

A Scoping Review on How HCI Researchers Visualize Results of Thematic Analysis

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Abstract

Thematic analysis (TA) is a widely adopted qualitative method in Human-Computer Interaction (HCI). While well-established guidelines exist for visualizing quantitative data, the visual representation of qualitative findings in TA remains underexplored. To bridge this gap, we survey the current landscape of TA result presentation through a scoping review of 187 CHI papers that use TA, published between 2012 and 2025. Based on the results, we contribute a taxonomy of visual representations for thematic analysis results, which consists of two dimensions: the type of result being communicated (e.g., theme, concept, quantitative) and the graphical techniques used to represent it (e.g., table, image, diagram). Our analysis showed that despite the growing use of TA, more than half of the visualizations focus on quantitative aspects rather than core qualitative insights. We conclude by discussing practices and opportunities to enhance the visual communication of qualitative insights in future HCI research.

CCS Concepts

• **Human-centered computing** → **Visualization theory, concepts and paradigms; Empirical studies in HCI.**

Keywords

Thematic analysis, qualitative data, visualization, scoping review

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1 Introduction

Thematic analysis (TA) is widely adopted in Human-Computer Interaction (HCI) research to interpret qualitative data derived from human participants and their interactions with technology [5, 13]. Given that the outcomes of TA are often complex and rich in nuance, effectively communicating these findings to an audience is critical [5, 7]. Consequently, it is essential not only to document qualitative findings and insights textually but also to leverage visual representations to enhance comprehension and engagement [7].

In the context of human cognition, vision plays a dominant role; thus, visualization serves as an efficient medium to convey data and its underlying meaning at a glance [17, 23]. For quantitative data, well-established visualization frameworks guide researchers on selecting optimal visual encodings for specific data attributes and analytical goals [17]. However, the theoretical foundations for visualizing qualitative data remain less developed, though they gain consistent interest from the research community [10, 20, 22].

While a limited number of studies outside the HCI domain explore visual representations of qualitative analysis, none specifically address thematic analysis or tailor their inquiries to the unique context of HCI. To bridge this gap, our study aims to survey the current landscape of visual representation practices for thematic analysis results within HCI research. We pose the following research question: *What are the current practices of HCI researchers in using visual representations of their findings in thematic analysis?*

To address this question, we conduct a scoping review of 187 papers published in CHI between 2012 and 2025 that utilize thematic analysis. We systematically analyze the visual representations (i.e., figures and tables) within these publications, adhering to established scoping review and code establishment protocols [2, 15]. Through this process, we develop a taxonomy of visual representations grounded in information visualization theory [9].

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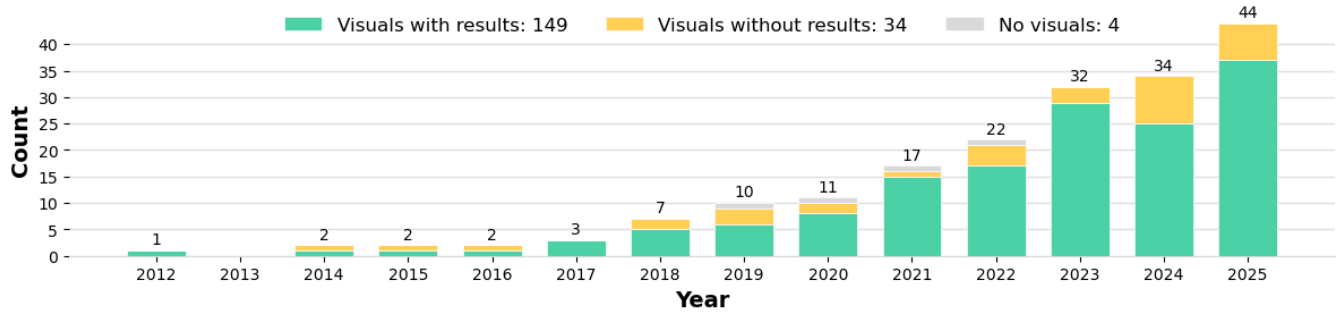


Figure 1: Yearly publication trend of CHI articles, including thematic analysis. The number of papers grows throughout 13 years, most of which include visual representations demonstrating analysis results.

Our analysis reveals that the resulting data of TA can be categorized into three main types: **Theme**, a recurring pattern of meaning organized from qualitative data; **Concept**, novel conceptual artifacts developed based on the results of a TA; and **Quantitative** results derived from or reported alongside the TA.

To represent these data types, researchers primarily utilize four visual encodings: **Table**, **Image**, **Diagram**, and **Chart**. As visual encodings heavily depend on the data [17], we observe distinct usage patterns across data types. **Table** emerges as the most prevalent format, serving as a versatile tool across all data types; researchers rely heavily on tables to structure themes and concepts textually. **Image** is employed mainly for descriptive purposes, using raw materials like photos or screenshots to exemplify themes, or illustrations to depict abstract concepts. **Diagrams** are predominantly used to provide an overview of the relationships between themes and concepts. Finally, **Charts** are utilized to represent quantitative aspects, such as the frequency of themes, self-reported Likert scales, or time consumption metrics.

In conclusion, this study identifies the prevailing patterns in how HCI researchers visually communicate TA results. Building on this taxonomy, we plan to conduct in-depth interviews to uncover the underlying rationale behind these design choices, specifically investigating *how* and *why* researchers design visual representations for qualitative data in their specific contexts.

2 Related Work

HCI is a discipline focused on the relationship between humans and computers, often involving empirical research with human subjects [13]. While resulting data can be analyzed using various methods, qualitative approaches play a pivotal role in HCI by providing rich insights into the sociotechnical contexts of system use—nuances that quantitative measures alone often overlook [12, 16]. Among these approaches, Thematic Analysis (TA) has gained particular popularity due to its flexibility in structuring and interpreting complex datasets [3]. TA is defined as a method for identifying, analyzing, and reporting patterns of meaning, or *themes*, within data [5]. It enables researchers to interpret the dataset holistically, extract embedded semantics, and explore the underlying assumptions behind explicitly stated content [6].

Notably, a meta-review of 11,542 papers published at CHI (1981 – 2024) identified TA as a cornerstone method that has exerted

immense influence since its formal introduction [18]. Our own scoping review further corroborates this trajectory, demonstrating a dramatic increase in its adoption from 2012 to 2025. Within the community, researchers employ TA across a diverse array of sub-disciplines, ranging from user experience [8] and visualization [21] to the development of novel systems [14] and meta-analyses of research practices [4].

However, despite the active utilization of TA in the *analysis* phase, the *presentation* of its results remains underexplored within the HCI domain. This oversight is significant given that the six-phase process proposed by Braun and Clarke dedicates its final step entirely to producing the report [5]. This emphasizes the critical importance of organizing and presenting results in a manner that is easily comprehensible to others. Currently, many studies rely on text-heavy approaches, communicating findings primarily through extensive descriptive text. Yet, the principle that visualization is often more effective than text alone for communicating complex information applies equally to qualitative data [1].





While visual representation methods for quantitative data are theoretically well-established [17, 23], systematic frameworks for representing qualitative outcomes are lacking. Prior work has sought to organize qualitative visualizations for specific purposes, such as evaluation [10] or comparison [20], or within specific academic disciplines [22]. However, these studies are often limited in scope and do not fully encompass the broad range of research topics and result types characteristic of modern HCI. Thus, our work aims to characterize how HCI researchers currently use visual representations in TA results and identify opportunities for future research.






3 Scoping Review

To investigate how visual representations are utilized in CHI articles employing thematic analysis (TA), we conduct a scoping review. Our methodology is informed by the six-step framework proposed by Arksey and O’Malley [2] and recent reviews in the HCI domain [4]. The yearly number of publications is shown in Figure 1.

3.1 Data Collection (Steps 1-3)

We define our research question to identify current practices in visually representing qualitative findings from TA. We perform a systematic search in the ACM Digital Library for publications in CHI proceedings (2008–2025). To manage the scope and ensure

Table 1: A taxonomy of represented Data types, including subcategories, definitions, and total occurrences. The final columns show appearances across four Visual Encodings:  Table,  Image,  Diagram, and  Chart. The sum of individual appearances may exceed the total count (Tot.) as multiple visual encodings can be assigned to a single instance.

Cat.	Subcat.	Def.	Tot.					
Theme	Taxonomy	Hierarchical structure of themes and subthemes.	59	41	1	18	0	3
	Definition	Definitions or descriptions of themes.	55	31	20	3	0	2
	Example	Examples for detailed explanations of themes.	187	35	144	10	1	4
	Frequency	Frequencies of each theme.	62	44	2	2	18	0
	Other	Themes that cannot be categorized	21	11	0	6	3	0
Concept	Model/Framework	Novel conceptual structures that emerged from thematic analysis.	42	7	6	32	1	0
	Design Insight	Actionable insights such as design implications for future design.	30	12	12	4	0	1
	Other	Concepts that cannot be categorized.	5	0	2	2	0	1
Quant.	Self-reported	Quantitative result of self-reported values.	71	27	0	0	44	0
	Objectively-measured	Quantitative result of measured values.	88	43	0	0	45	0
Misc.	Miscellaneous Result	Results that cannot be categorized.	9	1	9	0	0	1
Total				252	196	77	112	12

relevance, we establish specific inclusion criteria. We begin with a preliminary search in the ACM Digital Library, where we search for “research articles” in all CHI proceedings that contained the keyword “thematic analysis” in their Title, Abstract, or Full text. This search yield a total of 5,513 papers from 2008 to 2025, which is an unmanageable amount for a scoping review. To narrow down our scope, we search for articles containing “*thematic analysis*” in the *Title or Abstract*, which yields 150 articles (Searched in July 2025). To capture papers that heavily utilize qualitative analysis but might not explicitly feature “thematic analysis” in the title, we conduct a supplementary search for articles with “*qualitative analysis*” or “*qualitative data analysis*” in the *Title or Abstract* AND “*thematic analysis*” in the *Full text* for the same period (2012-2025). This adds 39 papers that present qualitative results using TA. After removing duplicates, we establish a corpus of 187 papers. From these, we exclude four papers that contain no visual content. We then extract all visual representations (i.e., figures and tables) from the main body of the remaining 183 manuscripts, excluding appendices, which results in an initial dataset of 1,052 visual representations.

3.2 Analysis (Steps 4-5)

To categorize the extracted visuals, we develop a hierarchical coding scheme focusing on three dimensions: 1) **Research step**: The stage of research illustrated; 2) **Data type**: The specific subject matter depicted; and 3) **Visual encoding**: The visualization techniques employed. Since our primary goal is to understand the presentation of TA results, we first filter the 1,052 visuals by **Research step**. Visuals not classifying as research results or implications are excluded from further coding. We employ an iterative coding process involving four researchers to ensure reliability. Two authors initially develop the codebook, followed by validation with two additional independent coders. We assess inter-rater reliability

using Krippendorff’s α , achieving high consistency across all categories (Research step: 0.85, Data type: 0.78, Visual encoding: 0.97). Following this validation, we divide the remaining dataset among the coders. Consequently, we refine our final dataset to 572 visual representations from 149 papers.

Step 6 (Consultation) is reserved for future work involving expert interviews.

4 Scoping Review Results

We propose a taxonomy across two dimensions: the type of result being communicated (**Data type**) and the graphical techniques used to represent it (**Visual encoding**). Results of the survey are also available online (<https://taresultvis.github.io/>).

4.1 Data Type

Our analysis reveals three primary categories along with their respective subcategories (Table 1). **Theme** represents recurring patterns of meaning [6], visualized through hierarchical taxonomy, descriptive definition, illustrative example (e.g., quotes), and others. **Concept** involves a higher level of abstraction than themes, including a theoretical mode/framework or an actionable design insight. Some concepts that cannot be categorized are included in others. **Quant.** includes numerical data, such as self-reported ratings or objectively-measured performance metrics, reported alongside TA. Any remaining data types are classified as **Misc.**

4.2 Visual Encoding

Our taxonomy of visual representations aligns with established classification systems in information graphics [9], refined through iterative discussions among the authors. We classify these representations into four categories and their subcategories. Individual

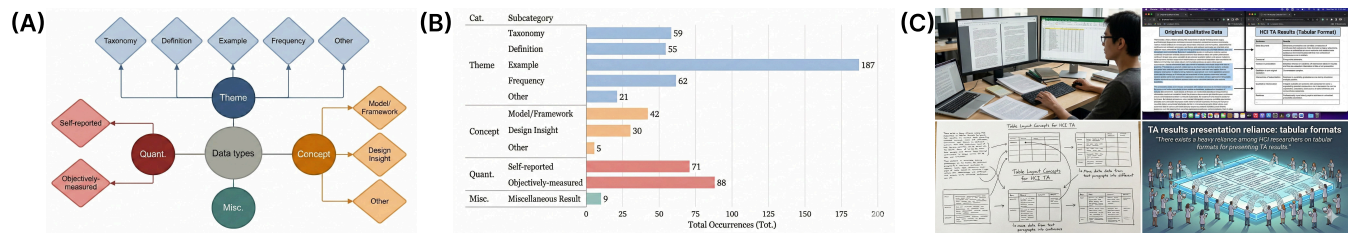


Figure 2: Representative examples of visual encodings identified in our taxonomy: Table 1 can be transformed into (A) Diagram or (B) Chart, to emphasize the taxonomy and the frequency of the theme, respectively. (C) Image and its subcategories are mainly utilized as descriptive examples. In this case, images are describing the quote: “HCI researchers heavily rely on tabular formats for presenting TA results”(subsection 5.2). All images are created with Gemini Nano Banana 2.

visual representations often encode multiple data types (e.g., a table showing a taxonomy of themes alongside their frequencies). In such cases, they were counted across all relevant categories. For detailed examples of **Visual Encoding**, please refer to our website.

Table/Matrix comprises structured representations organizing data into a grid of rows and columns. While “Table” and “Matrix” are often used interchangeably [9], we distinguish them based on their central focus: **Table** is text-centric, designed for detailed reading where cells contain alphanumeric data (e.g., descriptions, quotes). **Matrix** is visual-centric, designed for scanning relationships, where cells contain discrete visual marks (e.g., checks, dots). **Heatmap** is value-centric, utilizing color intensity to visually encode magnitude, frequency, or density. Our Table 1 is an example of a table combined with a heatmap that describes the taxonomy, definitions, and frequencies of themes.

Image captures a scene or concept visually. Subcategories are defined by their source (Figure 2.(C)): **Photo** captures real-world scenes; **Screenshot** depicts digital content from screens; **Sketch** refers to rough or unfinished drawings; and **Illustration** denotes polished graphics generated via design tools.

Diagram encompasses schematic representations illustrating relationships between entities (Figure 2.(A)). The most prevalent types use blocks and lines: **Block diagrams** lay out information in schematic blocks without explicit interconnections. **Network diagrams** illustrate relationships by connecting blocks with lines. Although literature often classifies network diagrams as a subset of block diagrams [9], we distinguish them here by the explicit use of connecting lines. Other prevalent representations utilize spatial areas: **Venn diagrams** show set relationships via overlapping shapes, and **Onion diagrams** illustrate hierarchical structures using concentric ellipses. Finally, **Timeline diagrams** are frequently observed, placing events along a temporal axis to show progression over time. Any other diagrams are classified as **Other**.

Chart maps quantitative data to visual elements (Figure 2.(B)). We define subcategories based on standard visualization literacy [17]. As bar charts are too prevalent, we further categorize them into: **Standard bar**, **Grouped bar**, **Stacked bar**, and **Diverging bar charts**. In addition to bar charts, **Box plot**, **Dot plot**, and **Line chart** are widely used. Charts that incorporate indicators for error or confidence intervals are also counted under the **Range Symbol**. Any charts that do not fit these categories are classified as **Other**.

5 Result

Based on our scoping review, we identify several key patterns in the visualization of TA findings.

5.1 The Evolving Landscape of TA Visualization

The adoption of TA in CHI publications demonstrates a consistent upward trend (Figure 1), aligning with broader community surveys [18]. However, while a substantial majority of papers in our corpus (149 out of 187) include visual representations, a detailed breakdown reveals that visuals specifically for reporting core qualitative findings (**Theme** and **Concept**) are less than half of all visuals found (406 out of 1,052). This indicates that a significant portion of researchers’ visualization efforts is directed toward aspects other than the core qualitative findings, suggesting an opportunity for further development in qualitative visualization methods.

5.2 The Dominance of Tables

With 252 appearances, tables emerge as the most dominant form of visual representation across all data types. This indicates a heavy reliance among HCI researchers on tabular formats for presenting TA results. Tables are effective at preserving the richness of qualitative findings by accommodating extensive textual descriptions. However, this reliance on text-heavy formats may compromise the visual efficiency of information delivery. It is crucial to investigate the underlying reasons for this dependence and explore strategies to transform tabular data into more visually effective representations.

5.3 Images for Descriptions

Images are primarily employed to provide examples of **Theme**, accounting for 138 out of 187 instances. This pattern is so pronounced that the vast majority of images in our corpus (138 out of 173) serve this specific purpose, often taking the form of photos, sketches, and screenshots depicting artifacts or contexts. In contrast, illustrations serve a distinct role compared to those raw images, to define or depict abstract concepts and themes according to their specific mental models. While this offers high freedom of expression for precise communication, it likely presents a higher barrier to entry for researchers without a design background. Understanding the design processes and usage patterns of illustrations is essential for lowering this barrier and enabling researchers to visually communicate qualitative nuances effectively.

5.4 Diagrams for Concepts

Diagrams are predominantly employed to represent the taxonomy of **Theme** and **Concept**. Notably, for **Concept**, the proportion of diagrams is significantly higher than for other visual encodings. This corroborates previous findings that diagrams are an effective medium for capturing relationships between concepts and visualizing abstract structures [11, 19]. However, diagrams share a similar trade-off with illustrations: while highly effective for conceptual representation, they entail significant design complexity. Identifying the specific support mechanisms researchers require to leverage diagrams more effectively is, therefore, crucial for enhancing the visual communication of qualitative findings.

5.5 Charts for Quantitatives

The use of charts is largely limited to **Quant.** and the frequency of **Theme**. This aligns with the inherent optimization of charts for representing numerical values. Among charts, variations of the bar chart (e.g., standard, grouped, stacked) appear 44 times, accounting for nearly half of all charts in our dataset. Analyzing these preferences can reveal which visual attributes resonate with researchers, thereby guiding the development of more compelling and accessible visualization techniques for quantitative TA results.

6 Limitation and Future Work

While the current investigation provides a comprehensive descriptive mapping of the visualization landscape, it is primarily limited to characterizing existing artifacts rather than extracting high-level insights. To address this, we will conduct follow-up interviews with domain experts to move beyond surface-level observations. By synthesizing these quantitative findings with qualitative interview data, we aim to uncover the underlying *why* and *how* of researchers' design choices, ultimately deriving actionable design implications and system requirements.

7 Conclusion

In this work, we present a taxonomy of data types and visual representations for thematic analysis (TA) results in HCI, derived from a scoping review of 187 CHI publications. Our findings reveal a heavy reliance on tables, whereas images, diagrams, and charts exhibit distinct usage patterns specific to certain data types. By mapping the landscape of current practices, this study not only highlights the underexplored potential of qualitative visualization but also lays the groundwork for future research to develop more expressive and standardized design frameworks for the HCI community.

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