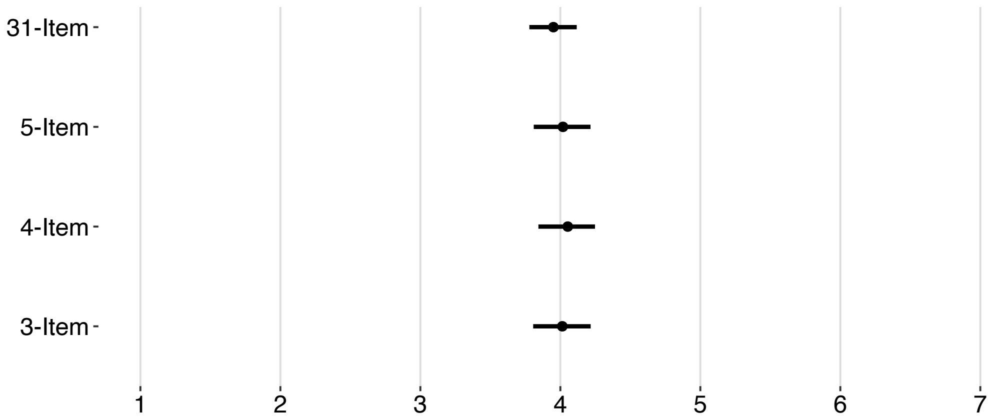


Figure B.45: Comparison of ratings from subsets of the rating items for Image 11.

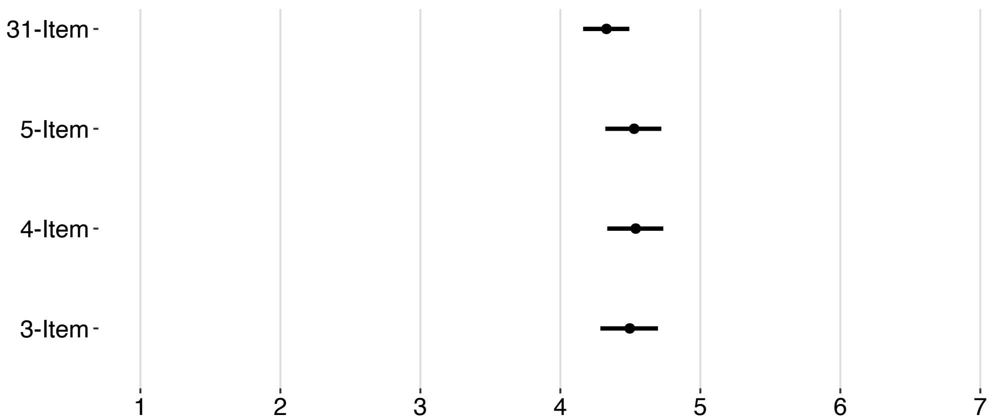


Figure B.46: Comparison of ratings from subsets of the rating items for Image 12.

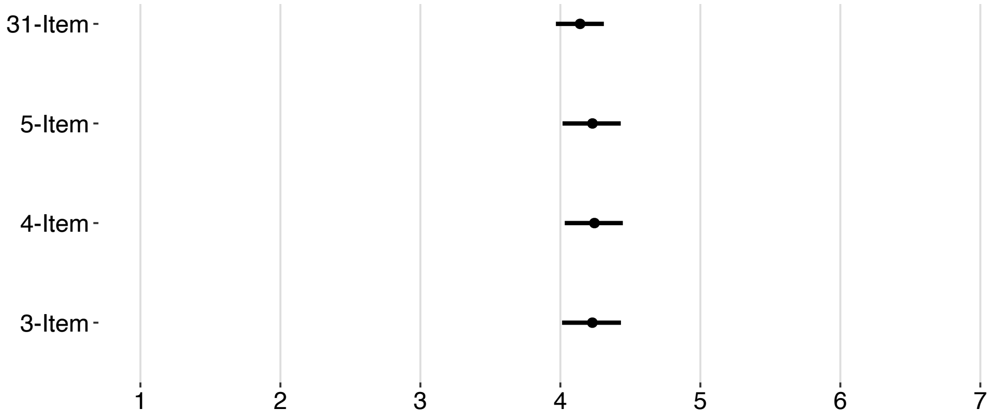


Figure B.47: Comparison of ratings from subsets of the rating items for Image 13.

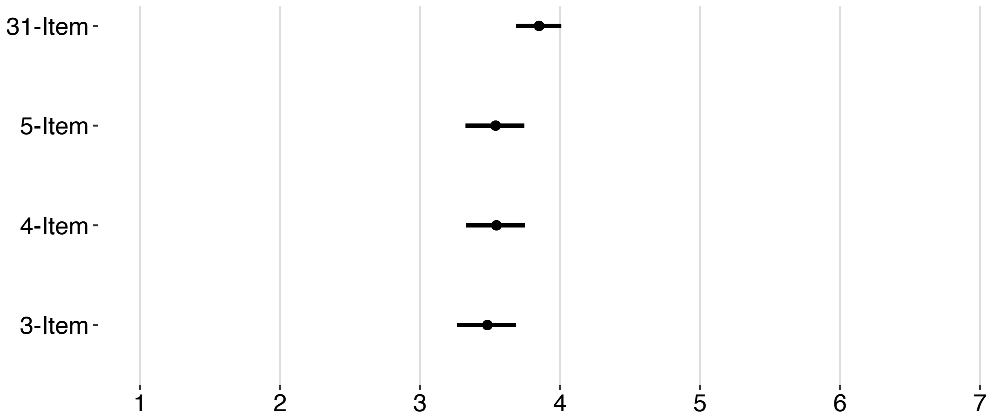


Figure B.48: Comparison of ratings from subsets of the rating items for Image 14.

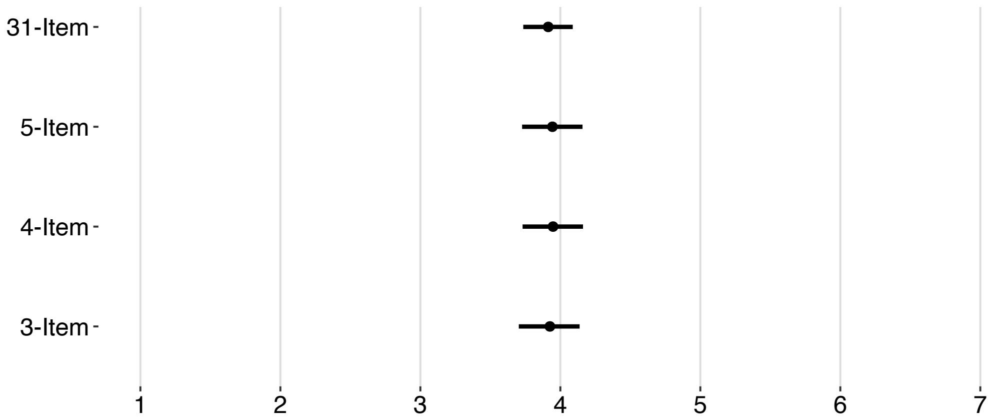


Figure B.49: Comparison of ratings from subsets of the rating items for Image 15.

Table B.7: Factor loading for 31 terms using an EFA for one factor for Image 1.

	PA1	h2	u2	com
vis01.appealing.	0.85	0.72	0.28	1
vis01.artistic.	0.52	0.27	0.73	1
vis01.attractive.	0.84	0.71	0.29	1
vis01.balanced.	0.69	0.48	0.52	1
vis01.beautiful.	0.84	0.71	0.29	1
vis01.clean.	0.73	0.53	0.47	1
vis01.cluttered.	0.30	0.09	0.91	1
vis01.colorHarmonious.	0.65	0.43	0.57	1
vis01.creative.	0.53	0.28	0.72	1
vis01.delightful.	0.86	0.73	0.27	1
vis01.elegant.	0.83	0.70	0.30	1
vis01.engaging.	0.79	0.62	0.38	1
vis01.enjoyable.	0.87	0.76	0.24	1
vis01.exciting.	0.79	0.63	0.38	1
vis01.fascinating.	0.68	0.46	0.54	1
vis01.harmonious.	0.79	0.62	0.38	1
vis01.interesting.	0.70	0.50	0.51	1
vis01.inviting.	0.83	0.69	0.31	1
vis01.likable.	0.91	0.82	0.18	1
vis01.lovely.	0.85	0.72	0.28	1
vis01.motivating.	0.74	0.55	0.45	1
vis01.nice.	0.90	0.82	0.18	1
vis01.organized.	0.59	0.35	0.65	1
vis01.pleasing.	0.85	0.72	0.28	1
vis01.pretty.	0.85	0.72	0.28	1
vis01.professional.	0.63	0.40	0.60	1
vis01.provoking.	0.17	0.03	0.97	1
vis01.satisfying.	0.77	0.60	0.40	1
vis01.sophisticated.	0.68	0.47	0.53	1
vis01.tasteful.	0.78	0.62	0.38	1
vis01.wellDesigned.	0.76	0.58	0.42	1

Table B.8: Factor loading for 31 terms using an EFA for one factor for Image 2.

	PA1	h2	u2	com
vis02.appealing.	0.80	0.64	0.36	1
vis02.artistic.	0.49	0.24	0.76	1
vis02.attractive.	0.78	0.60	0.40	1
vis02.balanced.	0.63	0.39	0.61	1
vis02.beautiful.	0.77	0.59	0.41	1
vis02.clean.	0.70	0.48	0.52	1
vis02.cluttered.	-0.33	0.11	0.89	1
vis02.colorHarmonious.	0.59	0.35	0.65	1
vis02.creative.	0.49	0.24	0.76	1
vis02.delightful.	0.74	0.55	0.45	1
vis02.elegant.	0.76	0.57	0.43	1
vis02.engaging.	0.70	0.49	0.51	1
vis02.enjoyable.	0.78	0.61	0.39	1
vis02.exciting.	0.66	0.44	0.56	1
vis02.fascinating.	0.64	0.41	0.59	1
vis02.harmonious.	0.69	0.48	0.52	1
vis02.interesting.	0.70	0.49	0.51	1
vis02.inviting.	0.74	0.54	0.46	1
vis02.likable.	0.79	0.62	0.38	1
vis02.lovely.	0.75	0.56	0.44	1
vis02.motivating.	0.65	0.42	0.58	1
vis02.nice.	0.81	0.65	0.35	1
vis02.organized.	0.61	0.38	0.62	1
vis02.pleasing.	0.80	0.65	0.35	1
vis02.pretty.	0.76	0.57	0.43	1
vis02.professional.	0.67	0.45	0.55	1
vis02.provoking.	0.20	0.04	0.96	1
vis02.satisfying.	0.73	0.54	0.46	1
vis02.sophisticated.	0.63	0.39	0.61	1
vis02.tasteful.	0.64	0.41	0.59	1
vis02.wellDesigned.	0.71	0.50	0.50	1

Table B.9: Factor loading for 31 terms using an EFA for one factor for Image 3.

	PA1	h2	u2	com
viso3.appealing.	0.80	0.64	0.36	1
viso3.artistic.	0.51	0.26	0.74	1
viso3.attractive.	0.81	0.66	0.34	1
viso3.balanced.	0.61	0.38	0.62	1
viso3.beautiful.	0.76	0.58	0.42	1
viso3.clean.	0.71	0.51	0.49	1
viso3.cluttered.	0.03	0.00	1.00	1
viso3.colorHarmonious.	0.63	0.40	0.60	1
viso3.creative.	0.55	0.31	0.69	1
viso3.delightful.	0.78	0.60	0.40	1
viso3.elegant.	0.71	0.50	0.50	1
viso3.engaging.	0.76	0.58	0.42	1
viso3.enjoyable.	0.83	0.70	0.30	1
viso3.exciting.	0.72	0.53	0.47	1
viso3.fascinating.	0.73	0.54	0.46	1
viso3.harmonious.	0.76	0.58	0.42	1
viso3.interesting.	0.71	0.50	0.50	1
viso3.inviting.	0.71	0.51	0.49	1
viso3.likable.	0.88	0.77	0.23	1
viso3.lovely.	0.78	0.60	0.40	1
viso3.motivating.	0.71	0.51	0.49	1
viso3.nice.	0.81	0.65	0.35	1
viso3.organized.	0.62	0.38	0.62	1
viso3.pleasing.	0.84	0.70	0.30	1
viso3.pretty.	0.77	0.60	0.40	1
viso3.professional.	0.52	0.27	0.73	1
viso3.provoking.	0.22	0.05	0.95	1
viso3.satisfying.	0.77	0.59	0.41	1
viso3.sophisticated.	0.62	0.39	0.61	1
viso3.tasteful.	0.68	0.47	0.53	1
viso3.wellDesigned.	0.67	0.45	0.55	1

Table B.10: Factor loading for 31 terms using an EFA for one factor for Image 4.

	PA1	h2	u2	com
viso4.appealing.	0.84	0.71	0.29	1
viso4.artistic.	0.59	0.35	0.65	1
viso4.attractive.	0.81	0.66	0.34	1
viso4.balanced.	0.73	0.54	0.46	1
viso4.beautiful.	0.79	0.63	0.37	1
viso4.clean.	0.64	0.41	0.59	1
viso4.cluttered.	0.15	0.02	0.98	1
viso4.colorHarmonious.	0.63	0.40	0.60	1
viso4.creative.	0.60	0.36	0.64	1
viso4.delightful.	0.85	0.72	0.28	1
viso4.elegant.	0.78	0.60	0.40	1
viso4.engaging.	0.74	0.55	0.45	1
viso4.enjoyable.	0.86	0.74	0.26	1
viso4.exciting.	0.76	0.58	0.42	1
viso4.fascinating.	0.77	0.59	0.41	1
viso4.harmonious.	0.75	0.56	0.44	1
viso4.interesting.	0.74	0.54	0.46	1
viso4.inviting.	0.73	0.54	0.47	1
viso4.likable.	0.87	0.75	0.25	1
viso4.lovely.	0.82	0.67	0.33	1
viso4.motivating.	0.77	0.59	0.41	1
viso4.nice.	0.82	0.68	0.32	1
viso4.organized.	0.74	0.54	0.46	1
viso4.pleasing.	0.88	0.77	0.23	1
viso4.pretty.	0.78	0.61	0.39	1
viso4.professional.	0.61	0.37	0.63	1
viso4.provoking.	0.28	0.08	0.92	1
viso4.satisfying.	0.83	0.70	0.30	1
viso4.sophisticated.	0.63	0.40	0.60	1
viso4.tasteful.	0.72	0.52	0.48	1
viso4.wellDesigned.	0.77	0.59	0.41	1

Table B.11: Factor loading for 31 terms using an EFA for one factor for Image 5.

	PA1	h2	u2	com
viso5.appealing.	0.87	0.75	0.25	1
viso5.artistic.	0.66	0.43	0.57	1
viso5.attractive.	0.86	0.74	0.26	1
viso5.balanced.	0.71	0.51	0.49	1
viso5.beautiful.	0.84	0.70	0.30	1
viso5.clean.	0.70	0.49	0.51	1
viso5.cluttered.	0.39	0.15	0.85	1
viso5.colorHarmonious.	0.64	0.41	0.59	1
viso5.creative.	0.67	0.45	0.55	1
viso5.delightful.	0.83	0.69	0.31	1
viso5.elegant.	0.74	0.54	0.46	1
viso5.engaging.	0.78	0.61	0.39	1
viso5.enjoyable.	0.86	0.75	0.25	1
viso5.exciting.	0.81	0.66	0.34	1
viso5.fascinating.	0.70	0.49	0.51	1
viso5.harmonious.	0.82	0.68	0.33	1
viso5.interesting.	0.76	0.58	0.42	1
viso5.inviting.	0.82	0.68	0.32	1
viso5.likable.	0.86	0.75	0.25	1
viso5.lovely.	0.80	0.64	0.36	1
viso5.motivating.	0.83	0.69	0.31	1
viso5.nice.	0.87	0.77	0.23	1
viso5.organized.	0.67	0.45	0.55	1
viso5.pleasing.	0.89	0.79	0.21	1
viso5.pretty.	0.81	0.65	0.35	1
viso5.professional.	0.62	0.38	0.62	1
viso5.provoking.	0.28	0.08	0.92	1
viso5.satisfying.	0.85	0.73	0.28	1
viso5.sophisticated.	0.61	0.37	0.63	1
viso5.tasteful.	0.77	0.59	0.41	1
viso5.wellDesigned.	0.81	0.66	0.34	1

Table B.12: Factor loading for 31 terms using an EFA for one factor for Image 6.

	PA1	h2	u2	com
viso6.appealing.	0.83	0.69	0.31	1
viso6.artistic.	0.63	0.40	0.61	1
viso6.attractive.	0.87	0.76	0.24	1
viso6.balanced.	0.69	0.48	0.52	1
viso6.beautiful.	0.78	0.60	0.40	1
viso6.clean.	0.60	0.36	0.64	1
viso6.cluttered.	0.18	0.03	0.97	1
viso6.colorHarmonious.	0.63	0.40	0.60	1
viso6.creative.	0.62	0.39	0.61	1
viso6.delightful.	0.81	0.66	0.34	1
viso6.elegant.	0.68	0.46	0.54	1
viso6.engaging.	0.78	0.60	0.40	1
viso6.enjoyable.	0.84	0.70	0.30	1
viso6.exciting.	0.76	0.57	0.43	1
viso6.fascinating.	0.72	0.52	0.48	1
viso6.harmonious.	0.74	0.55	0.45	1
viso6.interesting.	0.71	0.51	0.49	1
viso6.inviting.	0.80	0.64	0.36	1
viso6.likable.	0.84	0.71	0.29	1
viso6.lovely.	0.77	0.59	0.41	1
viso6.motivating.	0.78	0.61	0.39	1
viso6.nice.	0.83	0.69	0.31	1
viso6.organized.	0.59	0.35	0.65	1
viso6.pleasing.	0.87	0.76	0.24	1
viso6.pretty.	0.81	0.66	0.34	1
viso6.professional.	0.53	0.28	0.72	1
viso6.provoking.	0.33	0.11	0.89	1
viso6.satisfying.	0.80	0.65	0.35	1
viso6.sophisticated.	0.62	0.39	0.61	1
viso6.tasteful.	0.78	0.61	0.39	1
viso6.wellDesigned.	0.73	0.53	0.47	1

Table B.13: Factor loading for 31 terms using an EFA for one factor for Image 7.

	PA1	h2	u2	com
viso7.appealing.	0.88	0.77	0.23	1
viso7.artistic.	0.69	0.47	0.53	1
viso7.attractive.	0.89	0.80	0.20	1
viso7.balanced.	0.59	0.34	0.66	1
viso7.beautiful.	0.87	0.76	0.24	1
viso7.clean.	0.66	0.43	0.57	1
viso7.cluttered.	0.27	0.07	0.93	1
viso7.colorHarmonious.	0.48	0.23	0.77	1
viso7.creative.	0.66	0.43	0.57	1
viso7.delightful.	0.89	0.79	0.21	1
viso7.elegant.	0.83	0.69	0.31	1
viso7.engaging.	0.82	0.67	0.33	1
viso7.enjoyable.	0.88	0.78	0.22	1
viso7.exciting.	0.81	0.66	0.34	1
viso7.fascinating.	0.80	0.65	0.35	1
viso7.harmonious.	0.74	0.55	0.45	1
viso7.interesting.	0.73	0.53	0.47	1
viso7.inviting.	0.84	0.70	0.30	1
viso7.likable.	0.90	0.81	0.19	1
viso7.lovely.	0.83	0.69	0.31	1
viso7.motivating.	0.84	0.71	0.29	1
viso7.nice.	0.87	0.76	0.24	1
viso7.organized.	0.55	0.30	0.70	1
viso7.pleasing.	0.90	0.80	0.20	1
viso7.pretty.	0.88	0.77	0.23	1
viso7.professional.	0.60	0.36	0.64	1
viso7.provoking.	0.19	0.04	0.96	1
viso7.satisfying.	0.90	0.81	0.19	1
viso7.sophisticated.	0.73	0.53	0.47	1
viso7.tasteful.	0.80	0.64	0.36	1
viso7.wellDesigned.	0.69	0.47	0.53	1

Table B.14: Factor loading for 31 terms using an EFA for one factor for Image 8.

	PA1	h2	u2	com
viso8.appealing.	0.85	0.72	0.28	1
viso8.artistic.	0.61	0.37	0.63	1
viso8.attractive.	0.84	0.70	0.30	1
viso8.balanced.	0.70	0.49	0.51	1
viso8.beautiful.	0.81	0.65	0.35	1
viso8.clean.	0.70	0.48	0.52	1
viso8.cluttered.	0.34	0.11	0.89	1
viso8.colorHarmonious.	0.55	0.30	0.70	1
viso8.creative.	0.70	0.48	0.52	1
viso8.delightful.	0.82	0.67	0.33	1
viso8.elegant.	0.69	0.47	0.53	1
viso8.engaging.	0.83	0.69	0.31	1
viso8.enjoyable.	0.87	0.76	0.24	1
viso8.exciting.	0.77	0.59	0.41	1
viso8.fascinating.	0.71	0.50	0.50	1
viso8.harmonious.	0.74	0.55	0.45	1
viso8.interesting.	0.74	0.55	0.45	1
viso8.inviting.	0.85	0.72	0.28	1
viso8.likable.	0.88	0.77	0.23	1
viso8.lovely.	0.81	0.66	0.34	1
viso8.motivating.	0.75	0.56	0.44	1
viso8.nice.	0.87	0.76	0.24	1
viso8.organized.	0.60	0.36	0.64	1
viso8.pleasing.	0.84	0.71	0.29	1
viso8.pretty.	0.79	0.63	0.37	1
viso8.professional.	0.46	0.21	0.79	1
viso8.provoking.	0.37	0.14	0.86	1
viso8.satisfying.	0.80	0.65	0.35	1
viso8.sophisticated.	0.65	0.43	0.57	1
viso8.tasteful.	0.81	0.65	0.35	1
viso8.wellDesigned.	0.71	0.50	0.50	1

Table B.15: Factor loading for 31 terms using an EFA for one factor for Image 9.

	PA1	h2	u2	com
vis09.appealing.	0.85	0.72	0.28	1
vis09.artistic.	0.56	0.32	0.68	1
vis09.attractive.	0.84	0.71	0.29	1
vis09.balanced.	0.65	0.42	0.58	1
vis09.beautiful.	0.76	0.57	0.43	1
vis09.clean.	0.60	0.36	0.64	1
vis09.cluttered.	0.41	0.17	0.83	1
vis09.colorHarmonious.	0.43	0.19	0.81	1
vis09.creative.	0.62	0.39	0.61	1
vis09.delightful.	0.79	0.62	0.38	1
vis09.elegant.	0.71	0.50	0.50	1
vis09.engaging.	0.74	0.54	0.46	1
vis09.enjoyable.	0.84	0.71	0.29	1
vis09.exciting.	0.70	0.49	0.51	1
vis09.fascinating.	0.72	0.51	0.49	1
vis09.harmonious.	0.69	0.48	0.52	1
vis09.interesting.	0.61	0.37	0.63	1
vis09.inviting.	0.78	0.61	0.39	1
vis09.likable.	0.84	0.71	0.29	1
vis09.lovely.	0.74	0.54	0.46	1
vis09.motivating.	0.75	0.56	0.44	1
vis09.nice.	0.81	0.66	0.34	1
vis09.organized.	0.59	0.35	0.65	1
vis09.pleasing.	0.80	0.65	0.35	1
vis09.pretty.	0.76	0.58	0.42	1
vis09.professional.	0.50	0.25	0.75	1
vis09.provoking.	0.32	0.10	0.90	1
vis09.satisfying.	0.82	0.68	0.32	1
vis09.sophisticated.	0.66	0.43	0.57	1
vis09.tasteful.	0.81	0.65	0.35	1
vis09.wellDesigned.	0.73	0.53	0.47	1

Table B.16: Factor loading for 31 terms using an EFA for one factor for Image 10.

	PA1	h2	u2	com
vis10.appealing.	0.88	0.77	0.23	1
vis10.artistic.	0.66	0.44	0.56	1
vis10.attractive.	0.86	0.73	0.27	1
vis10.balanced.	0.77	0.60	0.40	1
vis10.beautiful.	0.82	0.68	0.32	1
vis10.clean.	0.68	0.46	0.54	1
vis10.cluttered.	0.45	0.20	0.80	1
vis10.colorHarmonious.	0.62	0.38	0.62	1
vis10.creative.	0.68	0.46	0.54	1
vis10.delightful.	0.82	0.67	0.33	1
vis10.elegant.	0.84	0.71	0.29	1
vis10.engaging.	0.76	0.58	0.42	1
vis10.enjoyable.	0.87	0.76	0.25	1
vis10.exciting.	0.77	0.59	0.41	1
vis10.fascinating.	0.66	0.44	0.56	1
vis10.harmonious.	0.80	0.64	0.36	1
vis10.interesting.	0.64	0.41	0.59	1
vis10.inviting.	0.78	0.61	0.39	1
vis10.likable.	0.86	0.74	0.26	1
vis10.lovely.	0.81	0.66	0.34	1
vis10.motivating.	0.77	0.60	0.40	1
vis10.nice.	0.85	0.72	0.28	1
vis10.organized.	0.66	0.43	0.57	1
vis10.pleasing.	0.88	0.77	0.23	1
vis10.pretty.	0.80	0.64	0.36	1
vis10.professional.	0.61	0.38	0.62	1
vis10.provoking.	0.27	0.08	0.92	1
vis10.satisfying.	0.85	0.72	0.28	1
vis10.sophisticated.	0.63	0.40	0.61	1
vis10.tasteful.	0.80	0.64	0.36	1
vis10.wellDesigned.	0.74	0.55	0.45	1

Table B.17: Factor loading for 31 terms using an EFA for one factor for Image 11.

	PA1	h2	u2	com
vis11.appealing.	0.85	0.73	0.27	1
vis11.artistic.	0.64	0.42	0.58	1
vis11.attractive.	0.85	0.72	0.29	1
vis11.balanced.	0.74	0.54	0.46	1
vis11.beautiful.	0.85	0.72	0.28	1
vis11.clean.	0.71	0.50	0.50	1
vis11.cluttered.	0.21	0.04	0.96	1
vis11.colorHarmonious.	0.51	0.26	0.74	1
vis11.creative.	0.65	0.42	0.58	1
vis11.delightful.	0.86	0.74	0.26	1
vis11.elegant.	0.76	0.57	0.43	1
vis11.engaging.	0.79	0.63	0.37	1
vis11.enjoyable.	0.85	0.73	0.27	1
vis11.exciting.	0.82	0.67	0.33	1
vis11.fascinating.	0.73	0.53	0.47	1
vis11.harmonious.	0.77	0.60	0.40	1
vis11.interesting.	0.70	0.49	0.51	1
vis11.inviting.	0.83	0.70	0.30	1
vis11.likable.	0.85	0.72	0.28	1
vis11.lovely.	0.86	0.73	0.27	1
vis11.motivating.	0.78	0.62	0.38	1
vis11.nice.	0.84	0.71	0.29	1
vis11.organized.	0.64	0.41	0.59	1
vis11.pleasing.	0.87	0.76	0.24	1
vis11.pretty.	0.84	0.70	0.30	1
vis11.professional.	0.52	0.27	0.73	1
vis11.provoking.	0.40	0.16	0.84	1
vis11.satisfying.	0.86	0.73	0.27	1
vis11.sophisticated.	0.63	0.40	0.60	1
vis11.tasteful.	0.82	0.67	0.33	1
vis11.wellDesigned.	0.76	0.57	0.43	1

Table B.18: Factor loading for 31 terms using an EFA for one factor for Image 12.

	PA1	h2	u2	com
vis12.appealing.	0.88	0.77	0.23	1
vis12.artistic.	0.69	0.48	0.52	1
vis12.attractive.	0.87	0.76	0.24	1
vis12.balanced.	0.66	0.44	0.56	1
vis12.beautiful.	0.85	0.73	0.27	1
vis12.clean.	0.71	0.50	0.50	1
vis12.cluttered.	-0.05	0.00	1.00	1
vis12.colorHarmonious.	0.62	0.38	0.62	1
vis12.creative.	0.64	0.41	0.59	1
vis12.delightful.	0.88	0.77	0.23	1
vis12.elegant.	0.80	0.65	0.35	1
vis12.engaging.	0.77	0.59	0.41	1
vis12.enjoyable.	0.88	0.77	0.23	1
vis12.exciting.	0.77	0.59	0.41	1
vis12.fascinating.	0.77	0.60	0.40	1
vis12.harmonious.	0.80	0.64	0.36	1
vis12.interesting.	0.73	0.53	0.47	1
vis12.inviting.	0.78	0.60	0.40	1
vis12.likable.	0.89	0.79	0.21	1
vis12.lovely.	0.86	0.74	0.26	1
vis12.motivating.	0.71	0.51	0.49	1
vis12.nice.	0.82	0.67	0.33	1
vis12.organized.	0.66	0.43	0.57	1
vis12.pleasing.	0.88	0.78	0.22	1
vis12.pretty.	0.85	0.72	0.28	1
vis12.professional.	0.67	0.45	0.55	1
vis12.provoking.	0.32	0.11	0.89	1
vis12.satisfying.	0.87	0.76	0.24	1
vis12.sophisticated.	0.75	0.56	0.44	1
vis12.tasteful.	0.76	0.58	0.42	1
vis12.wellDesigned.	0.81	0.66	0.34	1

Table B.19: Factor loading for 31 terms using an EFA for one factor for Image 13.

	PA1	h2	u2	com
vis13.appealing.	0.88	0.78	0.22	1
vis13.artistic.	0.55	0.30	0.70	1
vis13.attractive.	0.86	0.73	0.27	1
vis13.balanced.	0.68	0.46	0.54	1
vis13.beautiful.	0.78	0.62	0.38	1
vis13.clean.	0.63	0.39	0.61	1
vis13.cluttered.	0.12	0.02	0.99	1
vis13.colorHarmonious.	0.43	0.18	0.82	1
vis13.creative.	0.58	0.33	0.67	1
vis13.delightful.	0.89	0.79	0.21	1
vis13.elegant.	0.78	0.62	0.38	1
vis13.engaging.	0.80	0.65	0.35	1
vis13.enjoyable.	0.83	0.70	0.30	1
vis13.exciting.	0.79	0.62	0.38	1
vis13.fascinating.	0.76	0.58	0.42	1
vis13.harmonious.	0.76	0.58	0.42	1
vis13.interesting.	0.74	0.54	0.46	1
vis13.inviting.	0.84	0.70	0.30	1
vis13.likable.	0.87	0.76	0.24	1
vis13.lovely.	0.83	0.68	0.32	1
vis13.motivating.	0.83	0.69	0.31	1
vis13.nice.	0.89	0.80	0.21	1
vis13.organized.	0.65	0.43	0.57	1
vis13.pleasing.	0.87	0.76	0.24	1
vis13.pretty.	0.83	0.68	0.32	1
vis13.professional.	0.67	0.46	0.54	1
vis13.provoking.	0.22	0.05	0.95	1
vis13.satisfying.	0.85	0.73	0.27	1
vis13.sophisticated.	0.71	0.50	0.50	1
vis13.tasteful.	0.81	0.66	0.34	1
vis13.wellDesigned.	0.81	0.65	0.35	1

Table B.20: Factor loading for 31 terms using an EFA for one factor for Image 14.

	PA1	h2	u2	com
vis14.appealing.	0.83	0.68	0.32	1
vis14.artistic.	0.58	0.34	0.66	1
vis14.attractive.	0.84	0.71	0.29	1
vis14.balanced.	0.71	0.51	0.49	1
vis14.beautiful.	0.82	0.67	0.33	1
vis14.clean.	0.73	0.54	0.46	1
vis14.cluttered.	0.05	0.00	1.00	1
vis14.colorHarmonious.	0.64	0.41	0.59	1
vis14.creative.	0.54	0.29	0.71	1
vis14.delightful.	0.84	0.70	0.30	1
vis14.elegant.	0.74	0.55	0.45	1
vis14.engaging.	0.73	0.54	0.46	1
vis14.enjoyable.	0.85	0.73	0.27	1
vis14.exciting.	0.75	0.57	0.43	1
vis14.fascinating.	0.70	0.49	0.51	1
vis14.harmonious.	0.75	0.57	0.43	1
vis14.interesting.	0.59	0.34	0.66	1
vis14.inviting.	0.76	0.57	0.43	1
vis14.likable.	0.87	0.76	0.24	1
vis14.lovely.	0.79	0.63	0.37	1
vis14.motivating.	0.76	0.58	0.42	1
vis14.nice.	0.82	0.68	0.32	1
vis14.organized.	0.62	0.39	0.61	1
vis14.pleasing.	0.84	0.71	0.29	1
vis14.pretty.	0.86	0.74	0.26	1
vis14.professional.	0.62	0.38	0.62	1
vis14.provoking.	0.22	0.05	0.95	1
vis14.satisfying.	0.81	0.66	0.34	1
vis14.sophisticated.	0.71	0.50	0.50	1
vis14.tasteful.	0.77	0.59	0.41	1
vis14.wellDesigned.	0.66	0.43	0.57	1

Table B.21: Factor loading for 31 terms using an EFA for one factor for Image 15.

	PA1	h2	u2	com
vis15.appealing.	0.90	0.81	0.19	1
vis15.artistic.	0.67	0.44	0.56	1
vis15.attractive.	0.85	0.72	0.28	1
vis15.balanced.	0.74	0.54	0.46	1
vis15.beautiful.	0.84	0.70	0.30	1
vis15.clean.	0.67	0.45	0.55	1
vis15.cluttered.	0.24	0.06	0.94	1
vis15.colorHarmonious.	0.64	0.41	0.59	1
vis15.creative.	0.65	0.42	0.58	1
vis15.delightful.	0.88	0.78	0.22	1
vis15.elegant.	0.80	0.63	0.37	1
vis15.engaging.	0.80	0.65	0.35	1
vis15.enjoyable.	0.89	0.79	0.21	1
vis15.exciting.	0.79	0.62	0.38	1
vis15.fascinating.	0.71	0.50	0.50	1
vis15.harmonious.	0.81	0.65	0.35	1
vis15.interesting.	0.74	0.54	0.46	1
vis15.inviting.	0.83	0.69	0.31	1
vis15.likable.	0.89	0.79	0.21	1
vis15.lovely.	0.83	0.68	0.32	1
vis15.motivating.	0.77	0.59	0.41	1
vis15.nice.	0.89	0.80	0.20	1
vis15.organized.	0.65	0.43	0.57	1
vis15.pleasing.	0.88	0.77	0.23	1
vis15.pretty.	0.85	0.73	0.27	1
vis15.professional.	0.60	0.36	0.64	1
vis15.provoking.	0.35	0.13	0.87	1
vis15.satisfying.	0.84	0.71	0.29	1
vis15.sophisticated.	0.71	0.50	0.50	1
vis15.tasteful.	0.83	0.68	0.32	1
vis15.wellDesigned.	0.76	0.58	0.42	1

Table B.22: Factor loading for 31 terms using an EFA for two factors with Varimax rotation for Image 1.

	PA1	PA2	h2	u2	com
vis01.appealing.	0.61	0.59	0.72	0.28	2.0
vis01.artistic.	0.16	0.61	0.40	0.60	1.1
vis01.attractive.	0.60	0.59	0.71	0.29	2.0
vis01.balanced.	0.78	0.17	0.63	0.37	1.1
vis01.beautiful.	0.60	0.59	0.71	0.29	2.0
vis01.clean.	0.79	0.20	0.67	0.33	1.1
vis01.cluttered.	0.35	0.05	0.13	0.87	1.0
vis01.colorHarmonious.	0.52	0.40	0.43	0.57	1.9
vis01.creative.	0.17	0.62	0.42	0.58	1.2
vis01.delightful.	0.64	0.56	0.73	0.27	2.0
vis01.elegant.	0.68	0.48	0.70	0.30	1.8
vis01.engaging.	0.58	0.54	0.62	0.38	2.0
vis01.enjoyable.	0.61	0.63	0.77	0.23	2.0
vis01.exciting.	0.47	0.67	0.67	0.33	1.8
vis01.fascinating.	0.30	0.69	0.57	0.43	1.4
vis01.harmonious.	0.69	0.41	0.64	0.36	1.6
vis01.interesting.	0.28	0.76	0.66	0.34	1.3
vis01.inviting.	0.68	0.48	0.70	0.30	1.8
vis01.likable.	0.66	0.62	0.82	0.18	2.0
vis01.lovely.	0.63	0.57	0.71	0.29	2.0
vis01.motivating.	0.60	0.43	0.55	0.45	1.8
vis01.nice.	0.68	0.59	0.82	0.18	2.0
vis01.organized.	0.72	0.07	0.53	0.47	1.0
vis01.pleasing.	0.61	0.60	0.72	0.28	2.0
vis01.pretty.	0.60	0.60	0.72	0.28	2.0
vis01.professional.	0.67	0.20	0.49	0.52	1.2
vis01.provoking.	-0.01	0.27	0.07	0.93	1.0
vis01.satisfying.	0.54	0.55	0.60	0.40	2.0
vis01.sophisticated.	0.55	0.41	0.47	0.53	1.9
vis01.tasteful.	0.61	0.49	0.62	0.39	1.9
vis01.wellDesigned.	0.69	0.37	0.61	0.39	1.5

Table B.23: Factor loading for 31 terms using an EFA for two factors with Promax rotation for Image 1.

	PA1	PA2	h2	u2	com
vis01.appealing.	0.47	0.44	0.72	0.28	2.0
vis01.artistic.	-0.13	0.72	0.40	0.60	1.1
vis01.attractive.	0.46	0.45	0.71	0.29	2.0
vis01.balanced.	0.94	-0.22	0.63	0.37	1.1
vis01.beautiful.	0.46	0.45	0.71	0.29	2.0
vis01.clean.	0.95	-0.19	0.67	0.33	1.1
vis01.cluttered.	0.44	-0.13	0.13	0.87	1.2
vis01.colorHarmonious.	0.47	0.23	0.43	0.57	1.5
vis01.creative.	-0.12	0.73	0.42	0.58	1.1
vis01.delightful.	0.53	0.38	0.73	0.27	1.8
vis01.elegant.	0.64	0.25	0.70	0.30	1.3
vis01.engaging.	0.46	0.39	0.62	0.38	1.9
vis01.enjoyable.	0.46	0.49	0.77	0.23	2.0
vis01.exciting.	0.24	0.63	0.67	0.33	1.3
vis01.fascinating.	0.01	0.74	0.57	0.43	1.0
vis01.harmonious.	0.68	0.15	0.64	0.36	1.1
vis01.interesting.	-0.06	0.85	0.66	0.34	1.0
vis01.inviting.	0.63	0.25	0.70	0.30	1.3
vis01.likable.	0.53	0.44	0.82	0.18	1.9
vis01.lovely.	0.51	0.39	0.71	0.29	1.9
vis01.motivating.	0.56	0.23	0.55	0.45	1.3
vis01.nice.	0.58	0.39	0.82	0.18	1.8
vis01.organized.	0.93	-0.32	0.53	0.47	1.2
vis01.pleasing.	0.47	0.45	0.72	0.28	2.0
vis01.pretty.	0.45	0.46	0.72	0.28	2.0
vis01.professional.	0.78	-0.12	0.49	0.52	1.0
vis01.provoking.	-0.17	0.37	0.07	0.93	1.4
vis01.satisfying.	0.41	0.42	0.60	0.40	2.0
vis01.sophisticated.	0.49	0.24	0.47	0.53	1.4
vis01.tasteful.	0.53	0.31	0.62	0.39	1.6
vis01.wellDesigned.	0.71	0.09	0.61	0.39	1.0

Table B.24: Factor loading for 31 terms using an EFA for two factors with Varimax rotation for Image 2.

	PA1	PA2	h2	u2	com
vis02.appealing.	0.61	0.52	0.64	0.36	1.9
vis02.artistic.	0.06	0.68	0.47	0.53	1.0
vis02.attractive.	0.57	0.52	0.60	0.40	2.0
vis02.balanced.	0.73	0.14	0.55	0.45	1.1
vis02.beautiful.	0.46	0.64	0.61	0.39	1.8
vis02.clean.	0.77	0.19	0.63	0.37	1.1
vis02.cluttered.	-0.46	0.02	0.21	0.79	1.0
vis02.colorHarmonious.	0.67	0.14	0.47	0.53	1.1
vis02.creative.	0.07	0.67	0.45	0.55	1.0
vis02.delightful.	0.41	0.66	0.61	0.39	1.7
vis02.elegant.	0.51	0.56	0.58	0.42	2.0
vis02.engaging.	0.40	0.60	0.52	0.48	1.8
vis02.enjoyable.	0.58	0.51	0.61	0.39	2.0
vis02.exciting.	0.20	0.79	0.66	0.34	1.1
vis02.fascinating.	0.21	0.74	0.59	0.41	1.2
vis02.harmonious.	0.68	0.28	0.54	0.46	1.3
vis02.interesting.	0.48	0.52	0.50	0.50	2.0
vis02.inviting.	0.41	0.65	0.59	0.41	1.7
vis02.likable.	0.72	0.38	0.66	0.34	1.5
vis02.lovely.	0.47	0.59	0.58	0.42	1.9
vis02.motivating.	0.27	0.69	0.54	0.46	1.3
vis02.nice.	0.75	0.37	0.70	0.30	1.5
vis02.organized.	0.79	0.05	0.63	0.37	1.0
vis02.pleasing.	0.67	0.46	0.65	0.35	1.8
vis02.pretty.	0.53	0.54	0.57	0.43	2.0
vis02.professional.	0.75	0.17	0.60	0.40	1.1
vis02.provoking.	-0.06	0.37	0.14	0.86	1.1
vis02.satisfying.	0.61	0.42	0.55	0.45	1.8
vis02.sophisticated.	0.30	0.60	0.45	0.55	1.5
vis02.tasteful.	0.58	0.32	0.43	0.57	1.6
vis02.wellDesigned.	0.68	0.30	0.55	0.45	1.4

Table B.25: Factor loading for 31 terms using an EFA for two factors with Promax rotation for Image 2.

	PA1	PA2	h2	u2	com
vis02.appealing.	0.52	0.37	0.64	0.36	1.8
vis02.artistic.	-0.22	0.80	0.47	0.53	1.2
vis02.attractive.	0.47	0.38	0.60	0.40	1.9
vis02.balanced.	0.82	-0.15	0.55	0.45	1.1
vis02.beautiful.	0.28	0.57	0.61	0.39	1.5
vis02.clean.	0.86	-0.10	0.63	0.37	1.0
vis02.cluttered.	-0.56	0.22	0.21	0.79	1.3
vis02.colorHarmonious.	0.76	-0.12	0.47	0.53	1.1
vis02.creative.	-0.20	0.78	0.45	0.55	1.1
vis02.delightful.	0.20	0.63	0.61	0.39	1.2
vis02.elegant.	0.38	0.46	0.58	0.42	1.9
vis02.engaging.	0.23	0.55	0.52	0.48	1.3
vis02.enjoyable.	0.49	0.37	0.61	0.39	1.9
vis02.exciting.	-0.10	0.87	0.66	0.34	1.0
vis02.fascinating.	-0.06	0.81	0.59	0.41	1.0
vis02.harmonious.	0.70	0.05	0.54	0.46	1.0
vis02.interesting.	0.36	0.42	0.50	0.50	1.9
vis02.inviting.	0.22	0.61	0.59	0.41	1.3
vis02.likable.	0.70	0.15	0.66	0.34	1.1
vis02.lovely.	0.32	0.52	0.58	0.42	1.7
vis02.motivating.	0.03	0.72	0.54	0.46	1.0
vis02.nice.	0.75	0.13	0.70	0.30	1.1
vis02.organized.	0.94	-0.28	0.63	0.37	1.2
vis02.pleasing.	0.61	0.27	0.65	0.35	1.4
vis02.pretty.	0.42	0.42	0.57	0.43	2.0
vis02.professional.	0.84	-0.12	0.60	0.40	1.0
vis02.provoking.	-0.23	0.47	0.14	0.86	1.5
vis02.satisfying.	0.56	0.25	0.55	0.45	1.4
vis02.sophisticated.	0.11	0.60	0.45	0.55	1.1
vis02.tasteful.	0.56	0.14	0.43	0.57	1.1
vis02.wellDesigned.	0.69	0.08	0.55	0.45	1.0

Table B.26: Factor loading for 31 terms using an EFA for two factors with Varimax rotation for Image 3.

	PA1	PA2	h2	u2	com
vis03.appealing.	0.62	0.51	0.64	0.36	1.9
vis03.artistic.	0.54	0.16	0.32	0.68	1.2
vis03.attractive.	0.74	0.39	0.70	0.30	1.5
vis03.balanced.	0.18	0.73	0.56	0.44	1.1
vis03.beautiful.	0.75	0.31	0.65	0.35	1.3
vis03.clean.	0.34	0.70	0.60	0.40	1.4
vis03.cluttered.	0.04	0.00	0.00	1.00	1.0
vis03.colorHarmonious.	0.55	0.33	0.41	0.59	1.7
vis03.creative.	0.67	0.09	0.45	0.55	1.0
vis03.delightful.	0.69	0.39	0.63	0.37	1.6
vis03.elegant.	0.57	0.42	0.50	0.50	1.8
vis03.engaging.	0.47	0.62	0.60	0.40	1.9
vis03.enjoyable.	0.62	0.56	0.69	0.31	2.0
vis03.exciting.	0.60	0.41	0.53	0.47	1.8
vis03.fascinating.	0.66	0.36	0.57	0.43	1.6
vis03.harmonious.	0.50	0.58	0.59	0.41	2.0
vis03.interesting.	0.68	0.30	0.56	0.44	1.4
vis03.inviting.	0.40	0.62	0.55	0.45	1.7
vis03.likable.	0.65	0.58	0.77	0.23	2.0
vis03.lovely.	0.69	0.39	0.63	0.37	1.6
vis03.motivating.	0.48	0.54	0.52	0.48	2.0
vis03.nice.	0.57	0.57	0.65	0.35	2.0
vis03.organized.	0.13	0.80	0.66	0.34	1.1
vis03.pleasing.	0.63	0.55	0.70	0.30	2.0
vis03.pretty.	0.75	0.32	0.67	0.33	1.4
vis03.professional.	0.11	0.66	0.45	0.55	1.1
vis03.provoking.	0.18	0.12	0.05	0.95	1.8
vis03.satisfying.	0.59	0.49	0.59	0.41	1.9
vis03.sophisticated.	0.42	0.46	0.39	0.61	2.0
vis03.tasteful.	0.60	0.35	0.49	0.51	1.6
vis03.wellDesigned.	0.24	0.74	0.61	0.39	1.2

Table B.27: Factor loading for 31 terms using an EFA for two factors with Promax rotation for Image 3.

	PA1	PA2	h2	u2	com
vis03.appealing.	0.53	0.32	0.64	0.36	1.6
vis03.artistic.	0.63	-0.09	0.32	0.68	1.0
vis03.attractive.	0.76	0.10	0.70	0.30	1.0
vis03.balanced.	-0.16	0.86	0.56	0.44	1.1
vis03.beautiful.	0.82	-0.02	0.65	0.35	1.0
vis03.clean.	0.06	0.73	0.60	0.40	1.0
vis03.cluttered.	0.06	-0.03	0.00	1.00	1.4
vis03.colorHarmonious.	0.54	0.13	0.41	0.59	1.1
vis03.creative.	0.83	-0.26	0.45	0.55	1.2
vis03.delightful.	0.70	0.12	0.63	0.37	1.1
vis03.elegant.	0.53	0.23	0.50	0.50	1.4
vis03.engaging.	0.28	0.55	0.60	0.40	1.5
vis03.enjoyable.	0.50	0.39	0.69	0.31	1.9
vis03.exciting.	0.57	0.20	0.53	0.47	1.3
vis03.fascinating.	0.67	0.11	0.57	0.43	1.0
vis03.harmonious.	0.33	0.49	0.59	0.41	1.8
vis03.interesting.	0.73	0.02	0.56	0.44	1.0
vis03.inviting.	0.19	0.59	0.55	0.45	1.2
vis03.likable.	0.54	0.40	0.77	0.23	1.8
vis03.lovely.	0.70	0.13	0.63	0.37	1.1
vis03.motivating.	0.33	0.44	0.52	0.48	1.8
vis03.nice.	0.43	0.44	0.65	0.35	2.0
vis03.organized.	-0.27	0.99	0.66	0.34	1.2
vis03.pleasing.	0.53	0.37	0.70	0.30	1.8
vis03.pretty.	0.82	0.00	0.67	0.33	1.0
vis03.professional.	-0.22	0.81	0.45	0.55	1.1
vis03.provoking.	0.17	0.06	0.05	0.95	1.2
vis03.satisfying.	0.51	0.32	0.59	0.41	1.7
vis03.sophisticated.	0.31	0.37	0.39	0.61	1.9
vis03.tasteful.	0.61	0.12	0.49	0.51	1.1
vis03.wellDesigned.	-0.09	0.84	0.61	0.39	1.0

Table B.28: Factor loading for 31 terms using an EFA for two factors with Varimax rotation for Image 4.

	PA1	PA2	h2	u2	com
vis04.appealing.	0.75	0.41	0.73	0.27	1.6
vis04.artistic.	0.67	0.10	0.47	0.54	1.0
vis04.attractive.	0.77	0.33	0.71	0.29	1.4
vis04.balanced.	0.38	0.72	0.65	0.35	1.5
vis04.beautiful.	0.78	0.29	0.70	0.30	1.3
vis04.clean.	0.27	0.70	0.57	0.43	1.3
vis04.cluttered.	-0.01	0.26	0.07	0.93	1.0
vis04.colorHarmonious.	0.53	0.35	0.41	0.59	1.7
vis04.creative.	0.65	0.15	0.44	0.56	1.1
vis04.delightful.	0.64	0.55	0.72	0.29	1.9
vis04.elegant.	0.53	0.58	0.62	0.38	2.0
vis04.engaging.	0.53	0.53	0.56	0.44	2.0
vis04.enjoyable.	0.74	0.45	0.75	0.25	1.7
vis04.exciting.	0.67	0.38	0.60	0.40	1.6
vis04.fascinating.	0.74	0.30	0.64	0.36	1.3
vis04.harmonious.	0.45	0.63	0.61	0.39	1.8
vis04.interesting.	0.64	0.38	0.55	0.45	1.6
vis04.inviting.	0.52	0.53	0.54	0.46	2.0
vis04.likable.	0.70	0.51	0.75	0.25	1.8
vis04.lovely.	0.67	0.48	0.67	0.33	1.8
vis04.motivating.	0.50	0.61	0.62	0.38	1.9
vis04.nice.	0.73	0.40	0.70	0.30	1.6
vis04.organized.	0.32	0.79	0.73	0.27	1.3
vis04.pleasing.	0.73	0.49	0.78	0.22	1.7
vis04.pretty.	0.79	0.26	0.69	0.31	1.2
vis04.professional.	0.24	0.69	0.53	0.47	1.2
vis04.provoking.	0.31	0.06	0.10	0.90	1.1
vis04.satisfying.	0.61	0.58	0.70	0.30	2.0
vis04.sophisticated.	0.46	0.44	0.41	0.59	2.0
vis04.tasteful.	0.58	0.43	0.52	0.48	1.8
vis04.wellDesigned.	0.51	0.60	0.61	0.39	1.9

Table B.29: Factor loading for 31 terms using an EFA for two factors with Promax rotation for Image 4.

	PA1	PA2	h2	u2	com
vis04.appealing.	0.76	0.13	0.73	0.27	1.1
vis04.artistic.	0.84	-0.25	0.47	0.54	1.2
vis04.attractive.	0.84	0.00	0.71	0.29	1.0
vis04.balanced.	0.09	0.74	0.65	0.35	1.0
vis04.beautiful.	0.88	-0.07	0.70	0.30	1.0
vis04.clean.	-0.04	0.79	0.57	0.43	1.0
vis04.cluttered.	-0.17	0.35	0.07	0.93	1.4
vis04.colorHarmonious.	0.51	0.16	0.41	0.59	1.2
vis04.creative.	0.78	-0.17	0.44	0.56	1.1
vis04.delightful.	0.55	0.36	0.72	0.29	1.7
vis04.elegant.	0.37	0.47	0.62	0.38	1.9
vis04.engaging.	0.41	0.40	0.56	0.44	2.0
vis04.enjoyable.	0.73	0.18	0.75	0.25	1.1
vis04.exciting.	0.68	0.12	0.60	0.40	1.1
vis04.fascinating.	0.82	-0.02	0.64	0.36	1.0
vis04.harmonious.	0.24	0.58	0.61	0.39	1.3
vis04.interesting.	0.64	0.14	0.55	0.45	1.1
vis04.inviting.	0.39	0.41	0.54	0.46	2.0
vis04.likable.	0.64	0.28	0.75	0.25	1.4
vis04.lovely.	0.62	0.25	0.67	0.33	1.3
vis04.motivating.	0.31	0.53	0.62	0.38	1.6
vis04.nice.	0.75	0.12	0.70	0.30	1.0
vis04.organized.	-0.03	0.88	0.73	0.27	1.0
vis04.pleasing.	0.70	0.23	0.78	0.22	1.2
vis04.pretty.	0.90	-0.10	0.69	0.31	1.0
vis04.professional.	-0.07	0.78	0.53	0.47	1.0
vis04.provoking.	0.38	-0.09	0.10	0.90	1.1
vis04.satisfying.	0.48	0.42	0.70	0.30	2.0
vis04.sophisticated.	0.36	0.33	0.41	0.59	2.0
vis04.tasteful.	0.52	0.24	0.52	0.48	1.4
vis04.wellDesigned.	0.33	0.51	0.61	0.39	1.7

Table B.30: Factor loading for 31 terms using an EFA for two factors with Varimax rotation for Image 5.

	PA1	PA2	h2	u2	com
vis05.appealing.	0.67	0.55	0.75	0.25	1.9
vis05.artistic.	0.69	0.21	0.53	0.47	1.2
vis05.attractive.	0.72	0.49	0.76	0.24	1.8
vis05.balanced.	0.30	0.74	0.64	0.36	1.3
vis05.beautiful.	0.77	0.39	0.75	0.25	1.5
vis05.clean.	0.25	0.78	0.67	0.33	1.2
vis05.cluttered.	0.15	0.41	0.19	0.81	1.3
vis05.colorHarmonious.	0.43	0.47	0.41	0.59	2.0
vis05.creative.	0.70	0.23	0.54	0.46	1.2
vis05.delightful.	0.63	0.54	0.69	0.31	2.0
vis05.elegant.	0.46	0.60	0.56	0.44	1.9
vis05.engaging.	0.62	0.48	0.62	0.38	1.9
vis05.enjoyable.	0.71	0.50	0.75	0.25	1.8
vis05.exciting.	0.79	0.35	0.74	0.26	1.4
vis05.fascinating.	0.78	0.18	0.64	0.36	1.1
vis05.harmonious.	0.52	0.65	0.70	0.31	1.9
vis05.interesting.	0.76	0.29	0.66	0.34	1.3
vis05.inviting.	0.54	0.63	0.69	0.31	1.9
vis05.likable.	0.68	0.54	0.75	0.25	1.9
vis05.lovely.	0.63	0.49	0.64	0.36	1.9
vis05.motivating.	0.63	0.53	0.68	0.32	1.9
vis05.nice.	0.65	0.59	0.76	0.24	2.0
vis05.organized.	0.17	0.84	0.73	0.27	1.1
vis05.pleasing.	0.64	0.62	0.79	0.21	2.0
vis05.pretty.	0.70	0.43	0.67	0.33	1.7
vis05.professional.	0.25	0.66	0.49	0.51	1.3
vis05.provoking.	0.30	0.09	0.10	0.90	1.2
vis05.satisfying.	0.66	0.54	0.72	0.28	1.9
vis05.sophisticated.	0.41	0.45	0.37	0.63	2.0
vis05.tasteful.	0.53	0.56	0.59	0.41	2.0
vis05.wellDesigned.	0.46	0.70	0.70	0.30	1.7

Table B.31: Factor loading for 31 terms using an EFA for two factors with Promax rotation for Image 5.

	PA1	PA2	h2	u2	com
viso5.appealing.	0.58	0.34	0.75	0.25	1.6
viso5.artistic.	0.84	-0.15	0.53	0.47	1.1
viso5.attractive.	0.70	0.21	0.76	0.24	1.2
viso5.balanced.	-0.06	0.84	0.64	0.36	1.0
viso5.beautiful.	0.82	0.05	0.75	0.25	1.0
viso5.clean.	-0.16	0.94	0.67	0.33	1.1
viso5.cluttered.	-0.06	0.48	0.19	0.81	1.0
viso5.colorHarmonious.	0.31	0.37	0.41	0.59	1.9
viso5.creative.	0.83	-0.13	0.54	0.46	1.0
viso5.delightful.	0.53	0.35	0.69	0.31	1.7
viso5.elegant.	0.25	0.54	0.56	0.44	1.4
viso5.engaging.	0.56	0.26	0.62	0.38	1.4
viso5.enjoyable.	0.67	0.24	0.75	0.25	1.3
viso5.exciting.	0.88	-0.03	0.74	0.26	1.0
viso5.fascinating.	0.97	-0.25	0.64	0.36	1.1
viso5.harmonious.	0.30	0.58	0.70	0.31	1.5
viso5.interesting.	0.88	-0.09	0.66	0.34	1.0
viso5.inviting.	0.34	0.54	0.69	0.31	1.7
viso5.likable.	0.60	0.32	0.75	0.25	1.5
viso5.lovely.	0.57	0.27	0.64	0.36	1.4
viso5.motivating.	0.54	0.34	0.68	0.32	1.7
viso5.nice.	0.53	0.40	0.76	0.24	1.9
viso5.organized.	-0.31	1.07	0.73	0.27	1.2
viso5.pleasing.	0.50	0.45	0.79	0.21	2.0
viso5.pretty.	0.71	0.14	0.67	0.33	1.1
viso5.professional.	-0.08	0.76	0.49	0.51	1.0
viso5.provoking.	0.36	-0.07	0.10	0.90	1.1
viso5.satisfying.	0.57	0.33	0.72	0.28	1.6
viso5.sophisticated.	0.29	0.36	0.37	0.63	1.9
viso5.tasteful.	0.38	0.44	0.59	0.41	1.9
viso5.wellDesigned.	0.20	0.68	0.70	0.30	1.2

Table B.32: Factor loading for 31 terms using an EFA for two factors with Varimax rotation for Image 6.

	PA1	PA2	h2	u2	com
viso6.appealing.	0.67	0.49	0.69	0.31	1.8
viso6.artistic.	0.79	0.02	0.63	0.37	1.0
viso6.attractive.	0.72	0.48	0.76	0.24	1.7
viso6.balanced.	0.34	0.69	0.60	0.40	1.5
viso6.beautiful.	0.72	0.33	0.64	0.36	1.4
viso6.clean.	0.16	0.78	0.64	0.36	1.1
viso6.cluttered.	0.06	0.22	0.05	0.95	1.1
viso6.colorHarmonious.	0.49	0.40	0.39	0.61	1.9
viso6.creative.	0.74	0.08	0.55	0.45	1.0
viso6.delightful.	0.66	0.47	0.66	0.34	1.8
viso6.elegant.	0.37	0.62	0.53	0.47	1.6
viso6.engaging.	0.67	0.40	0.61	0.39	1.6
viso6.enjoyable.	0.70	0.46	0.71	0.29	1.7
viso6.exciting.	0.76	0.26	0.65	0.35	1.2
viso6.fascinating.	0.76	0.20	0.63	0.38	1.1
viso6.harmonious.	0.46	0.62	0.60	0.40	1.8
viso6.interesting.	0.66	0.31	0.54	0.46	1.4
viso6.inviting.	0.56	0.58	0.65	0.35	2.0
viso6.likable.	0.74	0.42	0.72	0.28	1.6
viso6.lovely.	0.72	0.32	0.63	0.37	1.4
viso6.motivating.	0.58	0.53	0.61	0.39	2.0
viso6.nice.	0.65	0.51	0.69	0.31	1.9
viso6.organized.	0.13	0.80	0.66	0.34	1.1
viso6.pleasing.	0.71	0.51	0.76	0.24	1.8
viso6.pretty.	0.75	0.36	0.69	0.31	1.4
viso6.professional.	0.15	0.67	0.47	0.53	1.1
viso6.provoking.	0.32	0.12	0.12	0.88	1.3
viso6.satisfying.	0.61	0.52	0.64	0.36	1.9
viso6.sophisticated.	0.42	0.48	0.40	0.60	2.0
viso6.tasteful.	0.58	0.52	0.61	0.39	2.0
viso6.wellDesigned.	0.36	0.73	0.66	0.34	1.5

Table B.33: Factor loading for 31 terms using an EFA for two factors with Promax rotation for Image 6.

	PA1	PA2	h2	u2	com
vis06.appealing.	0.61	0.27	0.69	0.31	1.4
vis06.artistic.	1.02	-0.40	0.63	0.37	1.3
vis06.attractive.	0.69	0.24	0.76	0.24	1.2
vis06.balanced.	0.08	0.72	0.60	0.40	1.0
vis06.beautiful.	0.77	0.04	0.64	0.36	1.0
vis06.clean.	-0.21	0.93	0.64	0.36	1.1
vis06.cluttered.	-0.04	0.25	0.05	0.95	1.1
vis06.colorHarmonious.	0.43	0.25	0.39	0.61	1.6
vis06.creative.	0.92	-0.30	0.55	0.45	1.2
vis06.delightful.	0.61	0.25	0.66	0.34	1.3
vis06.elegant.	0.15	0.61	0.53	0.47	1.1
vis06.engaging.	0.66	0.16	0.61	0.39	1.1
vis06.enjoyable.	0.67	0.22	0.71	0.29	1.2
vis06.exciting.	0.85	-0.07	0.65	0.35	1.0
vis06.fascinating.	0.89	-0.16	0.63	0.38	1.1
vis06.harmonious.	0.26	0.57	0.60	0.40	1.4
vis06.interesting.	0.70	0.04	0.54	0.46	1.0
vis06.inviting.	0.41	0.46	0.65	0.35	2.0
vis06.likable.	0.74	0.15	0.72	0.28	1.1
vis06.lovely.	0.77	0.03	0.63	0.37	1.0
vis06.motivating.	0.48	0.37	0.61	0.39	1.9
vis06.nice.	0.58	0.31	0.69	0.31	1.5
vis06.organized.	-0.26	0.97	0.66	0.34	1.1
vis06.pleasing.	0.65	0.29	0.76	0.24	1.4
vis06.pretty.	0.79	0.06	0.69	0.31	1.0
vis06.professional.	-0.16	0.79	0.47	0.53	1.1
vis06.provoking.	0.36	-0.02	0.12	0.88	1.0
vis06.satisfying.	0.52	0.34	0.64	0.36	1.7
vis06.sophisticated.	0.29	0.39	0.40	0.60	1.9
vis06.tasteful.	0.48	0.37	0.61	0.39	1.9
vis06.wellDesigned.	0.08	0.75	0.66	0.34	1.0

Table B.34: Factor loading for 31 terms using an EFA for two factors with Varimax rotation for Image 7.

	PA1	PA2	h2	u2	com
vis07.appealing.	0.62	0.62	0.77	0.23	2.0
vis07.artistic.	0.25	0.74	0.60	0.40	1.2
vis07.attractive.	0.62	0.64	0.79	0.21	2.0
vis07.balanced.	0.59	0.23	0.41	0.59	1.3
vis07.beautiful.	0.57	0.67	0.77	0.23	1.9
vis07.clean.	0.78	0.16	0.63	0.37	1.1
vis07.cluttered.	0.34	0.04	0.12	0.88	1.0
vis07.colorHarmonious.	0.38	0.30	0.23	0.77	1.9
vis07.creative.	0.20	0.74	0.59	0.41	1.1
vis07.delightful.	0.63	0.63	0.79	0.21	2.0
vis07.elegant.	0.72	0.46	0.72	0.28	1.7
vis07.engaging.	0.50	0.66	0.69	0.31	1.9
vis07.enjoyable.	0.60	0.65	0.78	0.22	2.0
vis07.exciting.	0.47	0.68	0.68	0.32	1.8
vis07.fascinating.	0.36	0.79	0.76	0.24	1.4
vis07.harmonious.	0.62	0.43	0.57	0.43	1.8
vis07.interesting.	0.29	0.75	0.64	0.36	1.3
vis07.inviting.	0.60	0.59	0.70	0.30	2.0
vis07.likable.	0.62	0.65	0.81	0.19	2.0
vis07.lovely.	0.60	0.58	0.69	0.31	2.0
vis07.motivating.	0.63	0.55	0.71	0.29	2.0
vis07.nice.	0.62	0.61	0.76	0.24	2.0
vis07.organized.	0.72	0.06	0.52	0.48	1.0
vis07.pleasing.	0.67	0.60	0.80	0.20	2.0
vis07.pretty.	0.59	0.65	0.77	0.23	2.0
vis07.professional.	0.64	0.20	0.45	0.55	1.2
vis07.provoking.	-0.11	0.39	0.16	0.84	1.2
vis07.satisfying.	0.69	0.59	0.82	0.18	2.0
vis07.sophisticated.	0.58	0.45	0.54	0.46	1.9
vis07.tasteful.	0.60	0.53	0.64	0.36	2.0
vis07.wellDesigned.	0.63	0.34	0.51	0.49	1.5

Table B.35: Factor loading for 31 terms using an EFA for two factors with Promax rotation for Image 7.

	PA1	PA2	h2	u2	com
vis07.appealing.	0.47	0.48	0.77	0.23	2.0
vis07.artistic.	-0.07	0.83	0.60	0.40	1.0
vis07.attractive.	0.46	0.51	0.79	0.21	2.0
vis07.balanced.	0.65	-0.01	0.41	0.59	1.0
vis07.beautiful.	0.38	0.57	0.77	0.23	1.7
vis07.clean.	0.92	-0.21	0.63	0.37	1.1
vis07.cluttered.	0.42	-0.13	0.12	0.88	1.2
vis07.colorHarmonious.	0.33	0.18	0.23	0.77	1.6
vis07.creative.	-0.14	0.86	0.59	0.41	1.1
vis07.delightful.	0.48	0.48	0.79	0.21	2.0
vis07.elegant.	0.69	0.21	0.72	0.28	1.2
vis07.engaging.	0.29	0.60	0.69	0.31	1.4
vis07.enjoyable.	0.43	0.53	0.78	0.22	1.9
vis07.exciting.	0.25	0.63	0.68	0.32	1.3
vis07.fascinating.	0.04	0.84	0.76	0.24	1.0
vis07.harmonious.	0.58	0.22	0.57	0.43	1.3
vis07.interesting.	-0.02	0.82	0.64	0.36	1.0
vis07.inviting.	0.46	0.45	0.70	0.30	2.0
vis07.likable.	0.46	0.51	0.81	0.19	2.0
vis07.lovely.	0.46	0.44	0.69	0.31	2.0
vis07.motivating.	0.52	0.39	0.71	0.29	1.8
vis07.nice.	0.47	0.47	0.76	0.24	2.0
vis07.organized.	0.89	-0.29	0.52	0.48	1.2
vis07.pleasing.	0.55	0.42	0.80	0.20	1.9
vis07.pretty.	0.42	0.54	0.77	0.23	1.9
vis07.professional.	0.73	-0.08	0.45	0.55	1.0
vis07.provoking.	-0.35	0.56	0.16	0.84	1.7
vis07.satisfying.	0.58	0.40	0.82	0.18	1.8
vis07.sophisticated.	0.51	0.27	0.54	0.46	1.5
vis07.tasteful.	0.50	0.37	0.64	0.36	1.8
vis07.wellDesigned.	0.63	0.11	0.51	0.49	1.1

Table B.36: Factor loading for 31 terms using an EFA for two factors with Varimax rotation for Image 8.

	PA1	PA2	h2	u2	com
vis08.appealing.	0.76	0.40	0.74	0.26	1.5
vis08.artistic.	0.65	0.15	0.45	0.55	1.1
vis08.attractive.	0.74	0.40	0.72	0.28	1.5
vis08.balanced.	0.37	0.69	0.61	0.39	1.5
vis08.beautiful.	0.64	0.49	0.65	0.35	1.9
vis08.clean.	0.37	0.68	0.60	0.40	1.5
vis08.cluttered.	0.18	0.32	0.13	0.87	1.6
vis08.colorHarmonious.	0.43	0.34	0.30	0.70	1.9
vis08.creative.	0.71	0.22	0.55	0.45	1.2
vis08.delightful.	0.70	0.43	0.67	0.33	1.7
vis08.elegant.	0.33	0.72	0.63	0.37	1.4
vis08.engaging.	0.79	0.34	0.73	0.27	1.4
vis08.enjoyable.	0.79	0.39	0.78	0.22	1.5
vis08.exciting.	0.77	0.25	0.66	0.34	1.2
vis08.fascinating.	0.64	0.33	0.51	0.49	1.5
vis08.harmonious.	0.47	0.61	0.60	0.40	1.9
vis08.interesting.	0.70	0.30	0.58	0.42	1.4
vis08.inviting.	0.76	0.40	0.74	0.26	1.5
vis08.likable.	0.76	0.45	0.78	0.22	1.6
vis08.lovely.	0.72	0.39	0.67	0.33	1.6
vis08.motivating.	0.62	0.41	0.56	0.44	1.7
vis08.nice.	0.72	0.48	0.76	0.24	1.7
vis08.organized.	0.23	0.71	0.55	0.45	1.2
vis08.pleasing.	0.71	0.45	0.72	0.28	1.7
vis08.pretty.	0.70	0.39	0.64	0.36	1.6
vis08.professional.	0.05	0.71	0.51	0.49	1.0
vis08.provoking.	0.43	0.04	0.19	0.81	1.0
vis08.satisfying.	0.67	0.44	0.65	0.35	1.7
vis08.sophisticated.	0.41	0.54	0.47	0.53	1.9
vis08.tasteful.	0.65	0.48	0.65	0.35	1.8
vis08.wellDesigned.	0.33	0.76	0.68	0.32	1.4

Table B.37: Factor loading for 31 terms using an EFA for two factors with Promax rotation for Image 8.

	PA1	PA2	h2	u2	com
vis08.appealing.	0.79	0.09	0.74	0.26	1.0
vis08.artistic.	0.78	-0.17	0.45	0.55	1.1
vis08.attractive.	0.76	0.11	0.72	0.28	1.0
vis08.balanced.	0.11	0.70	0.61	0.39	1.0
vis08.beautiful.	0.58	0.29	0.65	0.35	1.5
vis08.clean.	0.10	0.70	0.60	0.40	1.0
vis08.cluttered.	0.06	0.32	0.13	0.87	1.1
vis08.colorHarmonious.	0.39	0.20	0.30	0.70	1.5
vis08.creative.	0.82	-0.11	0.55	0.45	1.0
vis08.delightful.	0.69	0.17	0.67	0.33	1.1
vis08.elegant.	0.03	0.78	0.63	0.37	1.0
vis08.engaging.	0.86	0.00	0.73	0.27	1.0
vis08.enjoyable.	0.83	0.07	0.78	0.22	1.0
vis08.exciting.	0.89	-0.11	0.66	0.34	1.0
vis08.fascinating.	0.66	0.08	0.51	0.49	1.0
vis08.harmonious.	0.28	0.55	0.60	0.40	1.5
vis08.interesting.	0.77	0.00	0.58	0.42	1.0
vis08.inviting.	0.79	0.09	0.74	0.26	1.0
vis08.likable.	0.75	0.17	0.78	0.22	1.1
vis08.lovely.	0.73	0.12	0.67	0.33	1.0
vis08.motivating.	0.59	0.20	0.56	0.44	1.2
vis08.nice.	0.69	0.23	0.76	0.24	1.2
vis08.organized.	-0.09	0.81	0.55	0.45	1.0
vis08.pleasing.	0.70	0.19	0.72	0.28	1.2
vis08.pretty.	0.71	0.11	0.64	0.36	1.1
vis08.professional.	-0.33	0.91	0.51	0.49	1.3
vis08.provoking.	0.55	-0.19	0.19	0.81	1.2
vis08.satisfying.	0.64	0.21	0.65	0.35	1.2
vis08.sophisticated.	0.24	0.49	0.47	0.53	1.5
vis08.tasteful.	0.59	0.27	0.65	0.35	1.4
vis08.wellDesigned.	0.01	0.82	0.68	0.32	1.0

Table B.38: Factor loading for 31 terms using an EFA for two factors with Varimax rotation for Image 9.

	PA1	PA2	h2	u2	com
vis09.appealing.	0.67	0.52	0.72	0.28	1.9
vis09.artistic.	0.74	0.01	0.54	0.46	1.0
vis09.attractive.	0.75	0.42	0.74	0.26	1.6
vis09.balanced.	0.29	0.67	0.53	0.47	1.4
vis09.beautiful.	0.69	0.36	0.60	0.40	1.5
vis09.clean.	0.14	0.78	0.63	0.37	1.1
vis09.cluttered.	0.22	0.37	0.18	0.82	1.6
vis09.colorHarmonious.	0.30	0.32	0.19	0.81	2.0
vis09.creative.	0.70	0.14	0.51	0.49	1.1
vis09.delightful.	0.67	0.43	0.63	0.37	1.7
vis09.elegant.	0.44	0.58	0.53	0.47	1.9
vis09.engaging.	0.63	0.40	0.55	0.45	1.7
vis09.enjoyable.	0.68	0.50	0.71	0.29	1.8
vis09.exciting.	0.68	0.28	0.54	0.46	1.3
vis09.fascinating.	0.69	0.30	0.56	0.44	1.4
vis09.harmonious.	0.37	0.64	0.55	0.45	1.6
vis09.interesting.	0.57	0.26	0.40	0.60	1.4
vis09.inviting.	0.64	0.45	0.62	0.38	1.8
vis09.likable.	0.67	0.51	0.71	0.29	1.9
vis09.lovely.	0.65	0.38	0.56	0.44	1.6
vis09.motivating.	0.62	0.43	0.57	0.43	1.8
vis09.nice.	0.64	0.50	0.66	0.34	1.9
vis09.organized.	0.18	0.71	0.53	0.47	1.1
vis09.pleasing.	0.58	0.55	0.65	0.35	2.0
vis09.pretty.	0.75	0.30	0.65	0.35	1.3
vis09.professional.	0.05	0.73	0.54	0.46	1.0
vis09.provoking.	0.35	0.08	0.13	0.87	1.1
vis09.satisfying.	0.56	0.61	0.69	0.31	2.0
vis09.sophisticated.	0.40	0.55	0.46	0.54	1.8
vis09.tasteful.	0.54	0.61	0.66	0.34	2.0
vis09.wellDesigned.	0.38	0.68	0.61	0.39	1.6

Table B.39: Factor loading for 31 terms using an EFA for two factors with Promax rotation for Image 9.

	PA1	PA2	h2	u2	com
vis09.appealing.	0.59	0.31	0.72	0.28	1.5
vis09.artistic.	0.97	-0.40	0.54	0.46	1.3
vis09.attractive.	0.76	0.13	0.74	0.26	1.1
vis09.balanced.	0.01	0.72	0.53	0.47	1.0
vis09.beautiful.	0.71	0.09	0.60	0.40	1.0
vis09.clean.	-0.25	0.95	0.63	0.37	1.1
vis09.cluttered.	0.09	0.36	0.18	0.82	1.1
vis09.colorHarmonious.	0.21	0.26	0.19	0.81	1.9
vis09.creative.	0.85	-0.20	0.51	0.49	1.1
vis09.delightful.	0.64	0.20	0.63	0.37	1.2
vis09.elegant.	0.26	0.52	0.53	0.47	1.5
vis09.engaging.	0.61	0.18	0.55	0.45	1.2
vis09.enjoyable.	0.62	0.28	0.71	0.29	1.4
vis09.exciting.	0.75	-0.02	0.54	0.46	1.0
vis09.fascinating.	0.74	0.01	0.56	0.44	1.0
vis09.harmonious.	0.13	0.64	0.55	0.45	1.1
vis09.interesting.	0.61	0.03	0.40	0.60	1.0
vis09.inviting.	0.60	0.23	0.62	0.38	1.3
vis09.likable.	0.60	0.30	0.71	0.29	1.5
vis09.lovely.	0.64	0.14	0.56	0.44	1.1
vis09.motivating.	0.58	0.22	0.57	0.43	1.3
vis09.nice.	0.57	0.30	0.66	0.34	1.5
vis09.organized.	-0.15	0.83	0.53	0.47	1.1
vis09.pleasing.	0.47	0.40	0.65	0.35	2.0
vis09.pretty.	0.82	-0.03	0.65	0.35	1.0
vis09.professional.	-0.34	0.94	0.54	0.46	1.3
vis09.provoking.	0.42	-0.10	0.13	0.87	1.1
vis09.satisfying.	0.40	0.49	0.69	0.31	1.9
vis09.sophisticated.	0.22	0.50	0.46	0.54	1.4
vis09.tasteful.	0.38	0.50	0.66	0.34	1.9
vis09.wellDesigned.	0.12	0.69	0.61	0.39	1.1

Table B.40: Factor loading for 31 terms using an EFA for two factors with Varimax rotation for Image 10.

	PA1	PA2	h2	u2	com
vis10.appealing.	0.57	0.68	0.79	0.21	1.9
vis10.artistic.	0.24	0.72	0.59	0.41	1.2
vis10.attractive.	0.55	0.67	0.75	0.25	1.9
vis10.balanced.	0.72	0.36	0.65	0.35	1.5
vis10.beautiful.	0.54	0.63	0.69	0.31	1.9
vis10.clean.	0.75	0.19	0.60	0.40	1.1
vis10.cluttered.	0.47	0.15	0.24	0.76	1.2
vis10.colorHarmonious.	0.50	0.36	0.38	0.62	1.8
vis10.creative.	0.32	0.67	0.54	0.46	1.4
vis10.delightful.	0.61	0.54	0.67	0.33	2.0
vis10.elegant.	0.68	0.51	0.71	0.29	1.9
vis10.engaging.	0.55	0.52	0.58	0.42	2.0
vis10.enjoyable.	0.57	0.66	0.76	0.24	2.0
vis10.exciting.	0.40	0.70	0.65	0.35	1.6
vis10.fascinating.	0.32	0.63	0.50	0.50	1.5
vis10.harmonious.	0.67	0.45	0.65	0.35	1.8
vis10.interesting.	0.31	0.62	0.48	0.52	1.5
vis10.inviting.	0.68	0.41	0.64	0.36	1.6
vis10.likable.	0.60	0.61	0.74	0.26	2.0
vis10.lovely.	0.65	0.50	0.66	0.34	1.9
vis10.motivating.	0.60	0.49	0.60	0.40	1.9
vis10.nice.	0.66	0.54	0.72	0.28	1.9
vis10.organized.	0.78	0.13	0.62	0.38	1.1
vis10.pleasing.	0.63	0.61	0.77	0.23	2.0
vis10.pretty.	0.47	0.68	0.68	0.32	1.8
vis10.professional.	0.62	0.24	0.43	0.57	1.3
vis10.provoking.	0.00	0.41	0.17	0.83	1.0
vis10.satisfying.	0.60	0.60	0.72	0.28	2.0
vis10.sophisticated.	0.54	0.34	0.41	0.59	1.7
vis10.tasteful.	0.62	0.51	0.64	0.36	1.9
vis10.wellDesigned.	0.74	0.29	0.63	0.37	1.3

Table B.41: Factor loading for 31 terms using an EFA for two factors with Promax rotation for Image 10.

	PA1	PA2	h2	u2	com
vis10.appealing.	0.36	0.58	0.79	0.21	1.7
vis10.artistic.	-0.12	0.85	0.59	0.41	1.0
vis10.attractive.	0.34	0.58	0.75	0.25	1.6
vis10.balanced.	0.77	0.04	0.65	0.35	1.0
vis10.beautiful.	0.34	0.54	0.69	0.31	1.7
vis10.clean.	0.92	-0.21	0.60	0.40	1.1
vis10.cluttered.	0.55	-0.09	0.24	0.76	1.1
vis10.colorHarmonious.	0.46	0.19	0.38	0.62	1.3
vis10.creative.	0.02	0.72	0.54	0.46	1.0
vis10.delightful.	0.51	0.36	0.67	0.33	1.8
vis10.elegant.	0.62	0.28	0.71	0.29	1.4
vis10.engaging.	0.43	0.38	0.58	0.42	2.0
vis10.enjoyable.	0.38	0.55	0.76	0.24	1.8
vis10.exciting.	0.11	0.72	0.65	0.35	1.0
vis10.fascinating.	0.05	0.67	0.50	0.50	1.0
vis10.harmonious.	0.64	0.20	0.65	0.35	1.2
vis10.interesting.	0.03	0.67	0.48	0.52	1.0
vis10.inviting.	0.68	0.14	0.64	0.36	1.1
vis10.likable.	0.45	0.47	0.74	0.26	2.0
vis10.lovely.	0.58	0.28	0.66	0.34	1.4
vis10.motivating.	0.52	0.30	0.60	0.40	1.6
vis10.nice.	0.57	0.33	0.72	0.28	1.6
vis10.organized.	0.99	-0.31	0.62	0.38	1.2
vis10.pleasing.	0.49	0.44	0.77	0.23	2.0
vis10.pretty.	0.22	0.65	0.68	0.32	1.2
vis10.professional.	0.70	-0.06	0.43	0.57	1.0
vis10.provoking.	-0.27	0.58	0.17	0.83	1.4
vis10.satisfying.	0.44	0.46	0.72	0.28	2.0
vis10.sophisticated.	0.54	0.13	0.41	0.59	1.1
vis10.tasteful.	0.54	0.31	0.64	0.36	1.6
vis10.wellDesigned.	0.85	-0.07	0.63	0.37	1.0

Table B.42: Factor loading for 31 terms using an EFA for two factors with Varimax rotation for Image 11.

	PA1	PA2	h2	u2	com
vis11.appealing.	0.62	0.58	0.72	0.28	2.0
vis11.artistic.	0.70	0.21	0.53	0.47	1.2
vis11.attractive.	0.69	0.50	0.73	0.27	1.8
vis11.balanced.	0.33	0.72	0.63	0.37	1.4
vis11.beautiful.	0.64	0.55	0.72	0.28	2.0
vis11.clean.	0.21	0.82	0.72	0.29	1.1
vis11.cluttered.	0.05	0.25	0.06	0.94	1.1
vis11.colorHarmonious.	0.41	0.31	0.26	0.74	1.9
vis11.creative.	0.74	0.18	0.58	0.42	1.1
vis11.delightful.	0.63	0.58	0.74	0.26	2.0
vis11.elegant.	0.36	0.72	0.65	0.35	1.5
vis11.engaging.	0.73	0.39	0.68	0.32	1.5
vis11.enjoyable.	0.68	0.53	0.73	0.27	1.9
vis11.exciting.	0.79	0.37	0.76	0.24	1.4
vis11.fascinating.	0.73	0.29	0.62	0.38	1.3
vis11.harmonious.	0.48	0.61	0.61	0.39	1.9
vis11.interesting.	0.76	0.23	0.63	0.37	1.2
vis11.inviting.	0.55	0.63	0.70	0.30	2.0
vis11.likable.	0.61	0.59	0.72	0.28	2.0
vis11.lovely.	0.62	0.58	0.73	0.27	2.0
vis11.motivating.	0.55	0.56	0.61	0.39	2.0
vis11.nice.	0.63	0.55	0.71	0.29	2.0
vis11.organized.	0.17	0.75	0.60	0.40	1.1
vis11.pleasing.	0.61	0.62	0.75	0.25	2.0
vis11.pretty.	0.70	0.48	0.72	0.28	1.8
vis11.professional.	0.11	0.65	0.43	0.57	1.1
vis11.provoking.	0.55	0.01	0.30	0.70	1.0
vis11.satisfying.	0.56	0.65	0.74	0.26	2.0
vis11.sophisticated.	0.31	0.59	0.45	0.55	1.5
vis11.tasteful.	0.56	0.60	0.67	0.33	2.0
vis11.wellDesigned.	0.37	0.71	0.64	0.36	1.5

Table B.43: Factor loading for 31 terms using an EFA for two factors with Promax rotation for Image 11.

	PA1	PA2	h2	u2	com
vis11.appealing.	0.50	0.41	0.72	0.28	1.9
vis11.artistic.	0.82	-0.13	0.53	0.47	1.1
vis11.attractive.	0.64	0.26	0.73	0.27	1.3
vis11.balanced.	0.03	0.78	0.63	0.37	1.0
vis11.beautiful.	0.54	0.37	0.72	0.28	1.8
vis11.clean.	-0.19	0.97	0.72	0.29	1.1
vis11.cluttered.	-0.07	0.30	0.06	0.94	1.1
vis11.colorHarmonious.	0.37	0.18	0.26	0.74	1.4
vis11.creative.	0.89	-0.19	0.58	0.42	1.1
vis11.delightful.	0.51	0.41	0.74	0.26	1.9
vis11.elegant.	0.06	0.76	0.65	0.35	1.0
vis11.engaging.	0.75	0.10	0.68	0.32	1.0
vis11.enjoyable.	0.60	0.31	0.73	0.27	1.5
vis11.exciting.	0.84	0.04	0.76	0.24	1.0
vis11.fascinating.	0.81	-0.03	0.62	0.38	1.0
vis11.harmonious.	0.29	0.54	0.61	0.39	1.5
vis11.interesting.	0.89	-0.14	0.63	0.37	1.0
vis11.inviting.	0.38	0.52	0.70	0.30	1.8
vis11.likable.	0.48	0.43	0.72	0.28	2.0
vis11.lovely.	0.50	0.42	0.73	0.27	1.9
vis11.motivating.	0.41	0.43	0.61	0.39	2.0
vis11.nice.	0.53	0.37	0.71	0.29	1.8
vis11.organized.	-0.20	0.91	0.60	0.40	1.1
vis11.pleasing.	0.46	0.47	0.75	0.25	2.0
vis11.pretty.	0.66	0.23	0.72	0.28	1.2
vis11.professional.	-0.22	0.80	0.43	0.57	1.2
vis11.provoking.	0.73	-0.31	0.30	0.70	1.3
vis11.satisfying.	0.38	0.54	0.74	0.26	1.8
vis11.sophisticated.	0.07	0.62	0.45	0.55	1.0
vis11.tasteful.	0.40	0.48	0.67	0.33	1.9
vis11.wellDesigned.	0.09	0.74	0.64	0.36	1.0

Table B.44: Factor loading for 31 terms using an EFA for two factors with Varimax rotation for Image 12.

	PA1	PA2	h2	u2	com
vis12.appealing.	0.69	0.53	0.77	0.23	1.9
vis12.artistic.	0.84	0.04	0.70	0.30	1.0
vis12.attractive.	0.70	0.51	0.76	0.24	1.8
vis12.balanced.	0.36	0.64	0.54	0.46	1.6
vis12.beautiful.	0.75	0.42	0.74	0.26	1.6
vis12.clean.	0.36	0.72	0.65	0.35	1.5
vis12.cluttered.	0.09	-0.21	0.05	0.95	1.4
vis12.colorHarmonious.	0.52	0.34	0.38	0.62	1.7
vis12.creative.	0.75	0.06	0.57	0.43	1.0
vis12.delightful.	0.76	0.44	0.77	0.23	1.6
vis12.elegant.	0.60	0.54	0.65	0.35	2.0
vis12.engaging.	0.64	0.42	0.59	0.41	1.7
vis12.enjoyable.	0.73	0.49	0.77	0.23	1.7
vis12.exciting.	0.71	0.33	0.62	0.38	1.4
vis12.fascinating.	0.74	0.29	0.64	0.36	1.3
vis12.harmonious.	0.58	0.56	0.65	0.35	2.0
vis12.interesting.	0.68	0.30	0.56	0.44	1.4
vis12.inviting.	0.61	0.48	0.60	0.40	1.9
vis12.likable.	0.74	0.49	0.79	0.21	1.7
vis12.lovely.	0.73	0.46	0.74	0.26	1.7
vis12.motivating.	0.60	0.39	0.51	0.49	1.7
vis12.nice.	0.71	0.42	0.68	0.32	1.6
vis12.organized.	0.25	0.80	0.70	0.30	1.2
vis12.pleasing.	0.74	0.48	0.78	0.22	1.7
vis12.pretty.	0.76	0.39	0.74	0.26	1.5
vis12.professional.	0.32	0.72	0.62	0.38	1.4
vis12.provoking.	0.42	-0.02	0.17	0.83	1.0
vis12.satisfying.	0.70	0.52	0.76	0.24	1.9
vis12.sophisticated.	0.59	0.47	0.57	0.44	1.9
vis12.tasteful.	0.59	0.47	0.58	0.42	1.9
vis12.wellDesigned.	0.57	0.61	0.69	0.31	2.0

Table B.45: Factor loading for 31 terms using an EFA for two factors with Promax rotation for Image 12.

	PA1	PA2	h2	u2	com
vis12.appealing.	0.62	0.33	0.77	0.23	1.5
vis12.artistic.	1.01	-0.34	0.70	0.30	1.2
vis12.attractive.	0.64	0.30	0.76	0.24	1.4
vis12.balanced.	0.16	0.62	0.54	0.46	1.1
vis12.beautiful.	0.74	0.17	0.74	0.26	1.1
vis12.clean.	0.13	0.72	0.65	0.35	1.1
vis12.cluttered.	0.21	-0.30	0.05	0.95	1.8
vis12.colorHarmonious.	0.49	0.18	0.38	0.62	1.3
vis12.creative.	0.90	-0.27	0.57	0.43	1.2
vis12.delightful.	0.74	0.19	0.77	0.23	1.1
vis12.elegant.	0.51	0.38	0.65	0.35	1.8
vis12.engaging.	0.60	0.22	0.59	0.41	1.3
vis12.enjoyable.	0.69	0.26	0.77	0.23	1.3
vis12.exciting.	0.74	0.07	0.62	0.38	1.0
vis12.fascinating.	0.79	0.02	0.64	0.36	1.0
vis12.harmonious.	0.47	0.42	0.65	0.35	2.0
vis12.interesting.	0.71	0.05	0.56	0.44	1.0
vis12.inviting.	0.54	0.30	0.60	0.40	1.6
vis12.likable.	0.70	0.26	0.79	0.21	1.3
vis12.lovely.	0.70	0.22	0.74	0.26	1.2
vis12.motivating.	0.57	0.19	0.51	0.49	1.2
vis12.nice.	0.69	0.19	0.68	0.32	1.1
vis12.organized.	-0.04	0.87	0.70	0.30	1.0
vis12.pleasing.	0.70	0.25	0.78	0.22	1.2
vis12.pretty.	0.77	0.13	0.74	0.26	1.1
vis12.professional.	0.08	0.74	0.62	0.38	1.0
vis12.provoking.	0.52	-0.22	0.17	0.83	1.3
vis12.satisfying.	0.63	0.32	0.76	0.24	1.5
vis12.sophisticated.	0.52	0.30	0.57	0.44	1.6
vis12.tasteful.	0.53	0.30	0.58	0.42	1.6
vis12.wellDesigned.	0.43	0.49	0.69	0.31	2.0

Table B.46: Factor loading for 31 terms using an EFA for two factors with Varimax rotation for Image 13.

	PA1	PA2	h2	u2	com
vis13.appealing.	0.67	0.57	0.78	0.22	2.0
vis13.artistic.	0.71	0.03	0.51	0.49	1.0
vis13.attractive.	0.66	0.54	0.73	0.27	1.9
vis13.balanced.	0.24	0.77	0.65	0.35	1.2
vis13.beautiful.	0.70	0.39	0.64	0.36	1.6
vis13.clean.	0.22	0.72	0.56	0.44	1.2
vis13.cluttered.	0.04	0.14	0.02	0.98	1.2
vis13.colorHarmonious.	0.31	0.29	0.18	0.82	2.0
vis13.creative.	0.65	0.13	0.44	0.56	1.1
vis13.delightful.	0.67	0.59	0.79	0.21	2.0
vis13.elegant.	0.56	0.55	0.62	0.38	2.0
vis13.engaging.	0.62	0.51	0.65	0.36	1.9
vis13.enjoyable.	0.66	0.51	0.70	0.30	1.9
vis13.exciting.	0.73	0.36	0.66	0.34	1.5
vis13.fascinating.	0.74	0.30	0.64	0.36	1.3
vis13.harmonious.	0.42	0.69	0.65	0.35	1.6
vis13.interesting.	0.70	0.32	0.59	0.41	1.4
vis13.inviting.	0.56	0.64	0.72	0.28	2.0
vis13.likable.	0.65	0.58	0.76	0.24	2.0
vis13.lovely.	0.72	0.42	0.71	0.29	1.6
vis13.motivating.	0.64	0.53	0.69	0.31	1.9
vis13.nice.	0.72	0.53	0.80	0.20	1.8
vis13.organized.	0.19	0.79	0.66	0.34	1.1
vis13.pleasing.	0.70	0.52	0.76	0.24	1.8
vis13.pretty.	0.79	0.35	0.75	0.25	1.4
vis13.professional.	0.32	0.66	0.55	0.46	1.4
vis13.provoking.	0.20	0.11	0.05	0.95	1.5
vis13.satisfying.	0.67	0.53	0.73	0.27	1.9
vis13.sophisticated.	0.57	0.42	0.51	0.50	1.8
vis13.tasteful.	0.59	0.56	0.66	0.34	2.0
vis13.wellDesigned.	0.43	0.75	0.74	0.26	1.6

Table B.47: Factor loading for 31 terms using an EFA for two factors with Promax rotation for Image 13.

	PA1	PA2	h2	u2	com
vis13.appealing.	0.57	0.37	0.78	0.22	1.7
vis13.artistic.	0.96	-0.41	0.51	0.49	1.3
vis13.attractive.	0.58	0.33	0.73	0.27	1.6
vis13.balanced.	-0.14	0.91	0.65	0.35	1.0
vis13.beautiful.	0.72	0.10	0.64	0.36	1.0
vis13.clean.	-0.15	0.85	0.56	0.44	1.1
vis13.cluttered.	-0.03	0.16	0.02	0.98	1.1
vis13.colorHarmonious.	0.25	0.20	0.18	0.82	1.9
vis13.creative.	0.82	-0.23	0.44	0.56	1.2
vis13.delightful.	0.56	0.39	0.79	0.21	1.8
vis13.elegant.	0.43	0.41	0.62	0.38	2.0
vis13.engaging.	0.53	0.32	0.65	0.36	1.6
vis13.enjoyable.	0.59	0.29	0.70	0.30	1.5
vis13.exciting.	0.78	0.04	0.66	0.34	1.0
vis13.fascinating.	0.84	-0.05	0.64	0.36	1.0
vis13.harmonious.	0.15	0.69	0.65	0.35	1.1
vis13.interesting.	0.77	0.00	0.59	0.41	1.0
vis13.inviting.	0.37	0.53	0.72	0.28	1.8
vis13.likable.	0.53	0.40	0.76	0.24	1.8
vis13.lovely.	0.74	0.13	0.71	0.29	1.1
vis13.motivating.	0.55	0.33	0.69	0.31	1.6
vis13.nice.	0.67	0.27	0.80	0.20	1.3
vis13.organized.	-0.22	0.96	0.66	0.34	1.1
vis13.pleasing.	0.65	0.27	0.76	0.24	1.3
vis13.pretty.	0.88	-0.02	0.75	0.25	1.0
vis13.professional.	0.03	0.71	0.55	0.46	1.0
vis13.provoking.	0.21	0.02	0.05	0.95	1.0
vis13.satisfying.	0.60	0.31	0.73	0.27	1.5
vis13.sophisticated.	0.53	0.22	0.51	0.50	1.3
vis13.tasteful.	0.47	0.40	0.66	0.34	1.9
vis13.wellDesigned.	0.13	0.76	0.74	0.26	1.1

Table B.48: Factor loading for 31 terms using an EFA for two factors with Varimax rotation for Image 14.

	PA1	PA2	h2	u2	com
vis14.appealing.	0.73	0.42	0.71	0.29	1.6
vis14.artistic.	0.33	0.51	0.36	0.64	1.7
vis14.attractive.	0.77	0.40	0.75	0.25	1.5
vis14.balanced.	0.37	0.67	0.58	0.42	1.6
vis14.beautiful.	0.71	0.42	0.69	0.31	1.6
vis14.clean.	0.35	0.72	0.64	0.36	1.4
vis14.cluttered.	0.08	-0.02	0.01	0.99	1.2
vis14.colorHarmonious.	0.36	0.56	0.45	0.55	1.7
vis14.creative.	0.32	0.46	0.31	0.69	1.8
vis14.delightful.	0.80	0.36	0.78	0.22	1.4
vis14.elegant.	0.54	0.50	0.55	0.45	2.0
vis14.engaging.	0.48	0.56	0.55	0.45	2.0
vis14.enjoyable.	0.78	0.41	0.77	0.23	1.5
vis14.exciting.	0.64	0.41	0.58	0.42	1.7
vis14.fascinating.	0.41	0.60	0.52	0.48	1.8
vis14.harmonious.	0.51	0.56	0.57	0.43	2.0
vis14.interesting.	0.32	0.52	0.38	0.62	1.7
vis14.inviting.	0.71	0.34	0.62	0.38	1.4
vis14.likable.	0.74	0.48	0.77	0.23	1.7
vis14.lovely.	0.75	0.35	0.69	0.31	1.4
vis14.motivating.	0.64	0.42	0.59	0.41	1.7
vis14.nice.	0.69	0.47	0.69	0.31	1.8
vis14.organized.	0.15	0.79	0.65	0.35	1.1
vis14.pleasing.	0.80	0.38	0.78	0.22	1.4
vis14.pretty.	0.78	0.42	0.78	0.22	1.5
vis14.professional.	0.13	0.81	0.67	0.33	1.1
vis14.provoking.	0.20	0.10	0.05	0.95	1.5
vis14.satisfying.	0.70	0.43	0.68	0.32	1.7
vis14.sophisticated.	0.43	0.59	0.53	0.47	1.8
vis14.tasteful.	0.59	0.49	0.59	0.41	1.9
vis14.wellDesigned.	0.21	0.76	0.62	0.38	1.2

Table B.49: Factor loading for 31 terms using an EFA for two factors with Promax rotation for Image 14.

	PA1	PA2	h2	u2	com
vis14.appealing.	0.73	0.15	0.71	0.29	1.1
vis14.artistic.	0.16	0.48	0.36	0.64	1.2
vis14.attractive.	0.79	0.10	0.75	0.25	1.0
vis14.balanced.	0.12	0.67	0.58	0.42	1.1
vis14.beautiful.	0.71	0.16	0.69	0.31	1.1
vis14.clean.	0.07	0.75	0.64	0.36	1.0
vis14.cluttered.	0.12	-0.07	0.01	0.99	1.7
vis14.colorHarmonious.	0.17	0.54	0.45	0.55	1.2
vis14.creative.	0.17	0.42	0.31	0.69	1.3
vis14.delightful.	0.86	0.03	0.78	0.22	1.0
vis14.elegant.	0.44	0.35	0.55	0.45	1.9
vis14.engaging.	0.34	0.46	0.55	0.45	1.8
vis14.enjoyable.	0.81	0.10	0.77	0.23	1.0
vis14.exciting.	0.62	0.18	0.58	0.42	1.2
vis14.fascinating.	0.22	0.55	0.52	0.48	1.3
vis14.harmonious.	0.38	0.44	0.57	0.43	2.0
vis14.interesting.	0.15	0.50	0.38	0.62	1.2
vis14.inviting.	0.76	0.05	0.62	0.38	1.0
vis14.likable.	0.71	0.22	0.77	0.23	1.2
vis14.lovely.	0.80	0.05	0.69	0.31	1.0
vis14.motivating.	0.62	0.20	0.59	0.41	1.2
vis14.nice.	0.65	0.23	0.69	0.31	1.2
vis14.organized.	-0.23	0.95	0.65	0.35	1.1
vis14.pleasing.	0.84	0.05	0.78	0.22	1.0
vis14.pretty.	0.80	0.12	0.78	0.22	1.0
vis14.professional.	-0.26	0.98	0.67	0.33	1.1
vis14.provoking.	0.21	0.02	0.05	0.95	1.0
vis14.satisfying.	0.69	0.18	0.68	0.32	1.1
vis14.sophisticated.	0.25	0.53	0.53	0.47	1.4
vis14.tasteful.	0.51	0.32	0.59	0.41	1.7
vis14.wellDesigned.	-0.13	0.87	0.62	0.38	1.0

Table B.50: Factor loading for 31 terms using an EFA for two factors with Varimax rotation for Image 15.

	PA1	PA2	h2	u2	com
vis15.appealing.	0.68	0.59	0.81	0.19	2.0
vis15.artistic.	0.26	0.69	0.55	0.45	1.3
vis15.attractive.	0.54	0.66	0.73	0.27	1.9
vis15.balanced.	0.76	0.28	0.66	0.34	1.3
vis15.beautiful.	0.54	0.65	0.71	0.29	1.9
vis15.clean.	0.75	0.20	0.60	0.40	1.1
vis15.cluttered.	0.24	0.09	0.07	0.93	1.3
vis15.colorHarmonious.	0.49	0.41	0.41	0.59	1.9
vis15.creative.	0.19	0.74	0.58	0.42	1.1
vis15.delightful.	0.66	0.59	0.78	0.22	2.0
vis15.elegant.	0.64	0.48	0.64	0.36	1.8
vis15.engaging.	0.49	0.65	0.66	0.34	1.9
vis15.enjoyable.	0.60	0.65	0.79	0.21	2.0
vis15.exciting.	0.44	0.68	0.66	0.34	1.7
vis15.fascinating.	0.28	0.74	0.62	0.38	1.3
vis15.harmonious.	0.76	0.38	0.72	0.28	1.5
vis15.interesting.	0.37	0.68	0.60	0.40	1.5
vis15.inviting.	0.56	0.61	0.69	0.31	2.0
vis15.likable.	0.63	0.63	0.79	0.21	2.0
vis15.lovely.	0.58	0.58	0.68	0.32	2.0
vis15.motivating.	0.48	0.61	0.60	0.40	1.9
vis15.nice.	0.67	0.59	0.80	0.21	2.0
vis15.organized.	0.83	0.10	0.69	0.31	1.0
vis15.pleasing.	0.67	0.57	0.77	0.23	2.0
vis15.pretty.	0.57	0.64	0.73	0.27	2.0
vis15.professional.	0.66	0.18	0.47	0.53	1.1
vis15.provoking.	-0.04	0.56	0.32	0.69	1.0
vis15.satisfying.	0.68	0.51	0.72	0.28	1.9
vis15.sophisticated.	0.45	0.55	0.51	0.49	1.9
vis15.tasteful.	0.53	0.64	0.69	0.31	1.9
vis15.wellDesigned.	0.72	0.36	0.65	0.36	1.5

Table B.51: Factor loading for 31 terms using an EFA for two factors with Promax rotation for Image 15.

	PA1	PA2	h2	u2	com
vis15.appealing.	0.57	0.40	0.81	0.19	1.8
vis15.artistic.	-0.06	0.78	0.55	0.45	1.0
vis15.attractive.	0.34	0.57	0.73	0.27	1.6
vis15.balanced.	0.86	-0.07	0.66	0.34	1.0
vis15.beautiful.	0.34	0.56	0.71	0.29	1.7
vis15.clean.	0.90	-0.18	0.60	0.40	1.1
vis15.cluttered.	0.28	-0.03	0.07	0.93	1.0
vis15.colorHarmonious.	0.41	0.27	0.41	0.59	1.7
vis15.creative.	-0.19	0.89	0.58	0.42	1.1
vis15.delightful.	0.53	0.41	0.78	0.22	1.9
vis15.elegant.	0.59	0.26	0.64	0.36	1.4
vis15.engaging.	0.28	0.59	0.66	0.34	1.4
vis15.enjoyable.	0.42	0.53	0.79	0.21	1.9
vis15.exciting.	0.19	0.66	0.66	0.34	1.2
vis15.fascinating.	-0.07	0.84	0.62	0.38	1.0
vis15.harmonious.	0.79	0.07	0.72	0.28	1.0
vis15.interesting.	0.08	0.71	0.60	0.40	1.0
vis15.inviting.	0.40	0.49	0.69	0.31	1.9
vis15.likable.	0.48	0.48	0.79	0.21	2.0
vis15.lovely.	0.44	0.45	0.68	0.32	2.0
vis15.motivating.	0.29	0.54	0.60	0.40	1.5
vis15.nice.	0.55	0.41	0.80	0.21	1.9
vis15.organized.	1.06	-0.36	0.69	0.31	1.2
vis15.pleasing.	0.56	0.38	0.77	0.23	1.8
vis15.pretty.	0.38	0.53	0.73	0.27	1.8
vis15.professional.	0.79	-0.15	0.47	0.53	1.1
vis15.provoking.	-0.40	0.79	0.32	0.69	1.5
vis15.satisfying.	0.61	0.29	0.72	0.28	1.4
vis15.sophisticated.	0.28	0.48	0.51	0.49	1.6
vis15.tasteful.	0.34	0.55	0.69	0.31	1.7
vis15.wellDesigned.	0.76	0.06	0.65	0.36	1.0

Bibliography

[1] Data visualization society. Global non-profit organization for data visualization practitioners and enthusiasts, url: www.datavisualizationsociety.org. Last accessed: March 2023.

[2] Icons8. Website and icons database, url: icons8.com. Last accessed: March 2023.

[3] K. Ajani, E. Lee, C. Xiong, C. N. Knaflic, W. Kemper, and S. Franconeri. Declutter and focus: Empirically evaluating design guidelines for effective data communication. *IEEE Trans Vis Comput Graph*, p. 3351–3364, Oct. 2022. doi: 10/gn984r

[4] M. Amadasun and R. King. Textural features corresponding to textural properties. *IEEE Trans Syst Man Cybern*, 19(5):1264–1274, 1989. doi: 10/b48tfv

[5] B. Bach, P. Dragicevic, S. Huron, P. Isenberg, Y. Jansen, C. Perin, A. Spritzer, R. Vuillemot, W. Willett, and T. Isenberg. Illustrative data graphics in 18^{th}–19^{th} century style: A case study. In *Posters of IEEE VIS*, 2013. https://hal.inria.fr/hal-00849079.

[6] M. Balzer and O. Deussen. Voronoi treemaps. In *Proc. InfoVis*, pp. 49–56. IEEE Comp. Soc., Los Alamitos, 2005. doi: 10/b6xbtv

[7] P. Barla, S. Breslav, J. Thollot, F. Sillion, and L. Markosian. Stroke pattern analysis and synthesis. *Comput Graph Forum*, 25(3):663–671, 2006. doi: 10/cv8vz7

[8] M. S. Bartlett. A note on the multiplying factors for various χ^2 approximations. *J R Stat Soc B*, 16(2):296–298, 1954.

[9] S. Bateman, R. L. Mandryk, C. Gutwin, A. Genest, D. McDine, and C. Brooks. Useful junk? The effects of visual embellishment on comprehension and memorability of charts. In *Proc. CHI*, pp. 2573–2582. ACM, New York, 2010. doi: 10/crhdc4

[10] F. Beck, M. Burch, and S. Diehl. Towards an aesthetic dimensions framework for dynamic graph visualisations. In *Proc. IV*, pp. 592–597. IEEE Comp. Soc., Los Alamitos, 2009. doi: 10/dfx59n

[11] B. Behrendt, P. Berg, O. Beuing, B. Preim, and S. Saalfeld. Explorative blood flow visualization using dynamic line filtering based on surface features. *Comput Graph Forum*, 37(3):183–194, June 2018. doi: 10/gdw92f

[12] C. Bennett, J. Ryall, L. Spalteholz, and A. Gooch. The aesthetics of graph visualization. In *Proc. CAe*. EG Assoc., Goslar, 2007. doi: 10/gn9kwr

[13] M. Bentvelzen, J. Niess, M. P. Woźniak, and P. W. Woźniak. The development and validation of the technology-supported reflection inventory. In *Proc. CHI*, pp. 366:1–366:8. ACM, New York, 2021. doi: 10/gksms5

[14] J. Bertin. *Sémiologie Graphique*. Éd. de l'EHESS, Paris, 3rd ed., 1998. url: editions.ehess.fr/ouvrages/ouvrage/semiologie-graphique/.

[15] J. Bertin. *Semiology of Graphics: Diagrams, Networks, Maps*. Esri Press, Redlands, 2011. url: esri.com/en-us/esri-press/browse/semiology-of-graphics-diagrams-networks-maps.

[16] L. Besançon and P. Dragicevic. The continued prevalence of dichotomous inferences at CHI. In *CHI Extended Abstracts*, pp. alt14:1–alt14:11. ACM, New York, 2019. doi: 10/ghs8mh

[17] T. Blascheck, L. Besançon, A. Bezerianos, B. Lee, A. Islam, T. He, and P. Isenberg. Studies of part-to-whole glanceable visualizations on smartwatch faces. In *Proc. PacificVis*, pp. 187–196. IEEE Comp. Soc., Los Alamitos, 2023. doi: 10/gsnjqj

[18] J. Blijlevens, C. Thurgood, P. Hekkert, L.-L. Chen, H. Leder, and T. Whitfield. The aesthetic pleasure in design scale: The development of a scale to measure aesthetic pleasure for designed artifacts. *Psychol Aesthet Creat Arts*, 11(1):86–98, Feb. 2017. doi: 10/f9w2bv

[19] J. F. Blinn and M. E. Newell. Texture and reflection in computer generated images. *Commun ACM*, 19(10):542–547, 1976. doi: 10/dct2v6

[20] G. O. Boateng, T. B. Neilands, E. A. Frongillo, H. R. Melgar-Quiñonez, and S. L. Young. Best practices for developing and validating scales for health, social, and behavioral research: A primer. *Front Public Health*, 6:149:1–149:18, June 2018. doi: 10/gfsqzs

[21] A. Boomsma and J. J. Hoogland. The robustness of LISREL modeling revisited. In R. Cudeck, S. du Toit, and D. Sörbom, eds., *Structural Equation Models: Present and Future. A Festschrift in Honor of Karl Jöreskog*, pp. 139–168. Scientific Software International, Lincolnwood, 2001.

[22] R. Borgo, J. Kehrer, D. H. Chung, E. Maguire, R. S. Laramee, H. Hauser, M. Ward, and M. Chen. Glyph-based visualization: Foundations, design guidelines, techniques and applications. In *Eurographics State of the Art Reports*, pp. 39–63. EG Assoc., Goslar, 2013. doi: 10/f3sttv

[23] M. A. Borkin, Z. Bylinskii, N. W. Kim, C. M. Bainbridge, C. S. Yeh, D. Borkin, H. Pfister, and A. Oliva. Beyond memorability: Visualization recognition and recall. *IEEE Trans Vis Comput Graph*, 22(1):519–528, 2016. doi: 10/ggf5r3

[24] M. A. Borkin, A. A. Vo, Z. Bylinskii, P. Isola, S. Sunkavalli, A. Oliva, and H. Pfister. What makes a visualization memorable? *IEEE Trans Vis Comput Graph*, 19(12):2306–2315, 2013. doi: 10/f5h3pd

[25] D. Borland and R. M. Taylor, II. Rainbow color map (still) considered harmful. *IEEE Comput Graph Appl*, 27(2):14–17, 2007. doi: 10/cf7nms

[26] Braille Authority of North America and Canadian Braille Authority. *Guidelines and Standards for Tactile Graphics*. Braille Authority of North America, 2022. Accessed: September 2024.

[27] R. Brath. Dashed and patterned lines for visualization (aka 1D texture). richardbrath.wordpress.com/2021/05/27/dashed-and-patterned-lines-for-visualization-aka-1d-texture/, 2021. Accessed: March 2024.

[28] R. Brath, M. Peters, and R. Senior. Visualization for communication: The importance of aesthetic sizzle. In *Proc. IV*, pp. 724–729. IEEE Comp. Soc., Los Alamitos, 2005. doi: 10/dn6ftk

[29] C. Brewer. *Designing Better Maps: A Guide for GIS Users*. Esri Press, Redlands, 2016. urn: urn:oclc:record:1310734651.

[30] W. C. Brinton. *Graphic Methods for Presenting Facts*. The Engineering Magazine Company, New York, 1914. urn: urn:oclc:record:1045528209.

[31] W. C. Brinton. *Graphic Presentation*. Brinton Assoc., New York, 1939. urn: urn:oclc:record:1045601113.

[32] P. Brodatz. *Textures: A Photographic Album for Artists and Designers*. Dover Publications, New York, 1966. urn: urn:oclc:record:1225861155.

[33] H. Buchholz and J. Döllner. View-dependent rendering of multiresolution texture-atlases. In *Proc. Visualization*, pp. 215–222. IEEE Comp. Soc., Los Alamitos, 2005. doi: 10/bcn554

[34] T. Büring, J. Gerken, and H. Reiterer. User interaction with scatterplots on small screens – A comparative evaluation of geometric-semantic zoom and fisheye distortion. *IEEE Trans Vis Comput Graph*, 12(5):829–836, Sept. 2006. doi: 10/fcndh7

[35] A. Burns, C. Xiong, S. Franconeri, A. Cairo, and N. Mahyar. Designing with pictographs: Envision topics without sacrificing understanding. *IEEE Trans Vis Comput Graph*, 28(12):4515–4530, 2022. doi: 10/gnswqz

[36] L. Byron and M. Wattenberg. Stacked graphs – Geometry & aesthetics. *IEEE Trans Vis Comput Graph*, 14(6):1245–1252, Nov. 2008. doi: 10/dq8747

[37] A.-F. Cabouat, T. He, P. Isenberg, and T. Isenberg. PREVis: Perceived readability evaluation for visualizations. *IEEE Trans Vis Comput Graph*, 31, 2025. doi: 10/njnz

[38] B. Cabral and L. C. Leedom. Imaging vector fields using line integral convolution. In *Proc. SIGGRAPH*, pp. 263–270. ACM, New York, 1993. doi: 10/drnq5c

[39] J. Caivano. Towards an order system for visual texture. *Lang Des*, 2(1):59–84, 1994. Online: `colorysemiotica.files.wordpress.com/2015/11/1994lang.pdf`.

[40] J. L. Caivano. Visual texture as a semiotic system. *Semiotica*, 80(3/4):239–252, 1990. doi: 10/c9tqj3

[41] S. Card, J. Mackinlay, and B. Shneiderman. *Readings in Information Visualization: Using Vision to Think*. Interactive Technologies. Elsevier Science, 1999.

[42] M. S. T. Carpendale. Considering visual variables as a basis for information visualisation. Technical Report 2001-693, University of Calgary, Canada, 2003. hdl: 1880/45758.

[43] E. Catmull. *A Subdivision Algorithm for Computer Display of Curved Surfaces*. PhD thesis, University of Utah, Salt Lake City, 1974. Online: `collections.lib.utah.edu/ark:/87278/s6cg2j21`.

[44] N. Cawthon and A. Vande Moere. A conceptual model for evaluating aesthetic effect within the user experience of information visualization. In *Proc. IV*, pp. 374–382. IEEE Comp. Soc., Los Alamitos, 2006. doi: 10/dfdfn9

[45] N. Cawthon and A. Vande Moere. The effect of aesthetic on the usability of data visualization. In *Proc. IV*, pp. 637–648. IEEE Comp. Soc., Los Alamitos, 2007. doi: 10/c8v6s8

[46] G. Y.-Y. Chan, P. Xu, Z. Dai, and L. Ren. ViBr: Visualizing bipartite relations at scale with the minimum description length principle. *IEEE Trans Vis Comput Graph*, 25(1):321–330, 2019. doi: 10/gnd8bg

[47] C. Chen. Top 10 unsolved information visualization problems. *IEEE Comput Graph Appl*, 25(4):12–16, July-Aug. 2005. doi: 10/dpzn25

[48] M. Chen and L. Floridi. An analysis of information visualisation. *Synthese*, 190(16):3421–3438, 2013. doi: 10/gdxwgz

[49] S. Chen, N. Andrienko, G. Andrienko, J. Li, and X. Yuan. Co-bridges: Pair-wise visual connection and comparison for multi-item data streams. *IEEE Trans Vis Comput Graph*, 27(2):1612–1622, Feb. 2020. doi: 10/mzvm

[50] E. H.-H. Chi. *A framework for information visualization spreadsheets*. PhD thesis, University of Minnesota, Computer Science Dept. 136 Lind Hall 207 Church Street Minneapolis, MN, United States, 1999. doi: 10.5555/928672

[51] D. Child. *The Essentials of Factor Analysis*. Continuum International Publishing Group, London, 3rd ed., 2006.

[52] R. Y. Cho, V. Yang, and P. E. Hallett. Reliability and dimensionality of judgments of visually textured materials. *Percept Psychophys*, 62(4):735–752, 2000. doi: 10/c7q45j

[53] D. H. S. Chung, D. Archambault, R. Borgo, D. J. Edwards, R. S. Laramee, and M. Chen. How ordered is it? On the perceptual orderability of visual channels. *Comput Graph Forum*, 35(3):131–140, 2016. doi: 10/f8v3ps

[54] W. S. Cleveland and R. McGill. Graphical perception and graphical methods for analyzing scientific data. *Science*, 229(4716):828–833, 1985. doi: 10/fkhq59

[55] A. Cockburn, P. Dragicevic, L. Besançon, and C. Gutwin. Threats of a replication crisis in empirical computer science. *Commun. ACM*, 63(8):70–79, jul 2020. doi: 10/gjbnx4

[56] C. Collins, G. Penn, and S. Carpendale. Bubble Sets: Revealing set relations with isocontours over existing visualizations. *IEEE Trans Vis Comput Graph*, 15(6):1009–1016, Nov./Dec. 2009. doi: 10/c99shd

[57] M. contributors. Mozilla developer network web docs – svg tutorial: Patterns. `developer.mozilla.org/en-US/docs/Web/SVG/Tutorial/Patterns`, 2023. Accessed: June 2024.

[58] B. Cornelissen, D. Holten, A. Zaidman, L. Moonen, J. J. van Wijk, and A. van Deursen. Understanding execution traces using massive sequence and circular bundle views. In *Proc. ICPC*, pp. 49–58. IEEE Comp. Soc., Los Alamitos, 2007. doi: 10/bfhbtb

[59] J. Cresswell. *Oxford Dictionary of Word Origins*. Oxford University Press, 2010. doi: 10/gtn794

[60] G. Cumming. *Understanding the New Statistics: Effect Sizes, Confidence Intervals, and Meta-Analysis*. Routledge, New York, 2012. doi: 10/ggk6fr

[61] B. Dent, J. Torguson, and T. Hodler. *Cartography: Thematic Map Design*. McGraw-Hill, Boston, 2009. urn: urn:oclc:record:1280806442.

[62] R. F. DeVellis and C. T. Thorpe. *Scale Development: Theory and Applications*. Sage Publications, 5th ed., 2021.

[63] P. Dragicevic. Fair statistical communication in HCI. In J. Robertson and M. Kaptein, eds., *Modern Statistical Methods for HCI*, chap. 13, pp. 291–330. Springer, Cham, 2016. doi: 10/ggd8gc

[64] I. K. Duncan, S. Tingsheng, S. T. Perrault, and M. T. Gastner. Task-based effectiveness of interactive contiguous area cartograms. *IEEE Trans Vis Comput Graph*, 27(3):2136–2152, Mar. 2020. doi: 10/g7h7dr

[65] D. Dutton. *The Art Instinct: Beauty, Pleasure, and Human Evolution*. Oxford University Press, USA, 2009.

[66] F. Elavsky, C. Bennett, and D. Moritz. How accessible is my visualization? evaluating visualization accessibility with chartability. *Computer Graphics Forum*, 41(3):57–70, June 2022. doi: 10/g7h7gj

[67] C. Engel, E. F. Müller, and G. Weber. Tactile heatmaps: A novel visualisation technique for data analysis with tactile charts. In *Proceedings of the 14th PErvasive Technologies Related to Assistive Environments Conference*, PETRA '21, p. 16–25. Association for Computing Machinery, New York, NY, USA, 2021. doi: 10/gk9jhg

[68] C. Engel and G. Weber. Analysis of tactile chart design. In *Proceedings of the 10th International Conference on PErvasive Technologies Related to Assistive Environments*, PETRA '17, p. 197–200. Association for Computing Machinery, New York, NY, USA, 2017. doi: 10/g8q2w9

[69] C. Engel and G. Weber. *Improve the Accessibility of Tactile Charts*, p. 187–195. Springer International Publishing, 2017. doi: 10/g8q2w8

[70] C. Engel and G. Weber. User study: A detailed view on the effectiveness and design of tactile charts. In D. Lamas, F. Loizides, L. Nacke, H. Petrie, M. Winckler, and P. Zaphiris, eds., *Human-Computer Interaction – INTERACT 2019*, pp. 63–82. Springer International Publishing, Cham, 2019. doi: 10/g8q2xb

[71] L. R. Fabrigar and D. T. Wegener. *Exploratory Factor Analysis*. Oxford University Press, 2012. doi: 10/kjrw

[72] L. R. Fabrigar, D. T. Wegener, R. C. MacCallum, and E. J. Strahan. Evaluating the use of exploratory factor analysis in psychological research. *Psychol Methods*, 4(3):272–299, Sept. 1999. doi: 10/b2ztct

[73] M. FC, T. L. Davis, and ggplot2 authors. ggpattern: 'ggplot2' pattern geoms. GitHub repository, github.com/coolbutuseless/ggpattern, 2022.

[74] J. A. Gatto, A. W. Porter, and J. Selleck. *Exploring Visual Design*. Davis Publications, Worcester, 1978. urn: urn:oclc:record:1310593305.

[75] C. Giacovazzo. *Fundamentals of Crystallography*. Fundamentals of Crystallography. International Union of Crystallography, 1992.

[76] J. A. Gliem and R. R. Gliem. Calculating, interpreting, and reporting Cronbach's alpha reliability coefficient for Likert-type scales. In *Midwest Research-to-Practice Conference in Adult, Continuing, and Community Education*, pp. 82–88, 2003. https://hdl.handle.net/1805/344.

[77] P. Goffin, W. Willett, J.-D. Fekete, and P. Isenberg. Exploring the placement and design of word-scale visualizations. *IEEE Trans Vis Comput Graph*, 20(12):2291–2300, 2014. doi: 10/f6qjwg

[78] L. K. M. Graf and J. R. Landwehr. A dual-process perspective on fluency-based aesthetics: The pleasure-interest model of aesthetic liking. *Pers Social Psychol Rev*, 19(4):395–410, Nov. 2015. doi: 10/f7vsbz

[79] L. K. M. Graf and J. R. Landwehr. Aesthetic pleasure versus aesthetic interest: The two routes to aesthetic liking. *Front Psychol*, 8:15:1–15:15, Jan. 2017. doi: 10/f9pgt2

[80] J. F. Hair. *Multivariate Data Analysis*. Pearson, 7th ed., 2009.

[81] S. Haroz, R. Kosara, and S. L. Franconeri. Isotype visualization: Working memory, performance, and engagement with pictographs. In *Proc. CHI*, pp. 1191–1200. ACM, New York, 2015. doi: 10/gf65d5

[82] R. Harris. *Information Graphics: A Comprehensive Illustrated Reference*. Oxford University Press, 2000. urn: urn:oclc:record:1012107199.

[83] L. Harrison, K. Reinecke, and R. Chang. Infographic aesthetics: Designing for the first impression. In *Proc. CHI*, pp. 1187–1190. ACM, New York, 2015. doi: 10/gpj9nx

[84] M. Hassenzahl, M. Burmester, and F. Koller. AttrakDiff: Ein Fragebogen zur Messung wahrgenommener hedonischer und pragmatischer Qualität. In *Mensch & Computer*, pp. 187–196. Vieweg+Teubner, Wiesbaden, 2003. doi: 10/fzpnxd

[85] T. He, P. Isenberg, R. Dachselt, and T. Isenberg. BeauVis: A validated scale for measuring the aesthetic pleasure of visual representations. *IEEE Trans Vis Comput Graph*, 29(1):363–373, 2023. doi: 10/kt3n

[86] T. He, P. Isenberg, and T. Isenberg. Data embroidery with black-and-white textures. In *Proceedings of the alt.VIS Workshop (at IEEE VIS, 23 October, Melbourne, Australia)*, 2023.

[87] T. He, Y. Zhong, P. Isenberg, and T. Isenberg. Design characterization for black-and-white textures in visualization. *IEEE Trans Vis Comput Graph*, 30(1):1019–1029, 2024. doi: 10/gtkwg3

[88] C. G. Healey and J. T. Enns. Building perceptual textures to visualize multidimensional datasets. In *Proc. Visualization*, pp. 111–118. IEEE Comp. Soc., Los Alamitos, 1998. doi: 10/dz9223

[89] C. G. Healey and J. T. Enns. Perception and painting: A search for effective, engaging visualizations. *IEEE Comput Graph Appl*, 22(2):10–15, Mar.-Apr. 2002. doi: 10/cqbq7k

[90] J. J. Higgins. *An Introduction to Modern Nonparametric Statistics*. Brooks/Cole, Pacific Grove, 2004.

[91] L. Holloway, M. Butler, and K. Marriott. Tacticons: Designing 3d printed map icons for people who are blind or have low vision. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI '23. Association for Computing Machinery, New York, NY, USA, 2023. doi: 10/g8q2xn

[92] L. Holloway, K. Marriott, M. Butler, and S. Reinders. 3d printed maps and icons for inclusion: Testing in the wild by people who are blind or have low vision. In *Proceedings of the 21st International ACM SIGACCESS Conference on Computers and Accessibility*, ASSETS '19, p. 183–195. Association for Computing Machinery, New York, NY, USA, 2019. doi: 10/ghtqwg

[93] J. D. Hunter. Matplotlib: A 2D graphics environment. *Computing in Science & Engineering*, 9(3):90–95, 2007. doi: 10/gtkwgw

[94] T. Hurtut, P.-E. Landes, J. Thollot, Y. Gousseau, R. Drouillhet, and J.-F. Coeurjolly. Appearance-guided synthesis of element arrangements by example. In *Proc. NPAR*, pp. 51–60. ACM, New York, 2009. doi: 10/dfvq9v

[95] H. Hutchinson, W. Mackay, B. Westerlund, B. B. Bederson, A. Druin, C. Plaisant, M. Beaudouin-Lafon, S. Conversy, H. Evans, H. Hansen, N. Roussel, and B. Eiderbäck. Technology probes: Inspiring design for and with families. In *Proc. CHI*, pp. 17–24. ACM, New York, 2003. doi: 10/cjb9tx

[96] A. Inselberg. Multidimensional detective. In *Proc. InfoVis*, pp. 100–107. IEEE Comp. Soc., Los Alamitos, 1997. doi: 10/ccxx9x

[97] Instituto de Expansão Commercial. *Graficos Economico-Estatisticos*. Rio de Janeiro, Brazil, 1929. Online: archive.org/details/institutodeexpan1929mini/page/n65/mode/2up.

[98] Y. Jansen, P. Dragicevic, P. Isenberg, J. Alexander, A. Karnik, J. Kildal, S. Subramanian, and K. Hornbæk. Opportunities and challenges for data physicalization. In *Proc. CHI*, pp. 3227–3236. ACM, New York, 2015. doi: 10/gg9fw7

[99] B. Jenny, M. Heitzler, D. Singh, M. Farmakis-Serebryakova, J. C. Liu, and L. Hurni. Cartographic relief shading with neural networks. *IEEE Trans Vis Comput Graph*, 27(2):1225–1235, Feb. 2020. doi: 10/ghv58f

[100] S. Johnson, F. Samsel, G. Abram, D. Olson, A. J. Solis, B. Herman, P. J. Wolfram, C. Lenglet, and D. F. Keefe. Artifact-based rendering: Harnessing natural and traditional visual media for more expressive and engaging 3D visualizations. *IEEE Trans Vis Comput Graph*, 26(1):492–502, 2020. doi: 10/gghbxx

[101] H. F. Kaiser. An index of factorial simplicity. *Psychometrika*, 39(1):31–36, Mar. 1974. doi: 10/cdm

[102] N. W. Kim, S. C. Joyner, A. Riegelhuth, and Y. Kim. Accessible visualization: Design space, opportunities, and challenges. *Computer Graphics Forum*, 40(3):173–188, June 2021. doi: 10/g7h7gm

[103] P. Kok, M. Baiker, E. A. Hendriks, F. H. Post, J. Dijkstra, C. W. Lowik, B. P. Lelieveldt, and C. P. Botha. Articulated planar reformation for change visualization in small animal imaging. *IEEE Trans Vis Comput Graph*, 16(6):1396–1404, Nov./Dec. 2010. doi: 10/bnfpqn

[104] S. M. Kosslyn. *Graph Design for the Eye and Mind*. Oxford University Press, 2006. doi: 10/g7h7f9

[105] M. Kraak and F. Ormeling. *Cartography: Visualization of Geospatial Data*. CRC Press, Boca Raton, 4th ed., 2020. doi: 10/gtn795

[106] J. Krygier and D. Wood. *Making Maps: A Visual Guide to Map Design for GIS*. Guilford Press, New York, 3rd ed., 2016. urn: urn:oclc:record:1194418017.

[107] K. Lai and S. B. Green. The problem with having two watches: Assessment of fit when RMSEA and CFI disagree. *Multivar Behav Res*, 51(2–3):220–239, Mar. 2016. doi: 10/gfpnvb

[108] A. Lau and A. Vande Moere. Towards a model of information aesthetics in information visualization. In *Proc. IV*, pp. 87–92. IEEE Comp. Soc., Los Alamitos, 2007. doi: 10/ck2h6t

[109] T. Lavie and N. Tractinsky. Assessing dimensions of perceived visual aesthetics of web sites. *Int J Hum Comput Stud*, 60(3):269–298, Mar. 2004. doi: 10/dpsmgw

[110] H. Leder, B. Belke, A. Oeberst, and D. Augustin. A model of aesthetic appreciation and aesthetic judgments. *Br J Psychol*, 95(4):489–508, Nov. 2004. doi: 10/cs7p65

[111] R. A. Likert. A technique for the measurement of attitudes. *Arch Psychol*, 22(140):5–55, 1932.

[112] S. Lin, J. Fortuna, C. Kulkarni, M. Stone, and J. Heer. Selecting semantically-resonant colors for data visualization. *Comput Graph Forum*, 32(3):401–410, 2013. doi: 10/tqd

[113] F. Liu and R. W. Picard. Periodicity, directionality, and randomness: Wold features for image modeling and retrieval. *IEEE Trans Pattern Anal Mach Intell*, 18(7):722–733, 1996. doi: 10/fjb4ss

[114] S. Liu, Y. Wu, E. Wei, M. Liu, and Y. Liu. StoryFlow: Tracking the evolution of stories. *IEEE Trans Vis Comput Graph*, 19(12):2436–2445, Dec. 2013. doi: 10/f5h3wh

[115] A. Lu and D. S. Ebert. Example-based volume illustrations. In *Proc. Visualization*, pp. 655–662. IEEE Comp. Soc., Los Alamitos, 2005. doi: 10/bhfj9w

[116] A. Lundgard, C. Lee, and A. Satyanarayan. Sociotechnical considerations for accessible visualization design. In *2019 IEEE Visualization Conference (VIS)*, p. 16–20. IEEE, Oct. 2019. doi: 10/gn65ch

[117] A. M. MacEachren. *How Maps Work: Representation, Visualization, and Design*. Guilford Press, New York, 2004. urn: urn:oclc:record:1409557208.

[118] A. M. MacEachren and J. H. Ganter. A pattern identification approach to cartographic visualization. *Cartographica*, 27(2):64–81, 1990. doi: 10/d689wm

[119] A. M. MacEachren, R. E. Roth, J. O'Brien, B. Li, D. Swingley, and M. Gahegan. Visual semiotics & uncertainty visualization: An empirical study. *IEEE Trans Vis Comput Graph*, 18(12):2496–2505, 2012. doi: 10/f4fvbf

[120] J. Mackinlay. Automating the design of graphical presentations of relational information. *ACM Trans Graph*, 5(2):110–141, 1986. doi: 10/dxdkkp

[121] J. Mankoff, A. K. Dey, G. Hsieh, J. Kientz, S. Lederer, and M. Ames. Heuristic evaluation of ambient displays. In *Proc. CHI*, pp. 169–176. ACM, New York, 2003. doi: 10/c8k77f

[122] G. E. Marai, B. Pinaud, K. Bühler, A. Lex, and J. H. Morris. Ten simple rules to create biological network figures for communication. *PLoS Comput Biol*, 15(9):e1007244:1–e1007244:16, Sept. 2019. doi: 10/ggf2xr

[123] D. Martín, G. Arroyo, A. Rodríguez, and T. Isenberg. A survey of digital stippling. *Comput Graph*, 67:24–44, 2017. doi: 10/gc6xf5

[124] E. Mathieu, H. Ritchie, E. Ortiz-Ospina, M. Roser, J. Hasell, C. Appel, C. Giattino, and L. Rodés-Guirao. A global database of COVID-19 vaccinations. *Nat Hum Behav*, 5:947–953, July 2021. doi: 10/gjxxq3

[125] V. Matvienko and J. Krüger. Explicit frequency control for high-quality texture-based flow visualization. In *Proc. SciVis*. IEEE Comp. Soc., Los Alamitos, 2015. doi: 10/k8sg

[126] C. M. McColeman, F. Yang, T. F. Brady, and S. Franconeri. Rethinking the ranks of visual channels. *IEEE Trans Vis Comput Graph*, 28(1):707–717, 2022. doi: 10/gnqjcb

[127] Merriam-Webster. texture. url: `merriam-webster.com/dictionar/texture/`; Accessed: Feburary 2024.

[128] M. Minge, M. Thüring, I. Wagner, and C. V. Kuhr. The meCUE questionnaire: A modular tool for measuring user experience. In *Advances in Ergonomics Modeling, Usability & Special Populations*, pp. 115–128. Springer, Cham, 2017. doi: 10/gh4jsr

[129] L. Morais, Y. Jansen, N. Andrade, and P. Dragicevic. Showing data about people: A design space of anthropographics. *IEEE Trans Vis Comput Graph*, 28(3):1661–1679, 2020. doi: 10/g7h7f7

[130] J. L. Morrison. A theoretical framework for cartographic generalization with the emphasis on the process of symbolization. In *International Yearbook of Cartography*, vol. 14, pp. 115–127. 1974.

[131] M. Moshagen and M. T. Thielsch. Facets of visual aesthetics. *Int J Hum Comput Stud*, 68(10):689–709, Oct. 2010. doi: 10/c7xxqr

[132] T. Munzner. *Visualization Analysis and Design*. CRC Press, Boca Raton, 2014. doi: 10/gd3xgq

[133] M. Nadal and O. Vartanian. Empirical aesthetics: An overview. In M. Nadal and O. Vartanian, eds., *The Oxford Handbook of Empirical Aesthetics*. Oxford University Press, 2022. doi: 10/g7h7dz

[134] R. Netzel, M. Burch, and D. Weiskopf. Comparative eye tracking study on node-link visualizations of trajectories. *IEEE Trans Vis Comput Graph*, 20(12):2221–2230, Dec. 2014. doi: 10/f6qj65

[135] O. Neurath. *From Hieroglyphics to Isotype: A Visual Autobiography*. Hyphen Press, London, 2010. Edited by M. Eve and C. Burke, url: perpensapress.com/books/from-hieroglyphics-to-isotype.

[136] Q. Nguyen, P. Eades, and S.-H. Hong. On the faithfulness of graph visualizations. In *Proc. GD*, pp. 566–568. Springer, Berlin, 2012. doi: 10/g7h7fv

[137] C. Nobre, D. Wootton, L. Harrison, and A. Lex. Evaluating multivariate network visualization techniques using a validated design and crowdsourcing approach. In *Proc. CHI*, pp. 254:1–254:12. ACM, New York, 2020. doi: 10/gpsvwt

[138] J. C. Nunnally and I. H. Bernstein. *Psychometric Theory*. McGraw-Hill, 3rd ed., 1994.

[139] J. W. Osborne, A. B. Costello, and J. T. Kellow. Best practices in exploratory factor analysis. In J. W. Osborne, ed., *Best Practices in Quantitative Methods*, chap. 6, pp. 86–99. Sage, 2020. doi: 10/bpprwv

[140] M. Phutane, J. Wright, B. V. Castro, L. Shi, S. R. Stern, H. M. Lawson, and S. Azenkot. Tactile materials in practice: Understanding the experiences of teachers of the visually impaired. *ACM Trans. Access. Comput.*, 15(3), July 2022. doi: 10/g8q2w7

[141] F. E. Pierce. The Tenement-House committee maps. *Harpers Weekly*, 39(1987):60–62, 1895. Online: lccn.loc.gov/2006629793.

[142] Plotly Technologies Inc. Collaborative data science, 2015.

[143] Z. Pousman, J. Stasko, and M. Mateas. Casual information visualization: Depictions of data in everyday life. *IEEE Trans Vis Comput Graph*, 13(6):1145–1152, 2007. doi: 10/ffd536

[144] D. Prescher and J. Bornschein. Richtlinien zur umsetzung taktiler grafiken: Richtlinien für bildbeschreibungen und zur erstellung taktiler grafiken, 2016. urn:nbn:de:bsz:14-qucosa-196167.

[145] H. C. Purchase. Metrics for graph drawing aesthetics. *J Vis Lang Comput*, 13(5):501–516, Oct. 2002. doi: 10/fdqd3w

[146] A. R. Rao and G. L. Lohse. Towards a texture naming system: Identifying relevant dimensions of texture. *Vision Res*, 36(11):1649–1669, 1996. doi: 10/ffnq8n

[147] R. Reber. Appreciation modes in empirical aesthetics. In M. Nadal and O. Vartanian, eds., *The Oxford Handbook of Empirical Aesthetics*. Oxford University Press, 2021. doi: 10/g7h7fq

[148] R. Reber, N. Schwarz, and P. Winkielman. Processing fluency and aesthetic pleasure: Is beauty in the perceiver's processing experience? *Pers Social Psychol Rev*, 8(4):364–382, Nov. 2004. doi: 10/c7cq8z

[149] D. P. Retchless and C. A. Brewer. Guidance for representing uncertainty on global temperature change maps. *Int J Climatol*, 36(3):1143–1159, 2015. doi: 10/f8c645

[150] W. Revelle. psych: Procedures for psychological, psychometric, and personality research. R package, 2022. https://CRAN.R-project.org/package=psych.

[151] R. Rosenholtz. Texture perception. In *The Oxford Handbook of Perceptual Organization*. Oxford University Press, 08 2015. doi: 10/gtn6ps

[152] Y. Rosseel. lavaan: An R package for structural equation modeling. *J Stat Software*, 48(2):1–36, 2012. doi: 10/f3r4v8

[153] R. E. Roth. Visual variables. In D. Richardson, N. Castree, M. F. Goodchild, A. Kobayashi, W. Liu, and R. Marston, eds., *International Encyclopedia of Geography: People, the Earth, Environment and Technology*. Wiley, 2017. doi: 10/gm53xj

[154] M. P. Salisbury, S. E. Anderson, R. Barzel, and D. H. Salesin. Interactive pen-and-ink illustration. In *Proc. SIGGRAPH*, pp. 101–108. ACM, New York, 1994. doi: 10/b549m9

[155] R. Scalco. Texture.js. riccardoscalco.it/textures/, 2021. Accessed: June 2024.

[156] K. Schermelleh-Engel, H. Moosbrugger, and H. Müller. Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures. *Methods Psychol Res Online*, 8(2):23–74, 2003.

[157] M. Schrepp, J. Thomaschewski, and A. Hinderks. Construction of a benchmark for the user experience questionnaire (UEQ). *Int J Interact Multimedia Artif Intell*, 4(4):40–44, June 2017. doi: 10/ggccnt

[158] M. Schuffelen. *On Editing Graphics for the Blind: A Manual with Examples and a Pictorial Overview for the Interested Layman*. Netherlands Library for Audio Books and Braille (Nederlandse Luister- en Braille-Bibliotheek), The Hague, Netherlands, 2002. Accessed: September 2024.

[159] T. Schultz and G. L. Kindlmann. Superquadric glyphs for symmetric second-order tensors. *IEEE Trans Vis Comput Graph*, 16(6):1595–1604, Sept./Dec. 2010. doi: 10/dxqp2q

[160] Y. Shi, P. Liu, S. Chen, M. Sun, and N. Cao. Supporting expressive and faithful pictorial visualization design with visual style transfer. *IEEE Trans Vis Comput Graph*, 29(1):236–246, 2023. doi: 10/gr6325

[161] J. Shin, J. Cho, and S. Lee. Please touch color: Tactile-color texture design for the visually impaired. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*, CHI '20. ACM, Apr. 2020. doi: 10/g7h7gk

[162] T. A. Slocum, R. B. McMaster, F. C. Kessler, and H. H. Howard. *Thematic Cartography and Geovisualization*. CRC Press, Boca Raton, 2022. doi: 10/gtkwks

[163] L. South, D. Saffo, O. Vitek, C. Dunne, and M. A. Borkin. Effective use of likert scales in visualization evaluations: A systematic review. *Computer Graphics Forum*, 41(3):43–55, 2022. doi: 10/m5t6

[164] S. Stusak, A. Tabard, F. Sauka, R. A. Khot, and A. Butz. Activity sculptures: Exploring the impact of physical visualizations on running activity. *IEEE Trans Vis Comput Graph*, 20(12):2201–2210, Dec. 2014. doi: 10/f6qhsz

[165] H. Tamura, S. Mori, and T. Yamawaki. Textural features corresponding to visual perception. *IEEE Trans Syst Man Cybern*, 8(6):460–473, 1978. doi: 10/d3b8fz

[166] L. G. Tateosian, C. G. Healey, and J. T. Enns. Engaging viewers through nonphotorealistic visualizations. In *Proc. NPAR*, pp. 93–102. ACM, New York, 2007. doi: 10/g7h7dn

[167] C. Tominski and H. Schumann. Enhanced interactive spiral display. In *Proc. SIGRAD*, pp. 53–56. LinkÃ¶ping University Electronic Press, Sweden, 2008.

[168] M. Tuceryan and A. K. Jain. Texture analysis. In *Handbook of Pattern Recognition and Computer Vision*, pp. 235–276. World Scientific, 1993. doi: 10/fww58x

[169] E. R. Tufte. *The Visual Display of Quantitative Information*. Graphics Press, Cheshire, 2nd ed., 2001. urn: urn:lcp:visualdisplayofq0000edwa:lcpdf:23aa8e83-25fc-4744-825e-0c38dee32975.

[170] J. Tyner. *Principles of Map Design*. Guilford Publications, 2017.

[171] R. Ulichney. *Digital Halftoning*. MIT Press, Cambridge, 1987. urn: urn:oclc:record:1033645312.

[172] J. J. van Wijk. Spot noise texture synthesis for data visualization. In *Proc. SI3D*, pp. 309–318. ACM, 1991. doi: 10/bj3xtn

[173] A. Vande Moere and H. Purchase. On the role of design in information visualization. *Inf Vis*, 10(4):356–371, Oct. 2011. doi: 10/djn5hr

[174] R. J. Vandenberg. Introduction: Statistical and methodological myths and urban legends: Where, pray tell, did they get this idea? *Organ Res Methods*, 9(2):194–201, Apr. 2006. doi: 10/b2hpxh

[175] I. Viola, M. Chen, and T. Isenberg. Visual abstraction. In M. Chen, H. Hauser, P. Rheingans, and G. Scheuermann, eds., *Foundations of Data Visualization*, chap. 2, pp. 15–37. Springer, Berlin, 2020. doi: 10/gk874c

[176] I. Viola and T. Isenberg. Pondering the concept of abstraction in (illustrative) visualization. *IEEE Trans Vis Comput Graph*, 24(9):2573–2588, Sept. 2018. doi: 10/gd3k7m

[177] S. Wang, Y. Tanahashi, N. Leaf, and K.-L. Ma. Design and effects of personal visualizations. *IEEE Comput Graph Appl*, 35(4):82–93, 2015. doi: 10/g7h7gg

[178] K. Wannamaker, W. J. Willett, L. A. Oehlberg, and S. Carpendale. Data embroidery: Exploring alternative mediums for personal physicalization. In *Posters at IEEE VIS*, 2019. Extended abstract and poster, handle: 1880/110218.

[179] C. Ware. Quantitative texton sequences for legible bivariate maps. *IEEE Trans Vis Comput Graph*, 15(6):1523–1530, 2009. doi: 10/bx9ccv

[180] C. Ware. *Information Visualization: Perception for Design*. Elsevier, Cambridge, MA, 4^{th} ed., 2020. doi: 10/mj55

[181] C. Ware and R. Bobrow. Motion to support rapid interactive queries on node–link diagrams. *ACM Trans Appl Percept*, 1(1):3–18, 2004. doi: 10/b35p7d

[182] C. Ware and C. Kastrisios. Evaluating countable texture elements to represent bathymetric uncertainty. In *EuroVis Short Papers*, pp. 1–5. EG Assoc., Goslar, 2022. doi: 10/gtmxrx

[183] C. Ware and W. Knight. Orderable dimensions of visual texture for data display: Orientation, size and contrast. In *Proc. CHI*, pp. 203–209. ACM, New York, 1992. doi: 10/bxpc4x

[184] C. Ware and W. Knight. Using visual texture for information display. *ACM Trans Graph*, 14(1):3–20, 1995. doi: 10/c578cv

[185] M. W. Watkins. Exploratory factor analysis: A guide to best practice. *J Black Psychol*, 44(3):219–246, Apr. 2018. doi: 10/gdk2zx

[186] M. Weiß, K. Angerbauer, A. Voit, M. Schwarzl, M. Sedlmair, and S. Mayer. Revisited: Comparison of empirical methods to evaluate visualizations supporting crafting and assembly purposes. *IEEE Trans Vis Comput Graph*, 27(2):1204–1213, Feb. 2020. doi: 10/ghgt5z

[187] L. Wilkinson. *The Grammar of Graphics*. Springer, New York, 2nd ed., 2005. doi: 10/bhsbp7

[188] G. Winkenbach and D. H. Salesin. Computer-generated pen-and-ink illustration. In *Proc. SIGGRAPH*, pp. 91–100. ACM, New York, 1994. doi: 10/cqcbjm

[189] J. Woodring, M. Petersen, A. Schmeißer, J. Patchett, J. Ahrens, and H. Hagen. In situ eddy analysis in a high-resolution ocean climate model. *IEEE Trans Vis Comput Graph*, 22(1):857–866, Jan. 2016. doi: 10/g7h7fg

[190] K. Xu, C. Rooney, P. Passmore, D.-H. Ham, and P. H. Nguyen. A user study on curved edges in graph visualization. *IEEE Trans Vis Comput Graph*, 18(12):2449–2456, Dec. 2012. doi: 10/f4ftr6

[191] Y. Yang, K. Marriott, M. Butler, C. Goncu, and L. Holloway. Tactile presentation of network data: Text, matrix or diagram? In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, CHI '20, p. 1–12. Association for Computing Machinery, New York, NY, USA, 2020. doi: 10/g8q2xm

[192] F. Yang-Wallentin and K. G. Jöreskog. Robust standard errors and Chi-squares for interaction models. In *New Developments and Techniques in Structural Equation Modeling*, chap. 6, pp. 159–171. Psychology Press, New York, 2001. doi: 10/g7h7fn

[193] Z. Zeng and L. Battle. A review and collation of graphical perception knowledge for visualization recommendation. In *Proc. CHI*. ACM, New York, 2023. doi: 10/kz36

[194] J. E. Zhang, N. Sultanum, A. Bezerianos, and F. Chevalier. DataQuilt: Extracting visual elements from images to craft pictorial visualizations. In *Proc. CHI*, pp. 45:1–45:13. ACM, New York, 2020. doi: 10/gh52th