Toward Visual Methods: Reflections on How Visuals Enrich Empirical Research

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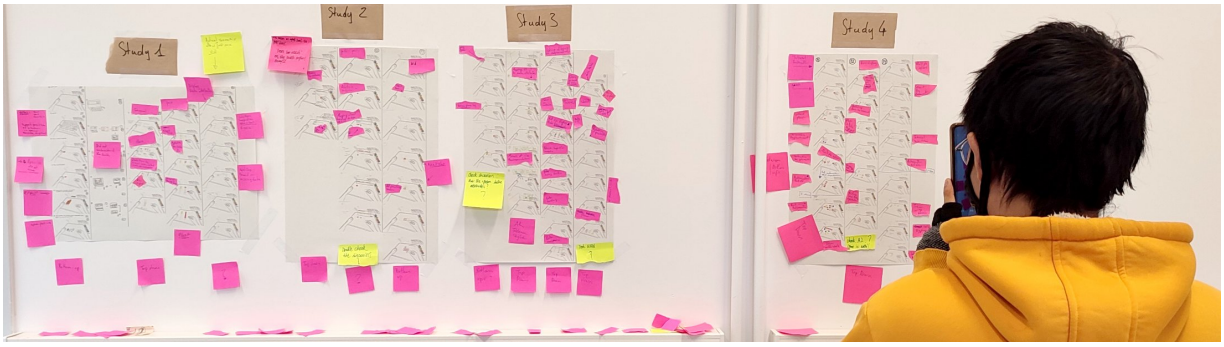

Figure 1: A researcher analyzing a mosaic of minified sketches of 93 speculative design sketches during different speculative design workshops described in Sect. 3.2. Photo by Samuel Huron, under Creative Commons CC BY, accessible on https://osf.io/fd6v8/.

Abstract

In design disciplines, particularly human-computer interaction (HCI) and information visualization (VIS), researchers often need to study qualitative material that is visual in nature, like screenshots, sketches, photographs, videos, or images of physical objects and spaces. Despite an existing literature on how to analyze visual artifacts in social science and the arts, few papers reflect on the value and the means to support such analysis in the context of information visualization or graphical user interface design. This is particularly intriguing, as visual design is often the primary channel for communicating data, and visual perception is one of humans' main epistemic sources in the world. Over the past 25 years, we have analyzed such visual artifacts across dozens of our own qualitative studies and surveys. We present six cases, reflect on four values and practical strategies for using visual methods for analyzing visual artifacts, and introduce an open archive of visual methods for HCI and VIS at visualmethods.pages.dev.

Keywords: Visual methods, visual data analysis, qualitative research, information visualization, human-computer interaction

Index Terms: H.5.2 [Information Interfaces and Presentation (e.g., HCI)]: User Interfaces—Evaluation/methodology; I.3.6 [Computer Graphics]: Methodology and Techniques—Interaction techniques

1 Introduction

Qualitative data analysis is a common method in social science [20], human-computer interaction [49], and information visualization research [47]. It can be conducted through different methodological approaches, including grounded theory [1], open coding [8], or thematic analysis [11]. These methods have been used to analyze various types of textual or oral data, such as documents, interview records, transcripts, and interaction behaviors [47]. However, in the literature on human-computer interaction and visualization design, despite the work of Jacques Bertin [7], little has been written explaining the process for analyzing visual data qualitatively. What we call *visual data* in this context of a qualitative study is data composed of visual elements that are not only language; this includes, but is not limited to, sketches, images, or videos of visualizations, of interfaces, of physicalization, of interactive devices, or of behaviors.

Analyzing visual data has a rich tradition across several disciplines, each offering distinct methodological lenses. In the history of art, Heinrich Wölfflin [99] defined *formal analysis* to study the visual structure of an image, including composition, color, light, perspective, texture, line, and movement, with the aim of identifying the evolution of styles across art history. In anthropology, for instance, Claude Lévi-Strauss [51] applied structural analysis to Northwest Coast masks, including sxwó:yxwey masks. Roland Barthes [6] later applied semiotic analysis to images, decomposing them into signs and studying the interactions between those signs. Erwin Panofsky [57] further introduced a three-level method distinguishing (1) what is represented, (2) its cultural, mythological, or religious meaning, and (3) its global interpretation within the context of production. In parallel, psychology has developed its own tradition of visual qualitative analysis [60] to support the elicitation of personal narratives [38], unconscious ideas [79], and gender constructions [29]. Visual ethnography has similarly built a dedicated body of literature [5, 30, 59, 63], focusing on studying humans in context and visual production as an elicitation of societal constructs, including rituals, inequalities, and interactions between objects, humans, and symbols. Similar approaches have recently been used in HCI to elicit attitudes and beliefs, as demonstrated by Li et al. [52]. Also, graphic elicitation through diagrams [16] and relational maps [15] has been used as interview stimuli. Much of this work across art history, psychology, and ethnography focuses on analyzing polysemic artifacts, i.e., images and visual objects open to multiple interpretations. In contrast, information visualization and graphical user interfaces are primarily designed to be *monosemic*: their visual elements are intended to carry specific, unambiguous

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meanings. For data visualization, Bertin's *Semiology of Graphics* [7] provides a foundational framework for studying the relationship between visual variables and data properties. Yet despite his central role in analyzing and designing visual data representations, Bertin does not formalize a methodology for qualitatively analyzing visual data. When asked, he mentions the "*painter eyes*".[1] Design principles, e.g., Tufte's data-ink ratio [77], have also been formalized to assess visualization design; however, these principles tend to be more normative and prescriptive than analytical.

This raises a key question: given the multiplicity of frameworks in art history and the human sciences, how can we draw inspiration from these methods and adapt them to the specific requirements of information visualization and human-computer interaction design?

Over the last 25 years, the authors of this paper have conducted dozens of qualitative studies and surveys that involved analyzing such visual artifacts [4,9,10,12,17–19,24,27,28,31,33–35,37,39,40, 42,43,45,46,50,61,62,64,65,70–75,80–88,90–93,95,96,98,100]. In this paper, we reflect on what we have learned through the process of analyzing visual data across six research projects, presenting strategies developed to reduce interpretive ambiguity and to examine the relationships between visual elements both within and across visual data records. This work builds on an initial discussion begun at an international workshop at ACM ISS [89], contributing:

- **Four values of using visual methods.** We identify that there are at least four values: *congruency* keeps the analysis in the phenomenon's own medium; *expressive reach* provides access to knowledge that verbal prompting cannot reach; *synopticity* makes structure and relationships perceptible at a glance; and *spatial evidence* reveals paths and traces of thought.
- **Practical strategies with case studies.** Drawing on six research projects, we share strategies for analyzing visual data in practice and for examining relationships between visual elements.
- **A call to action.** We create a digital archive, invite the community to share and crowd-source visual methods, and point to directions for future work.

2 Background

Visualization and HCI research has long collected visual artifacts as empirical material: visualizations drawn on whiteboards in the wild [80], data sketches [82], annotations from active reading [83], personal physicalizations [75], elicitation interviews around data representations [32], and input visualizations [12]. Most qualitative analysis methods, however, were developed for language-based data: procedures such as line-by-line coding [14], in-vivo coding [68], or grouping quotes into themes [11] work on data that can be segmented, labeled, and quoted as text. Visual material is therefore often translated early into textual descriptions so that it fits this apparatus, and the analytic moves performed on the visuals themselves are rarely reported in comparable detail. Only recently have researchers begun to reflect on such visual data analysis practices, with specific approaches such as visual annotations [69, 89] or adaptations of grounded theory to visualization research [21].

Our perspective comes from design, HCI, and data visualization practice, where producing intermediate artifacts such as visualizations, wireframes, sitemaps, and mockups is routine, and this background shapes how we read and analyze visual data. There is a rich tradition of visual analysis to draw on, much of it in psychology, which uses visual material to elicit personal narratives, constructs, and otherwise hard-to-verbalize ideas [29, 38, 60, 79], and in visual ethnography, with its dedicated literature [5, 30], Rose's *Visual Methodologies* [63] synthesizing approaches from compositional interpretation to discourse analysis and Pink's *Doing Visual Ethnography* [59] codifying the production and interpretation of visuals in fieldwork. HCI and visualization sometimes use these elicitation and ethnographic methods as well, but such methods target *polysemic* material, ambiguous and open to interpretation, and the elicitation of meaning more than the specific, largely *notational* artifacts, with clear, distinct units governed by syntactic and semantic rules [25], that our field also produces; how to analyze those remains comparatively undocumented.

[1] https://www.youtube.com/shorts/WLKsXdDog94

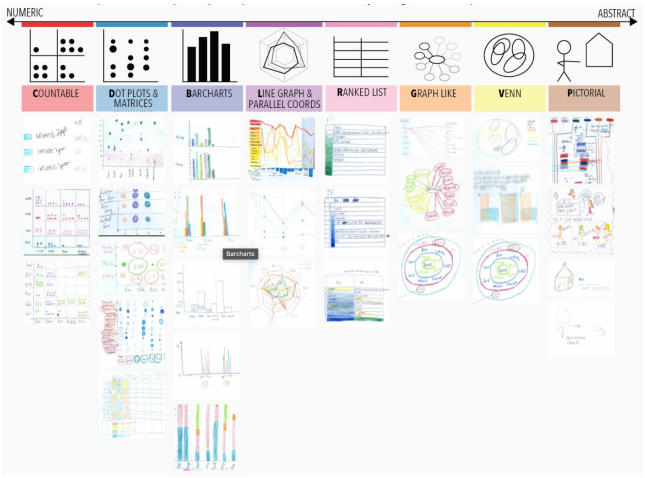


Figure 2: A spatial organization sketch representing the continuum of data sketches: From Numeracy to Abstractness [82], large version available here: https://supplemental-material.github.io/Data-Sketching/. Picture under CC BY accessible on https://osf.io/fd6v8/.

Across this body of work, attention concentrates on how to obtain visual data, through eliciting, creating, recording, or searching, and on interpreting what visuals mean, while what happens between collection and findings is far less documented. Beyond exceptions such as visual grounded theory [44], published papers tend to compress the analysis of visual data into a sentence ("we open-coded the sketches"), leaving the concrete analytic moves undocumented and repeatedly reinvented: how a corpus is laid out and compared, at which granularity visual elements are coded, and how interpretations are triangulated. Recent work has therefore explicitly called on researchers to document and share their visual analysis practices [69, 89]; the case studies that follow take up this call by making those analytic moves explicit.

3 Case Studies

We purposively selected six different information-rich cases from our published studies. Our intention is to showcase variation in visual data, spanning participant-generated sketches or annotations, physical artifacts, interfaces, and interactive media, by illustrating diversity in how visuals support gathering, understanding, and communicating research evidence. We chose cases where we have first-hand access to artifacts throughout the processes, to ongoing methodological decisions, and to the experience of discovering findings through our visual analysis. The visuals in these cases vary from participant-created to previously designed artifacts. Each of these case studies is rich in the use of visuals and in visual methodologies; for each we provide a link to much fuller explanations at the end of each description. Table 1 summarizes the six cases.

3.1 Analyzing Data Sketching

Walny et al. [82] (Fig. 2) explored the range and variation of what participants produced when sketching data.

Study design: Participants with varying degrees of visualization expertise were asked to manually sketch representations of a small,

easily understandable dataset using pencils and paper, and to report textually on what they learned or found interesting about the data. They were explicitly told that there were no wrong responses. The study took place in a simple classroom with ample tables, good lighting, blank sheets of paper, and a large variety of colored pencils (find more details here).

Analysis: The researchers collected the resulting sketches together with the participants' written data reports, and open-coded both the visual encodings of the sketches and the reports.

Results: The results were threefold: a data sketching representation continuum ranging from numeracy to abstraction that demonstrated the level of expressivity offered by this approach; a data report spectrum that included comments ranging from individual data items to speculative data hypotheses; and a demonstration of the correspondence between representation types and data reports. For instance, the participants who provided more abstract representations, such as pictorial sketches, tended to produce data reports with greater analytic potential. This observation raised deeper questions about whether the act of creating a sketch, rather than simply viewing a visualization, itself drove analytical thinking. These findings were an early contribution to understanding how people spontaneously sketch visual representations of data, with implications for visualization design, education, and tools that support the early, exploratory stages of visual data analysis.

Reflection and trade-offs: The data-report prompt was deliberately open to avoid interfering with participants' thinking, but this made it difficult to connect specific comments to features of their sketches during analysis. We would also have liked to capture the drawing process, which could have revealed how each sketch developed. Future studies should therefore capture synchronized explanations or drawing sequences while minimizing interference. Despite these limitations, engaging directly with the sketches was essential because the research question concerned a visual medium; it enabled comparison of representational structures and levels of abstraction that verbal reports alone could not reveal.

3.2 Analyzing How People Imagine Visualization Auto Complete

Constructing visualizations with sketching or tangible objects can be tedious and repetitive. To address this, Wei et al. [96] defined the notion of *visualization auto complete* and designed a speculative design study to better understand how it might be applied.

Study design: The study consisted of four speculative design workshops, each run with groups of 3–5 participants, totaling 15 participants. Each workshop consisted of three sessions: Construction, Ideation, and Discussion. In the Construction session, participants were introduced to constructive visualization by assembling physical tokens to represent a dataset. In the Ideation session, participants were presented with the concept of autocomplete as used in search engines and then asked to imagine how a fictional "*smart system*" with no technological limitations could help them create visualizations through autocomplete. They sketched their ideas on paper templates (Fig. 3). Participants then presented their designs and critiqued one another's (find more details here).

Analysis: The researchers collected 93 pages of sketches forming 17 design ideas, and analyzed the sketches on a Miro board and a physical wall, using thematic analysis through multiple rounds of collaborative coding, arriving at a codebook agreed upon by all.

Results: The study proposed the first definition of visualization autocomplete, identified three interaction design strategies, and discussed future research and design possibilities.

Reflection and trade-offs: Asking participants to present and point to their sketches helped disambiguate them, but this probing may also have shaped participants' explanations. The challenge is to elicit sufficient context without directing the interpretation. Nevertheless, sketching used the same expressive medium through

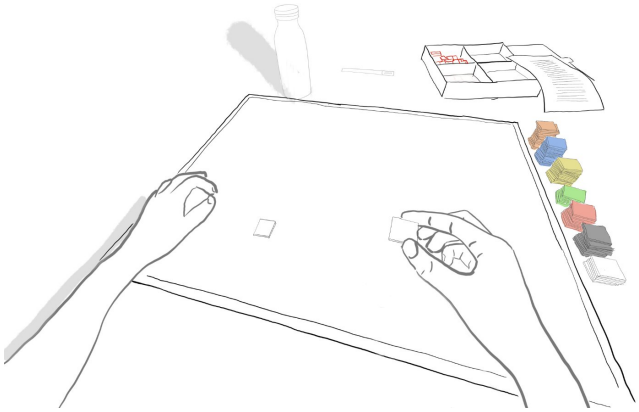


Figure 3: Example of a graphical template used in Auto Complete: the frame steers the participant's sketching activity by providing a context. Picture under CC BY accessible on https://osf.io/fd6v8/.

which interaction designers communicate intentions [26]; it enabled participants to situate their reflections in visual material and allowed the researchers to compare design intentions and derive interaction strategies for a fictional technology.

3.3 Analyzing Personal Physicalization Construction and Self Reflection

Thudt et al. [75] (Fig. 4) explored how constructive visualizations with physical objects supported self-reflection on personal data. Most of the prior work on constructive visualization had been limited to controlled, laboratory settings with researcher-provided datasets. This study moved beyond those constraints to examine how people engaged with physicalization in their everyday lives.

Study design: The researchers conducted a qualitative study investigating the construction of personal physicalizations in people's domestic environments over a period of 2 to 4 weeks. Crucially, participants chose their own personal data to collect and their own way to represent these data. The researchers first conducted a workshop to explain the aim of the study and how to collect and represent data, and then participants were invited to follow this process while keeping a journal of what they thought. A post-study interview was conducted (find more details here).

Analysis: The visual data in this study were the participants' pictures and photographs of the evolving physicalizations in their domestic contexts, as well as the final physicalizations. In addition, the researchers also drew on non-visual data, such as the participant journals and the interviews. The researchers open-coded the visual data encodings and the reflections documented alongside them.

Results: The study contributed an understanding of 1) the process of creating personal physicalizations, 2) the types of personal insights facilitated, 3) the integration of self-reflection in the physicalization process, and 4) its benefits and challenges for self-reflection. Observing participants' physicalizations over several weeks revealed the messiness, motivations, and meaning-making that arose as people collected and physically constructed representations of their own lives.

Reflection and trade-offs: Prioritizing ecological validity meant asking participants to document their activities through diaries and photographs rather than observing them continuously. Yet this documentation may itself have influenced their visual thinking, construction, and reflection, so balancing data capture against interference remained difficult. Nevertheless, photographs preserved the evolution and domestic context of the physicalizations without obtrusive researcher presence, enabling direct analysis of visual

Figure 4: Photograph of the nine physicalizations produced during the Construction and Self-Reflection study. Picture made by Alice Thudt.

mappings, structures, encoding decisions, and their relationship to self-reflection; the artifacts also grounded the post-study interviews.

3.4 Analyzing Debate Platforms Graphical User Interface Screenshots

Frappier et al. [24] (Fig. 5) studied the design of debate platforms (websites that support debate between citizens), which can significantly influence the quality of debates. In this research, the researchers conducted a comparative visual analysis of the graphical user interfaces of debate platforms.

Study design: The researchers collected and screened 218 off-the-shelf platforms from three civic technology directories; they selected 25 that were dedicated to debate and collected screenshots of each debate interface.

Analysis: The analysis process consisted of seven main phases conducted over three years: identifying and classifying the types of platforms, collecting screenshots of each debate interface, redrawing *detailed reverse wireframes* on top of each screenshot in Figma, visually coding the interfaces into blocks, abstracting the wireframes into diagrams, assembling a mosaic of all diagrams, and finally analyzing the mosaic collaboratively to identify similarities and differences. The method was grounded in Gestalt principles [76] and the grid system [55], using reverse wireframing, usually a design method, here applied as an analytical one (find more details here).

Results: This analysis identified four types of debate platform styles: participation, social network, skill, and encyclopedia. A similarity in the hierarchy of blocks across the styles and the platforms suggested that the graphical interface tended to prompt users to form and express an opinion before getting to know the previously expressed opinions in the deliberation.

Reflection and trade-offs: The analysis initially focused on the role of visualization, but few platforms contained visualizations, prompting us to shift toward layout. Our first coding pass was also too detailed to support comparison, requiring multiple, progressively coarser passes. These challenges show that analytical scope and granularity must remain adaptable to the corpus. Ultimately, *reverse wireframing* exposed blocks of information and their hierarchy, enabling comparison of the assumptions and design patterns embedded across debate platforms.

3.5 Analyzing Design Patterns in Interactive Comics

Wang et al. [91] (Fig. 6) studied how to add interactivity to data comics. As part of this work, they conducted a systematic visual analysis of existing interactive comics to understand how interactions

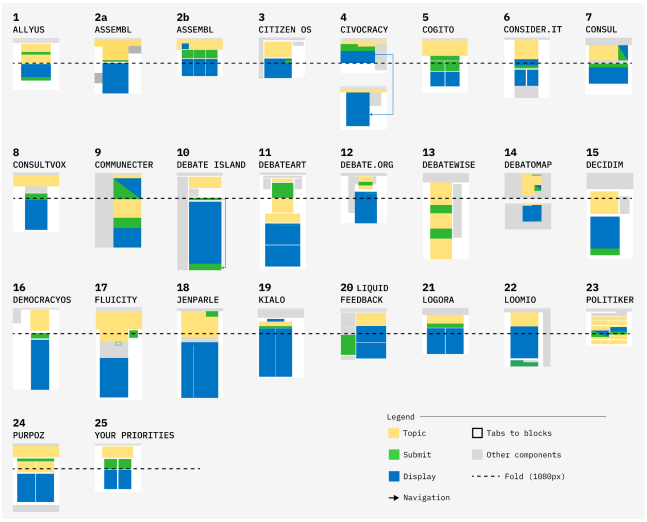


Figure 5: Examples of mosaics used as analysis and communication tools for the analysis of the graphical user interface of debate platforms. Picture under CC BY made by Tallulah Frappier, accessible on https://osf.io/fd6v8/.

were used and to inform a set of operations for interactive data comics.

Study design: They first collected 33 traditional (non-data) interactive comics found online.

Analysis: They open-coded the collection through repeated viewing. The coding process included identifying recurrent patterns and iteratively converging on a codebook, using visual icons (i.e., abstract symbolic elements) as codes to represent interactions and visual elements in interactive comics. They categorized the interactions into higher-level operations, such as adding or removing an element and reordering a panel. Each interaction was described along two dimensions: its *trigger* (how the interaction is activated, e.g., a visual element, a widget, a panel, or the whole canvas) and its *effects* (what changes in the comic). The effects were further separated into those that affected the *content within panels* and those that affected the *structure and layout of panels*, and each was related to six predefined goals of interaction for storytelling (find more details here).

Results: This analysis produced a structured design space of low-level interaction operations, organized by trigger and effect and mapped onto the six storytelling goals. It distinguished, for example, changes to panel content (changing the viewport, adding or removing elements, changing properties, inputting data) from changes to panel layout (reordering panels, adding or removing panels, changing panel properties). This design space directly informed the formalization of a core set of operations for interactive data comics. The visual icons used for coding were also used to communicate how those design patterns were applied in an interactive data comic (Fig. 6).

Reflection and trade-offs: Abstracting patterns from existing artifacts removes them from the contexts in which they were created and used. Without access to the original design context, the creators' intentions and the rationale connecting each pattern to its purpose may be lost, encouraging pattern reuse that reproduces form without achieving the same effect. Researchers therefore need to document and triangulate links among patterns, contexts, rationales, and observed effects. Despite this limitation, visual analysis exposed a repertoire of design operations and interaction patterns embedded in existing comics, providing concrete precedents and a structured design space for future designs.

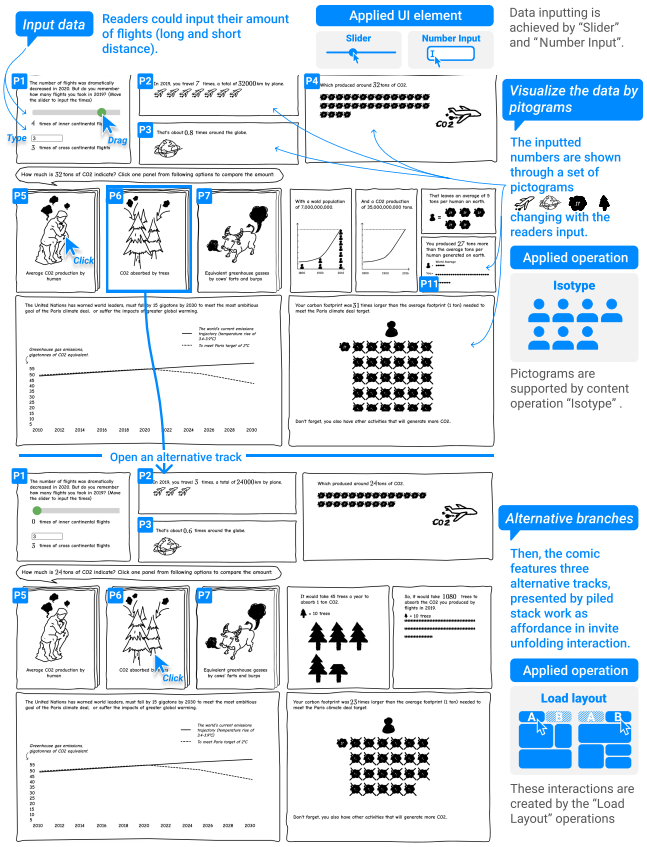


Figure 6: The interactive data comic of *CO_2 emissions* annotated with the visual icons used as codes; those blue icons and annotations are also used for communicating each interaction's *trigger* (e.g., inputting data via a widget) and its *effects* on panel content and layout. Picture under CC BY made by Zezhong Wang, accessible on https://osf.io/fd6v8/.

3.6 Analyzing Reader-Drawn Reading Sequences of Data Stories

As part of a comparison of data comics, infographics, and illustrated texts, Wang et al. [93] (Fig. 7) examined *reading sequences* that participants drew by hand after reading. Because readers drew paths directly onto the material, each trace combined the visual artifact with participant-generated data. This drawing technique served a dual role: it was at once a method for *collecting* data about reading behavior and a method for *analyzing* it, since the act of drawing already required the reader to interpret and structure their own reading experience.

Study design: After reading each story, participants drew lines and arrows on the black-and-white printed material while explaining the order in which they read text and viewed figures (find more details here).

Analysis: Because the participants themselves decided what counted as a meaningful step in their reading and condensed it into a trace, the elicitation step formed a first layer of analysis by the reader (e.g., Fig. 7 Top). The researchers then conducted a second layer of analysis by collecting the hand-drawn traces across all participants, stories, and formats and comparing them to identify recurring reading patterns (e.g., Fig. 7 Bottom).

Results: This analysis revealed distinct reading patterns across the three formats. Comic readers largely followed the predefined panel order, often jumping back to earlier panels for comparison; infographic readers typically entered through the title before following the layout of the text boxes, with no consistent order; and readers of illustrated texts prioritized the text, consulting figures during or after

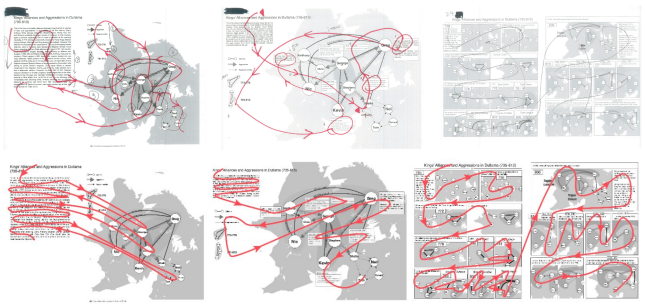


Figure 7: Reader-drawn reading sequences of the same data story. Top: reading orders drawn by hand by readers directly on the printed material in three formats (annotated infographic, illustrated text, and data comic). Bottom: typical reading paths drawn by the researchers after analyzing individual participants' hand-drawn traces. Picture under CC BY made by Zezhong Wang, accessible on https://osf.io/fd6v8/.

reading. The traces also showed that reading order was far more consistent across readers for comics than for the other two formats.

Reflection and trade-offs: Reader-drawn traces are self-reports rather than direct gaze records: participants may omit unnoticed visual jumps or rationalize their paths into more linear sequences. Triangulating them with eye tracking could help reveal these differences. Nevertheless, the traces provide a lightweight account of perceived reading paths and, by externalizing reading order as a drawing, capture intentional attention and readers' own sense-making that gaze records alone cannot reveal.

4 The Value of Visual Methods

Across the six cases, we identified four potentials of visual methods relative to text-, speech-, or number-based alternatives: what one gains, or avoids losing, by working visually. These values emerged through iterative discussion and draw on Rose's account of the sites at which the meanings of visual materials are made, from their production and the image itself to their circulation and audiencing [63, p. 25]. Because visual artifacts encode knowledge, social norms [97], and individual choices in the form of design decisions [2], they do not merely reflect the social world but actively take part in constructing it [63]: cues inside visual data are therefore evidence of a phenomenon, and visual methods expand what counts as research evidence. Visual materials also take many forms and levels of fidelity, from sketches, photographs, screenshots, and physical artifacts to video and emerging volumetric 3D capture [56], giving researchers a wide palette to match data collection and analysis to the phenomenon at hand. The four values are starting points rather than an exhaustive account.

V1 (*congruency*): the analysis stays in the phenomenon's own medium. In visualization and HCI, much of what we study exists in the world in visual form: information visualizations, graphical user interfaces, sketches, or traces of reading. Collecting visual data and working with them directly as visuals is a more direct form of inquiry. It keeps the analysis cognitively congruent with the object of study, following the congruence principle that the form of a representation should match the content it conveys [78], and it spares a round trip of translation, turning the visual into words or numbers and back, in which structures are lost during each translation, such as the levels of abstraction in Data Sketching.

V2 (*expressive reach*): access to knowledge that verbal prompting cannot reach. Beyond serving as a medium of expression, the act of creating a visual works as an elicitation device [32, 52] that prompts participants to discover, structure, and externalize tacit knowledge, assumptions, and imagined futures that they could not simply state verbally if asked. Asking participants to draw their ideal

Study	Object of analysis	Data collected	Triangulation	Analysis	Result
Sect. 3.1: **Data Sketching**	Visualization sketches	Sketches	Data reports	Open coding of data encoding and report	Spectrum of data representation and data report
Sect. 3.2: **Auto Complete**	Speculative techniques	Video, sketches	Oral presentation of the sketches	Open coding of graphical elements	New interaction techniques or strategies
Sect. 3.3: **Self Reflection**	Physicalization	Participants' and facilitators' photos	Interviews and journals	Open coding of data encoding and reflection	Level of reflection embedded in construction
Sect. 3.4: **Debate Platforms**	Website interfaces	Screenshots	About page and website	Reverse wireframing	Comparative visual analysis
Sect. 3.5: **Interactive Comics**	Interactive comics	Interactive (non-data) comics found online	Texts in comics	Open coding with visual icons of triggers and effects	Design space and patterns of interaction operations
Sect. 3.6: **Reading Sequences**	Reading of data stories	Reader-drawn traces on printed stories	Interview while drawing the traces	Comparing traces across participants and formats	Recurring reading patterns per format

Table 1: Synthesis of studies, their object of analysis, the types of visual data collected, the triangulation strategy, the analytic method used, and the results. Table under CC BY, by the authors of this paper.

interaction with a fictional technology surfaces design intentions they did not know they had (**Auto Complete**), and tracing their own reading path makes them reconstruct and articulate behavior that no interview question could retrieve spatially (**Reading Sequences**).

V3 (*synopticity*): structure and relations perceptible at a glance. A visual representation makes configuration, proportion, hierarchy, and similarity perceptible all at once, whereas linear text or speech would fragment them into a sequence; this is why a diagram can support inferences that an equivalent verbal description cannot [48]. This synoptic quality lets researchers grasp the whole, compare many instances side by side, and recognize structure that would otherwise stay hidden. Redrawing debate interfaces as reverse wireframes and assembling them into a single mosaic exposed shared layout hierarchies across platforms (**Debate Platforms**); arranging data sketches in space allowed us to identify a potential continuum of representations (**Data Sketching**); and coding interactions with visual icons laid out the design space of interactive comics as an inspectable whole (**Interactive Comics**).

V4 (*spatial evidence*): visuals can reveal paths and traces of thought. Because visuals are not neutral mirrors but are actively constructed [63], they carry the choices, norms, and interpretations of those who made them [2, 97]; the artifact itself becomes evidence of the cognitive and social world that produced it, regardless of whether the maker is a participant, designer, or visualizer. A reader-drawn trace is not a raw behavioral record but the reader's own condensed account of what they intentionally express about their experience (**Reading Sequences**), and the encoding decisions in a personal physicalization reveal what its maker considered worth collecting and representing (**Self Reflection**); likewise, the layouts of existing debate platforms expose the assumptions the platforms' designers held about how deliberation should unfold (**Debate Platforms**). Analyzing such visuals therefore includes reading them as interpretations, not merely transcribing them as records. For instance, the sketches in a previous work [10] reveal evidence (trace) of internally held thoughts, allowing researchers to identify shared gender stereotypes behind commonly used CHI terms that refer to people such as the term user.

These values do not come for free: visual data can be more ambiguous than text and demand deliberate strategies for collecting, framing, and analyzing them, which we discuss in the next section.

5 Considerations on Visual Methodologies

Working with visual data raises practical questions at every stage of a study. In this section, we discuss considerations for framing the production of visual data, collecting and triangulating them, and analyzing them.

5.1 Framing the Data Collection: Template, Workshop, Look-up Sheets, etc.

When the visual data are generated by a group of participants, as in any generative action, participants may interpret the task in many different ways, which makes providing a frame important. Research on creativity in psychology [94] and design framing [22] has also shown that providing a specific framework eases the creative process.

To ensure that participants were guided toward the expected task in most of our studies, we provided an appropriate frame of reference. For that, we used multiple strategies: organizing a workshop (**Self Reflection**) to introduce notions (like data, visual mappings, or other concepts) or tools and reduce the difficulty of the task, or providing templates (**Auto Complete**) to focus the sketching activity in a certain context with a certain perspective. In **Reading Sequences**, the printed stories themselves provided the frame: asking readers to draw directly on the material anchored the traces to the story layout and made them directly comparable across participants. During study design, providing this frame of reference always requires considering the trade-off between guiding the activity in the expected direction and stifling free creativity and spontaneity by over-constraining or biasing the participant with too much instruction. This frame of reference could be provided by a formal graphical template, as in **Auto Complete**, or by more complex materials such as a presentation, a toolkit, or look-up sheets to remind participants of the instructions, as in **Self Reflection**.

5.2 Collecting Data: Triangulation and Disambiguation Strategies

Triangulation reduces the ambiguity of visual data and enriches the analysis by combining several sources or methods to understand a phenomenon [13], either to disambiguate the visual data or to test whether the sources converge or diverge. Here, unlike in V2 (*expressive reach*), where new data are generated by creating new

visuals, elicitation also serves to disambiguate: participants explain their visuals so that their accounts support the interpretation.

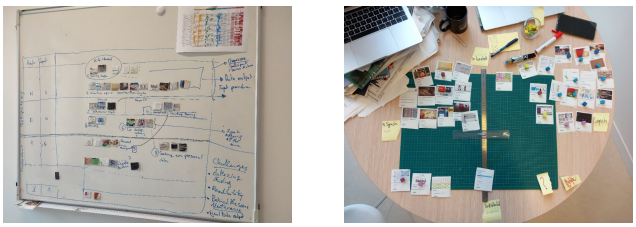
Collecting the explanation of the visual together with the visual itself helps with interpretation. Asking participants to describe, annotate, or talk through their sketch on video or audio, ideally while pointing at specific elements, gives the analyst a guide for interpreting it later. Capturing this metadata (e.g., annotations and descriptions) at collection time both prompts participants to make the meaning of their signs explicit and aids the work of the analyst; in our studies, the times we skipped this created interpretive difficulties. It is often worth planning triangulation in the study design.

Several of our cases illustrate the use of triangulation and disambiguation strategies. In **Self Reflection**, interviewing participants as they introduced and described their physicalization was instrumental, since the mapping was hard to read alone and the legends were not always consistent. In **Auto Complete**, participants presented their sketches orally while pointing at them, which was especially useful for the non-notational sketches. In **Reading Sequences**, the concurrent interview, drawing, and resulting trace helped disambiguate one another (Fig. 7).

Triangulation also reveals whether sources agree. **Data Sketching** is a case of convergence: comparing the sketches with their accompanying data reports, we found that more abstract representations align with more complex reports (Fig. 2). **Debate Platforms** is a case of divergence: comparing 25 platform screenshots with their self-descriptions, the layout hierarchy contradicts both the platforms' stated purpose and the way the literature suggests debate should occur. When the visual data come from a survey or an existing collection, their creators are often unavailable to describe the artifacts, so only a partial triangulation against contextual data is possible. In **Interactive Comics**, the comics collected online carried no accompanying author explanation, so the analysis relied on repeated viewing, on the textual elements within the comics that corroborated or contrasted with the visuals to support understanding of the narrative, and on describing their dynamic behavior with visual content.

5.3 Choosing a Level of Analysis

Visual analysis can operate at different levels depending on the research question and the type of visual data, from the concrete, such as visual primitives (marks, lines, points) and channels (color, hue, density, position, saturation, texture), to the abstract, such as the semantic elements (signs, symbols, icons), and a composition of elements within a visual structure. A visual structure is an assembly of these primitives, and analyzing it means examining relationships between signs, characterizing types of signs, and identifying systems of signs [33]. These relations may be simple, such as juxtaposition or superimposition [52], or more elaborate, such as visualization idioms [54] or interface layouts. Finding the right granularity is difficult, since the same data can be read at many levels. As a rule of thumb, the appropriate level follows from the research question together with the primitives that constitute the artifact. Across our cases we grounded the choice in existing practice or frameworks: in **Debate Platforms** we deconstructed each interface into its main GUI layout blocks, "coherent visual and interactive units within the layout" [24], and their hierarchy; in **Data Sketching** we drew on the idiom [54] and the properties, scales, and visual variables of the data [7]; for **Auto Complete** we analyzed the sequence of screens; for **Interactive Comics** we worked at the level of panels and their layout, and for **Reading Sequences** at the level of the drawn path relative to that layout. Once a granularity is fixed, the resulting elements can be related to one another: as in grounded theory [67], codes can be grouped into themes, categories, and higher-level abstractions.



(a) Physical whiteboard (b) Digital board in Miro

Figure 8: Example of the use of an affinity diagram to organize and analyze a corpus of collected artifacts from [12]. Picture under CC BY accessible on https://osf.io/fd6v8/.

5.4 Methods for Analyzing Visual Data

The methods we used divide by scope: some are applied within a single visual, while others work across many visuals at once, the latter being where the *synopticity* of Sect. 4 pays off and is specific to visual data.

Annotating means analyzing directly on top of the visual (Fig. 1), an established analytic practice in HCI [69]. In **Reading Sequences**, both readers and researchers worked inside the visual: readers drew their reading order onto the stories, and we redrew typical paths over the same layouts to compare and communicate recurring patterns (Fig. 7). In **Interactive Comics**, each comic's dynamic behavior was annotated with visual icons on the panels it affects, turning interactions into static, codable elements (Fig. 6). In **Debate Platforms**, reverse wireframes were drawn over each screenshot to expose the underlying blocks and their hierarchy. First, text, image, and graphical elements were abstracted into blocks that remained close to the screenshots; these were then redrawn as overall functional blocks. These layers differ in who makes them and when: in **Debate Platforms** they are an analysis layer added by us, whereas in **Reading Sequences** the marks are made by participants during collection and are themselves the data. The same gesture, drawing on top of an artifact, can serve either collection or analysis.

When many visuals are of the same kind, laying them out together exposes their differences and similarities. We use the term *mosaic* (a contact sheet in photography, comprising thumbnails produced from negatives) for such a layout, since it can be reordered along whatever dimension the analysis requires. We used mosaics in **Debate Platforms** to compare interface layouts (Fig. 5) and in **Auto Complete**, both physically and digitally, to code sketches of speculative interaction techniques. A mosaic is our "overview first" in Shneiderman's sense [66]: a quick structure to browse, annotate, and discuss, typically with participants as columns and tasks as rows. Mosaics often feed into affinity diagramming, "a technique used to externalize, make sense of, and organize large amounts of unstructured, far-ranging, and seemingly dissimilar qualitative data" [53], which we used across **Data Sketching**, **Auto Complete**, and **Debate Platforms**, on raw data or after a first pass such as reverse wireframing. In practice we tokenize the data into a movable form, physical cards or tiles in a tool such as Miro, and reorganize them into clusters, trees, or matrices to test categorizations as a group (Fig. 8).

6 Toward Formalizing Visual Methods

Formalizing visual methods calls for two complementary efforts: a shared vocabulary for describing visual data, and a shared collection of methods for working with them.

6.1 Vocabulary to Describe Levels of Visual Analysis

Visual data are harder to code than text because they are not always organized as symbols or sign systems. Goodman distinguishes *notational* systems, with clear, distinct units governed by syntactic and

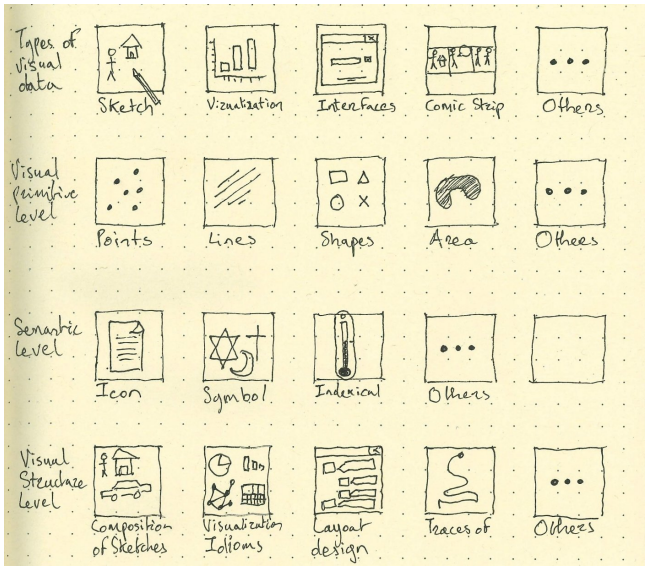


Figure 9: This diagram illustrates examples of various types of visual data and levels of coding, including samples of ways to use visual primitives (e.g., visual variables [7]), semantic coding [3, 58], and visual structures [33] (such as visualization idioms [54] and graphical user interface layout design). These levels and types can be combined and recombined in many possible configurations and are neither exhaustive nor mutually exclusive. Figure drawn by Samuel Huron under CC BY accessible on https://osf.io/fd6v8/.

semantic rules, from *non-notational* ones, which are ambiguous and open to interpretation [25]. Visualizations and interfaces tend toward the notational, and most of the visual data in our cases are partially notational; reader-drawn reading traces sit in between, since their freehand lines follow a shared convention for indicating order. A first step toward identifying the different levels of analysis is to name the primitives that define each type of visual data (Fig. 9): sketches are assemblies of strokes and points, screenshots are graphical user interface elements in a layout, visualizations are visual variables forming an idiom and other elements [41], physicalizations are assemblies of physical variables [36], interactive comics are panels linked by trigger–effect pairs, and reading traces are lines and arrows overlaid on a document. All of these visual structures embed different encodings [33]. These primitives and visual structures are not exhaustive, but they define their types and shape how each is analyzed: a monosemic visualization is read differently from a polysemic speculative sketch, and primitives can be embedded in one another. Being explicit about these types matters for study design, since non-notational elements typically require additional data to interpret.

6.2 A Call to Action: An Open Archive of Visual Methods

The methods we drew on across the six cases, from sketching and trace elicitation to reverse wireframing, design space coding, mosaicking, and affinity diagramming, were assembled ad hoc, partly from our own practice and partly borrowed from neighboring fields. They are neither named consistently nor collected anywhere a newcomer could find them. We see this as a central obstacle to visual methods maturing into a shared methodology: unlike the well-documented repertoire for analyzing text, the repertoire for visual data is largely tacit, scattered, and reinvented study by study.

As a first step toward formalizing this repertoire, we have built an open archive of visual methods[2] and seeded it with six methods extracted from the cases in this paper. The archive organizes methods by the stage of inquiry they support: *gathering* visual data (for example, eliciting data by asking participants to sketch a dataset or to draw their reading order), *understanding* them (for example, reverse wireframing an interface or coding interactions with visual icons), and *communicating* them (for example, assembling a mosaic of cases or an annotated exemplar).

Each method is documented along three questions: what it is, why and when to use it, and how to carry it out, so that a researcher from any field can apply it without prior exposure to visual methods. A submission template lets others contribute their own methods in the same format, so the collection can grow beyond what any single group practices. Organized this way, the archive operationalizes the values of Sect. 4: it is a practical route to the *congruency*, *expressive reach*, *synopticity*, and *spatial evidence* that visual methods provide. Over time, such a collection could do for visual data what methodological handbooks did for textual analysis, giving the field a common vocabulary, making methods teachable, and turning isolated techniques into a cumulative, citable body of practice. We invite the community to contribute.

6.3 Future Work

We recognize that this paper is merely a beginning. Several challenges remain open. Future research can explore variations in the use of visuals in empirical work, including variations in the details of the processes used. While many researchers have made use of visuals to better understand their work, we, as a community, are still missing the details of how to actually go about many of these processes. Such details, including many variations, are readily available to help us learn about and understand how to analyze verbal data. We hope the many members of the research community will respond to our call. We envision the archive as a collaborative platform for the community to accumulate, compare, and iteratively refine these methods, fostering long-term advancements in the field.

7 Conclusion

Visual data convey meanings and encode knowledges [23]. The qualitative analysis of visual data can be powerful for studying a diversity of aspects, including expressiveness, visual structures, reading paths, design patterns, construction processes, and designers' assumptions, to mention just a few. All these aspects are important for informing research on information visualization and interaction phenomena. However, the qualitative analysis of visual data also has its own challenges and techniques. We identified and formalized four values of using visual methods: congruency, expressive reach, synopticity, and spatial evidence. We also shared practical considerations for collecting, framing, and analyzing visual data. We propose that as a first step toward developing this practice, we explicitly expand our repertoire through a shared vocabulary of levels of visual elements. We hope our reflections on visual methods help the community better understand, appreciate, and use visual methods as part of our own research and teaching practices. To further this direction, we invite you to be part of creating a cumulative assemblage of visual methodologies that can enrich visualization and interaction research at visualmethods.pages.dev.

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[2] https://visualmethods.pages.dev

REFERENCES

[1] A. Adams, P. Lunt, and P. Cairns. A qualitative approach to HCI research. In P. Cairns and A. L. Cox, eds., *Research Methods for Human-Computer Interaction*, pp. 138–157. Cambridge University Press, 2008. doi: 10.1017/CBO9780511814570.008

[2] M. Akrich. The de-scription of technical objects. In W. E. Bijker and J. Law, eds., *Shaping Technology/Building Society: Studies in Sociotechnical Change*, pp. 205–224. MIT Press, Cambridge, MA, 1992.

[3] A. Atkin. Peirce's Theory of Signs. In E. N. Zalta and U. Nodelman, eds., *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, Spring 2023 ed., 2023.

[4] B. Bach, Z. Wang, M. Farinella, D. Murray-Rust, and N. Henry Riche. Design patterns for data comics. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, CHI '18, pp. 1–12. Association for Computing Machinery, New York, NY, USA, 2018. doi: 10.1145/3173574.3173612

[5] M. Banks. *Using Visual Data in Qualitative Research*, vol. 5. Sage, 2018.

[6] R. Barthes. Rhétorique de l'image. *Communications*, 4(1):40–51, 1964. doi: 10.3406/comm.1964.1027

[7] J. Bertin. *La graphique et le traitement graphique de l'information*. Flammarion, Paris, 1977.

[8] A. Blandford, D. Furniss, and S. Makri. *Qualitative HCI Research: Going Behind the Scenes*. Number 34 in Synthesis Lectures on Human-Centered Informatics. Morgan & Claypool Publishers, 2016. doi: 10.2200/S00706ED1V01Y201602HCI034

[9] T. Blascheck, L. M. Vermeulen, J. Vermeulen, C. Perin, W. Willett, T. Ertl, and S. Carpendale. Exploration strategies for discovery of interactivity in visualizations. *IEEE Transactions on Visualization and Computer Graphics*, 25(2):1407–1420, 2019. doi: 10.1109/TVCG.2018.2802520

[10] A. Bradley, C. MacArthur, M. Hancock, and S. Carpendale. Gendered or neutral? Considering the language of HCI. In *Proceedings of Graphics Interface 2015*, pp. 163–170. Canadian Human-Computer Communications Society, Waterloo, Ontario, Canada, 2015.

[11] V. Braun and V. Clarke. Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2):77–101, 2006. doi: 10.1191/1478088706qp063oa

[12] N. Bressa, J. Louis, W. Willett, and S. Huron. Input visualization: Collecting and modifying data with visual representations. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, CHI '24, pp. 1–18. Association for Computing Machinery, New York, NY, USA, 2024. doi: 10.1145/3613904.3642808

[13] N. Carter, D. Bryant-Lukosius, A. DiCenso, J. Blythe, and A. J. Neville. The use of triangulation in qualitative research. *Oncology Nursing Forum*, 41(5):545–547, 2014. doi: 10.1188/14.ONF.545-547

[14] K. Charmaz. *Constructing Grounded Theory*. Introducing Qualitative Methods. SAGE Publications, London, 2 ed., 2014.

[15] A. J. Copeland and D. E. Agosto. Diagrams and relational maps: The use of graphic elicitation techniques with interviewing for data collection, analysis, and display. *International Journal of Qualitative Methods*, 11(5):513–533, 2012. doi: 10.1177/160940691201100501

[16] N. Crilly, A. F. Blackwell, and P. J. Clarkson. Graphic elicitation: using research diagrams as interview stimuli. *Qualitative Research*, 6(3):341–366, 2006. doi: 10.1177/1468794106065007

[17] F. Daneshzand, S. Carpendale, and C. Perin. Exploring feedforward in data physicalization authoring tools: Supporting design exploration before fabrication. In *Proceedings of the 51st Graphics Interface Conference 2025*, pp. 12:1–12:10. Association for Computing Machinery, 2025. doi: 10.1145/3769872.3769875

[18] F. Daneshzand, C. Perin, and S. Carpendale. Kiriphys: Exploring new data physicalization opportunities. *IEEE Transactions on Visualization and Computer Graphics*, 29(1):225–235, 2023. doi: 10.1109/TVCG.2022.3209365

[19] F. Daneshzand, C. Perin, N. S. Grewal, T. Losev, and S. Carpendale. Designing with data: Supporting design processes in physicalization construction. In *Proceedings of the Nineteenth International Conference on Tangible, Embedded, and Embodied Interaction, TEI 2025, Bordeaux/Talence, France, March 4-7, 2025*, pp. 1:1–1:16. ACM, 2025. doi: 10.1145/3689050.3704943

[20] I. Dey. *Qualitative Data Analysis: A User-Friendly Guide for Social Scientists*. Routledge, London, 1993.

[21] A. Diehl, A. Abdul-Rahman, B. Bach, M. El-Assady, M. Kraus, R. S. Laramee, D. A. Keim, and M. Chen. An analysis of the interplay and mutual benefits of grounded theory and visualization. *IEEE Transactions on Visualization and Computer Graphics*, 31(9):5462–5479, 2025. doi: 10.1109/TVCG.2024.3452985

[22] K. Dorst. Frame creation and design in the expanded field. *She Ji: The Journal of Design, Economics, and Innovation*, 1(1):22–33, 2015. doi: 10.1016/j.sheji.2015.07.003

[23] J. Drucker. *Graphesis: Visual Forms of Knowledge Production*. MetaLABprojects. Harvard University Press, Cambridge, MA, 2014.

[24] T. Frappier, N. Bressa, and S. Huron. Jumping to conclusions: A visual comparative analysis of online debate platform layouts. In *Proceedings of the 13th Nordic Conference on Human-Computer Interaction*, pp. 1–15, 2024. doi: 10.1145/3679318.3685377

[25] N. Goodman. *Languages of art: An approach to a theory of symbols*. Hackett, 1976.

[26] S. Greenberg, S. Carpendale, N. Marquardt, and B. Buxton. *Sketching user experiences: The workbook*. Elsevier, 2011.

[27] J. Haber, M. A. Nacenta, and S. Carpendale. Paper vs. tablets: the effect of document media in co-located collaborative work. In *Proceedings of the 2014 International Working Conference on Advanced Visual Interfaces*, pp. 89–96. ACM, New York, 2014. doi: 10.1145/2598153.2598170

[28] H. A. He, J. Walny, S. Thoma, S. Carpendale, and W. Willett. Enthusiastic and grounded, avoidant and cautious: Understanding public receptivity to data and visualizations. *IEEE Transactions on Visualization and Computer Graphics*, 30(1):1435–1445, 2024. doi: 10.1109/TVCG.2023.3326917

[29] K. Henwood, F. Shirani, and M. Finn. 'So you think we've moved, changed, the representation got more what?': Methodological and analytical reflections on visual (photo-elicitation) methods used in the men-as-fathers study. In *A handbook of visual methods in psychology*, pp. 555–571. Routledge, 2020.

[30] C. Hine. *Virtual Ethnography*. SAGE Publications, London, 2000. doi: 10.4135/9780857020277

[31] U. Hinrichs and S. Carpendale. Gestures in the wild: studying multi-touch gesture sequences on interactive tabletop exhibits. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 3023–3032, 2011. doi: 10.1145/1978942.1979391

[32] T. Hogan, U. Hinrichs, and E. Hornecker. The elicitation interview technique: Capturing people's experiences of data representations. *IEEE Transactions on Visualization and Computer Graphics*, 22(12):2579–2593, 2016. doi: 10.1109/TVCG.2015.2511718

[33] S. Huron, S. Carpendale, A. Thudt, A. Tang, and M. Mauerer. Constructive visualization. In *Proceedings of the 2014 conference on Designing interactive systems*, DIS '14, pp. 433–442. ACM, New York, NY, USA, 2014. doi: 10.1145/2598510.2598566

[34] S. Huron, P. Gourlet, U. Hinrichs, T. Hogan, and Y. Jansen. Let's Get Physical: Promoting Data Physicalization in Workshop Formats. In *Proceedings of the 2017 Conference on Designing Interactive Systems*, DIS '17, pp. 1409–1422. Association for Computing Machinery, New York, NY, USA, 2017. doi: 10.1145/3064663.3064798

[35] S. Huron, Y. Jansen, and S. Carpendale. Constructing visual representations: Investigating the use of tangible tokens. *IEEE Transactions on Visualization and Computer Graphics*, 20(12):2102–2111, 2014. doi: 10.1109/TVCG.2014.2346292

[36] S. Huron, T. Nagel, L. Oehlberg, and W. Willett, eds. *Making with Data: Physical Design and Craft in a Data-Driven World*. A K Peters/CRC Press, New York, 1 ed., 2022. doi: 10.1201/9781003264903

[37] S. Huron, R. Vuillemot, and J.-D. Fekete. Visual sedimentation. *IEEE Transactions on Visualization and Computer Graphics*, 19(12):2446–2455, 2013. doi: 10.1109/TVCG.2013.227

[38] A. Iantaffi. Travelling along 'rivers of experience': personal construct psychology and visual metaphors in research. In *Visual Methods in Psychology*, pp. 305–317. Routledge, 2012.

[39] P. Isenberg, A. Tang, and S. Carpendale. An exploratory study of

visual information analysis. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 1217–1226. ACM, New York, 2008. doi: 10.1145/1357054.1357245

[40] T. Isenberg, P. Neumann, S. Carpendale, M. C. Sousa, and J. A. Jorge. Non-photorealistic rendering in context: an observational study. In *Proceedings of the 4th International Symposium on Non-Photorealistic Animation and Rendering*, pp. 115–126. ACM, New York, 2006. doi: 10.1145/1124728.1124747

[41] Y. Jansen and P. Dragicevic. An interaction model for visualizations beyond the desktop. *IEEE Transactions on Visualization and Computer Graphics*, 19(12):2396–2405, 2013. doi: 10.1109/TVCG.2013.134

[42] M. Jolivet-Duval, S. Safin, and S. Huron. Design territorial, représentations spatiales et participation citoyenne: revue de cas et analyse d'outils. *Sciences du Design*, 14(2):55–75, 2021. doi: 10.3917/sdd.014.0055

[43] J. Keijser, S. Carpendale, M. Hancock, and T. Isenberg. Exploring 3D interaction in alternate control-display space mappings. In *Proceedings of the 2007 IEEE Symposium on 3D User Interfaces*, pp. 17–24. IEEE Computer Society, Los Alamitos, CA, 2007. doi: 10.1109/3DUI.2007.340769

[44] K. T. Konecki. Visual grounded theory: A methodological outline and examples from empirical work. *Revija za sociologiju*, 41(2):131–160, 2011. doi: 10.5613/rzs.41.2.1

[45] R. Kruger, S. Carpendale, S. D. Scott, and S. Greenberg. Roles of orientation in tabletop collaboration: Comprehension, coordination and communication. *Computer Supported Cooperative Work (CSCW)*, 13(5–6):501–537, 2004. doi: 10.1007/s10606-004-5062-8

[46] S. Lacroix. *Domestiquer l'information énergétique : Confronter les choix de conception de dispositifs de feedback et les pratiques des usagers pour proposer une démarche de design. (Domesticating the energy information. : Comparing the feedback device design choices and user practices to develop a new design approach)*. PhD thesis, Polytechnic Institute of Paris, France, 2020.

[47] H. Lam, E. Bertini, P. Isenberg, C. Plaisant, and S. Carpendale. Empirical studies in information visualization: Seven scenarios. *IEEE Transactions on Visualization and Computer Graphics*, 18(9):1520–1536, 2012. doi: 10.1109/TVCG.2011.279

[48] J. H. Larkin and H. A. Simon. Why a diagram is (sometimes) worth ten thousand words. *Cognitive Science*, 11(1):65–100, 1987. doi: 10.1111/j.1551-6708.1987.tb00863.x

[49] J. Lazar, J. H. Feng, and H. Hochheiser. *Research Methods in Human-Computer Interaction*. Morgan Kaufmann, Cambridge, MA, 2 ed., 2017.

[50] M. Le Goc, P. Dragicevic, S. Huron, J. Boy, and J.-D. Fekete. A better grasp on pictures under glass: Comparing touch and tangible object manipulation using physical proxies. In *Proceedings of the International Working Conference on Advanced Visual Interfaces*, pp. 76–83, 2016. doi: 10.1145/2909132.2909247

[51] C. Lévi-Strauss. *La voie des masques*. Skira, Genève, 1975.

[52] S. Li, R. Deva, A. Narechania, A. Karduni, C. X. Bearfield, and E. Wall. Does a picture paint a thousand words? Using visual and textual channels to understand attitudes and beliefs. In *Proceedings of the 2026 CHI Conference on Human Factors in Computing Systems*, pp. 1–17, 2026. doi: 10.1145/3772318.3791303

[53] A. Lucero. Using affinity diagrams to evaluate interactive prototypes. In J. Abascal, S. Barbosa, M. Fetter, T. Gross, P. Palanque, and M. Winckler, eds., *Human-Computer Interaction – INTERACT 2015*, vol. 9297 of *Lecture Notes in Computer Science*, pp. 231–248. Springer International Publishing, Cham, 2015. doi: 10.1007/978-3-319-22668-2_19

[54] T. Munzner. *Visualization Analysis and Design*. A K Peters/CRC Press, Boca Raton, FL, 2014. doi: 10.1201/b17511

[55] J. Müller-Brockmann. *Grid Systems in Graphic Design: A Visual Communication Manual for Graphic Designers, Typographers and Three Dimensional Designers*. Niggli, 1981.

[56] S. Orts-Escolano, C. Rhemann, S. R. Fanello, W. Chang, A. Kowdle, Y. Degtyarev, D. Kim, P. Davidson, S. Khamis, M. Dou, V. Tankovich, C. T. Loop, Q. Cai, P. A. Chou, S. Mennicken, J. P. C. Valentin, V. Pradeep, S. Wang, S. B. Kang, P. Kohli, Y. Lutchyn, C. Keskin, and S. Izadi. Holoportation: Virtual 3D teleportation in real-time. In J. Rekimoto, T. Igarashi, J. O. Wobbrock, and D. Avrahami, eds., *Proceedings of the 29th Annual Symposium on User Interface Software and Technology, UIST 2016, Tokyo, Japan, October 16-19, 2016*, pp. 741–754. ACM, 2016. doi: 10.1145/2984511.2984517

[57] E. Panofsky. *Essais d'iconologie: Thèmes humanistes dans l'art de la Renaissance*. Gallimard, Paris, 1967. Translated by Claude Herbette and Bernard Teyssèdre.

[58] C. S. Peirce. *Collected Papers of Charles Sanders Peirce*, vol. 5. Harvard University Press, Cambridge, MA, 1934. Edited by Charles Hartshorne and Paul Weiss.

[59] S. Pink. Visual methods. In C. Seale, G. Gobo, J. F. Gubrium, and D. Silverman, eds., *Qualitative Research Practice*, pp. 391–406. SAGE Publications, London, 2004.

[60] P. Reavey, ed. *Visual Methods in Psychology: Using and Interpreting Images in Qualitative Research*. Psychology Press, Hove, UK, 2011. doi: 10.4324/9780203829042

[61] M. Rezaie, S. Huron, P. Taghipour, L. Quach, V. Cheung, and S. Carpendale. Studying visual evidence from using physical space to think. *Proceedings of the ACM on Human-Computer Interaction*, 9(8):233–255, 2025. doi: 10.1145/3773068

[62] M. Rezaie, M. Tory, and S. Carpendale. Struggles and strategies in understanding information visualizations. *IEEE Transactions on Visualization and Computer Graphics*, 30(6):3035–3048, 2024. doi: 10.1109/TVCG.2024.3388560

[63] G. Rose. *Visual Methodologies: An Introduction to Researching with Visual Materials*. SAGE Publications, London, 5 ed., 2022.

[64] B. Saket, S. Huron, C. Perin, and A. Endert. Investigating direct manipulation of graphical encodings as a method for user interaction. *IEEE Transactions on Visualization and Computer Graphics*, 26(1):482–491, 2020. doi: 10.1109/TVCG.2019.2934534

[65] S. D. Scott, M. S. T. Carpendale, and K. Inkpen. Territoriality in collaborative tabletop workspaces. In *Proceedings of the 2004 ACM conference on Computer supported cooperative work*, pp. 294–303, 2004. doi: 10.1145/1031607.1031655

[66] B. Shneiderman. The eyes have it: A task by data type taxonomy for information visualizations. In *Proceedings of the 1996 IEEE Symposium on Visual Languages*, pp. 336–343. IEEE Computer Society, 1996. doi: 10.1109/VL.1996.545307

[67] A. Strauss and J. Corbin. Grounded theory methodology: An overview. In N. K. Denzin and Y. S. Lincoln, eds., *Handbook of Qualitative Research*, pp. 273–285. SAGE Publications, Thousand Oaks, CA, 1994.

[68] A. L. Strauss and J. M. Corbin. *Basics of Qualitative Research: Grounded Theory Procedures and Techniques*. SAGE Publications, Newbury Park, CA, 1990.

[69] M. Sturdee. A step toward formalising visual data analysis practices in human computer interaction. *Interacting with Computers*, 38(2):149–162, 2026. doi: 10.1093/iwc/iwae063

[70] M. Sturdee, S. Knudsen, and S. Carpendale. Data-painting: Expressive free-form visualisation. In *Proceedings of DRS2022*. Design Research Society, 2022. doi: 10.21606/drs.2022.257

[71] A. Tang, M. Pahud, S. Carpendale, and B. Buxton. Vistaco: visualizing tabletop collaboration. In *Proceedings of the ACM International Conference on Interactive Tabletops and Surfaces*, pp. 29–38. ACM, New York, 2010. doi: 10.1145/1936652.1936659

[72] A. Tang, M. Tory, B. Po, P. Neumann, and S. Carpendale. Collaborative coupling over tabletop displays. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 1181–1190. ACM, New York, 2006. doi: 10.1145/1124772.1124950

[73] C. Tang and S. Carpendale. An observational study on information flow during nurses' shift change. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 219–228. ACM, New York, 2007. doi: 10.1145/1240624.1240661

[74] A. Thudt, D. Baur, S. Huron, and S. Carpendale. Visual mementos: Reflecting memories with personal data. *IEEE Transactions on Visualization and Computer Graphics*, 22(1):369–378, 2016. doi: 10.1109/TVCG.2015.2467831

[75] A. Thudt, U. Hinrichs, S. Huron, and S. Carpendale. Self-reflection and personal physicalization construction. In *Proceedings of the 2018*

CHI Conference on Human Factors in Computing Systems, CHI '18, pp. 1–13. Association for Computing Machinery, New York, NY, USA, 2018. doi: 10.1145/3173574.3173728

[76] D. Todorović. Gestalt principles. *Scholarpedia*, 3(12):5345, 2008. doi: 10.4249/scholarpedia.5345

[77] E. R. Tufte. *The Visual Display of Quantitative Information*. Graphics Press, Cheshire, CT, 1983.

[78] B. Tversky, J. B. Morrison, and M. Bétrancourt. Animation: can it facilitate? *International Journal of Human-Computer Studies*, 57(4):247–262, 2002. doi: 10.1006/IJHC.2002.1017

[79] J. Urist. The Rorschach test and the assessment of object relations. *Journal of Personality Assessment*, 41(1):3–9, 1977. doi: 10.1207/s15327752jpa4101_1

[80] J. Walny, S. Carpendale, N. H. Riche, G. Venolia, and P. Fawcett. Visual thinking in action: Visualizations as used on whiteboards. *IEEE Transactions on Visualization and Computer Graphics*, 17(12):2508–2517, 2011. doi: 10.1109/TVCG.2011.251

[81] J. Walny, J. Haber, M. Dörk, J. Sillito, and S. Carpendale. Follow that sketch: Lifecycles of diagrams and sketches in software development. In *Proceedings of the 6th IEEE International Workshop on Visualizing Software for Understanding and Analysis (VISSOFT)*, pp. 1–8, 2011. doi: 10.1109/VISSOF.2011.6069462

[82] J. Walny, S. Huron, and S. Carpendale. An exploratory study of data sketching for visual representation. *Computer Graphics Forum*, 34(3):231–240, 2015. doi: 10.1111/cgf.12635

[83] J. Walny, S. Huron, C. Perin, T. Wun, R. Pusch, and S. Carpendale. Active reading of visualizations. *IEEE Transactions on Visualization and Computer Graphics*, 24(1):770–780, 2018. doi: 10.1109/TVCG.2017.2745958

[84] J. Walny, B. Lee, P. Johns, N. Henry Riche, and S. Carpendale. Understanding pen and touch interaction for data exploration on interactive whiteboards. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2779–2788, 2012. doi: 10.1109/TVCG.2012.275

[85] Z. Wang and S. Carpendale. Diegetic data stories for climate communication. In *Visualising Climate 2026 Proceedings*. Bologna, Italy, Nov. 2026.

[86] Z. Wang, H. Dingwall, and B. Bach. Teaching data visualization and storytelling with data comic workshops. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*, CHI EA '19, pp. 1–9. Association for Computing Machinery, New York, NY, USA, 2019. doi: 10.1145/3290607.3299043

[87] Z. Wang, S. Hao, and S. Carpendale. Flirting charts: Expressive motion design in information visualization inspired by animal courtship performances. In *IEEE VIS 2025 poster*, 2025.

[88] Z. Wang, S. Hao, and S. Carpendale. AI4VIS EthiCards: A card-based approach to exploring ethics in AI for data visualization applications. *Computer Graphics Forum*, 45(3), 2026. doi: 10.1111/cgf.70444

[89] Z. Wang, S. Huron, M. Sturdee, and S. Carpendale. Summary of the workshop on visual methods and analyzing visual data in human computer interaction. In *Companion Proceedings of the 2024 Conference on Interactive Surfaces and Spaces*, ISS Companion '24, pp. 29–32. Association for Computing Machinery, New York, NY, USA, 2024. doi: 10.1145/3696762.3698047

[90] Z. Wang, J. Ritchie, J. Zhou, F. Chevalier, and B. Bach. Data comics for reporting controlled user studies in human-computer interaction. *IEEE Transactions on Visualization and Computer Graphics*, 27(2):967–977, 2021. doi: 10.1109/TVCG.2020.3030433

[91] Z. Wang, H. Romat, F. Chevalier, N. H. Riche, D. Murray-Rust, and B. Bach. Interactive data comics. *IEEE Transactions on Visualization and Computer Graphics*, 28(1):944–954, 2022. doi: 10.1109/TVCG.2021.3114849

[92] Z. Wang, L. Sundin, D. Murray-Rust, and B. Bach. Cheat sheets for data visualization techniques. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, CHI '20, pp. 1–13. Association for Computing Machinery, New York, NY, USA, 2020. doi: 10.1145/3313831.3376271

[93] Z. Wang, S. Wang, M. Farinella, D. Murray-Rust, N. Henry Riche, and B. Bach. Comparing effectiveness and engagement of data comics and infographics. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, CHI '19, pp. 1–12. Association for Computing Machinery, New York, NY, USA, 2019. doi: 10.1145/3290605.3300483

[94] T. B. Ward, M. J. Patterson, and C. M. Sifonis. The role of specificity and abstraction in creative idea generation. *Creativity Research Journal*, 16(1):1–9, 2004. doi: 10.1207/s15326934crj1601_1

[95] K. Waseem, M. Sturdee, Z. Wang, R. A. Lewis, M. Tonelli, and S. Carpendale. Exploring using personalised comics for healthcare communication for patients living with hemodialysis. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference*, pp. 859–873, 2024. doi: 10.1145/3643834.3661506

[96] W. Wei, S. Huron, and Y. Jansen. Towards autocomplete strategies for visualization construction. In *2023 IEEE Visualization and Visual Analytics (VIS)*, pp. 141–145. IEEE, 2023. doi: 10.1109/VIS54172.2023.00037

[97] L. Winner. Do artifacts have politics? In J. Weckert, ed., *Computer Ethics*, pp. 177–192. Routledge, London, 2017. doi: 10.4324/9781315259697-21

[98] T. Wun, J. Payne, S. Huron, and S. Carpendale. Comparing bar chart authoring with Microsoft Excel and tangible tiles. *Computer Graphics Forum*, 35(3):111–120, 2016. doi: 10.1111/cgf.12887

[99] H. Wölfflin. *Principles of Art History: The Problem of the Development of Style in Later Art*. Dover Publications, New York, 1950. Translated by Marie Donald Hottinger.

[100] A. Zanella, M. S. T. Carpendale, and M. Rounding. On the effects of viewing cues in comprehending distortions. In *Proceedings of the Second Nordic Conference on Human-Computer Interaction*, pp. 119–128. ACM, New York, 2002. doi: 10.1145/572020.572035