Does a Picture Paint a Thousand Words? Using Visual and Textual Channels to Understand Attitudes and Beliefs

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Abstract

In Human-Computer Interaction, eliciting user attitudes and beliefs is crucial for understanding user interactions with technology. Existing elicitation methods range from expressive open-ended text to structured formats like Likert scales. Expressive methods yield rich insights but are difficult to systematically analyze. On the other hand, structured methods guide users to efficiently map attitudes and beliefs to clear visual scales, yet may oversimplify complex attitudes and beliefs. Recent work has explored alternative methods including visual elicitation techniques; however, the understanding of how users mentally represent attitudes and beliefs remains limited, making it challenging to validate the effectiveness of these techniques. Through a qualitative study of US-based participants (N=41), we captured how people mentally represent their attitudes and beliefs through free-form drawings and complementary textual descriptions. Our findings reveal how the strategies participants employed to represent attitudes and beliefs can inform the design of future visual elicitation techniques that balance both expressiveness and analyzability.

CCS Concepts

• **Human-centered computing → Empirical studies in HCI**.

Keywords

Elicitation, Attitude, Belief, Visualization, Visual representation, Survey tools

ACM Reference Format:

Shiyao Li, Roshini Deva, Arpit Narechania, Alireza Karduni, Cindy Xiong Bearfield, and Emily Wall. 2026. 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 (CHI '26), April 13–17, 2026, Barcelona, Spain.* ACM, New York, NY, USA, 17 pages. https://doi.org/10.1145/3772318.3791303

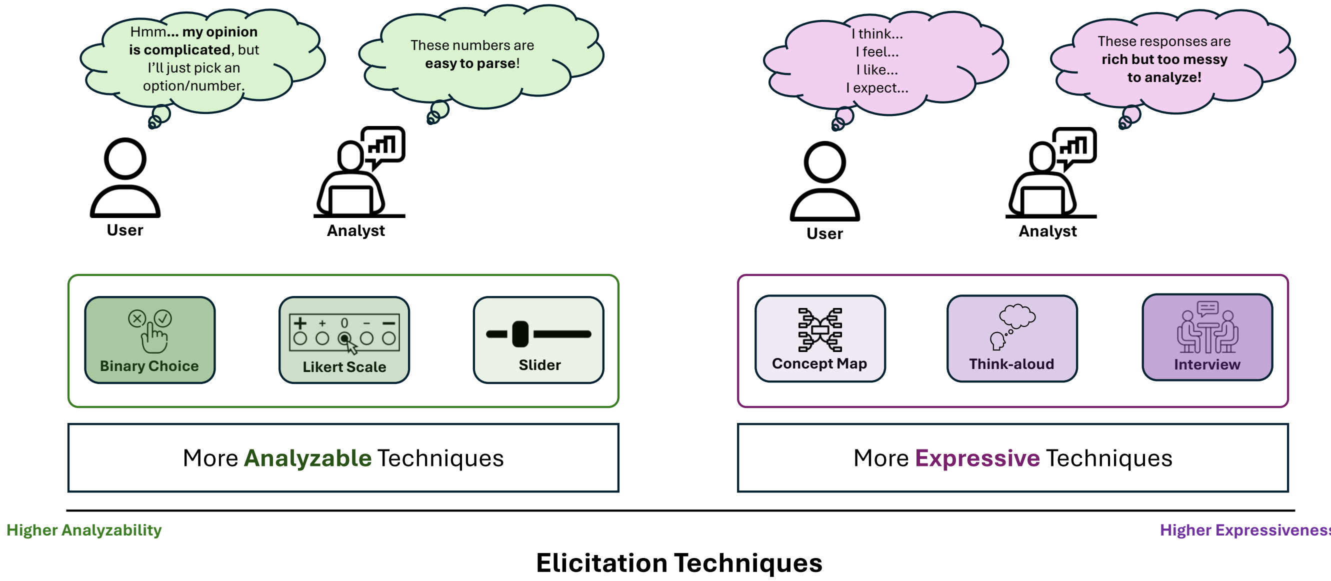
ACM ISBN 979-8-4007-2278-3/26/04
https://doi.org/10.1145/3772318.3791303

1 Introduction

In Human-Computer Interaction (HCI) research, obtaining user attitudes and beliefs is a common practice aimed at improving technology design by deepening the understanding of users [60]. This process, known as elicitation, spans a spectrum from expressive to structured methods. As depicted in Figure 1-Right, *expressive* elicitation techniques, such as open-ended text input, or statements made during think-aloud protocols and interviews [23, 55], rely on textual or verbal responses to provide rich insights into user attitudes and beliefs. However, while expressive methods capture detailed perspectives, they can be difficult to analyze systematically. To improve analyzability, *structured* elicitation methods, such as Likert scales and sliders (Figure 1-Left) streamline analysis for researchers while requiring users to map their beliefs onto a set of pre-defined options. Yet, this efficiency also comes at a cost: pre-coded response options may constrain expressiveness, making it difficult to capture nuanced attitudes and beliefs. Thus, the choice of elicitation method involves a trade-off between analyzability and expressiveness, requiring researchers to balance the richness of responses with the need for structured data collection. This tension reflects a broader challenge during elicitation processes: **elicitation methods do not always align with how people mentally represent what researchers are asking**, and such misalignment can produce responses that are distorted, oversimplified, or harder to interpret [8].

We posit that a key reason structured methods improve efficiency lies in their reliance on the *visual channel*. For instance, Likert scales and slider formats used to assess attitudes or beliefs display response options along a visual scale—either horizontally or vertically—guiding users to input their responses directly within these structured, yet simple, visualizations. However, complex attitudes and beliefs may still be difficult for individuals to map to these simplistic scales. Prior work has also proposed pictorial self-report instruments such as emoji-based emotion surveys [34], the

Figure 1: Elicitation techniques from more analyzable to more expressive.



Self-Assessment Manikin (SAM) [53], and other image-based questionnaire scales [64]; however, these tools still rely on researcher designed visual scales that measure predefined constructs such as **affective valence** or **discrete emotional states**. Although highly effective for reporting emotional states, such instruments do not show how people would independently choose to visually represent broader attitudes and beliefs when unconstrained by prescribed icons or scale formats.

Similarly, work in cognitive psychology has examined how diagrams and illustrations support reasoning and problem solving [14], but has not explored how individuals spontaneously externalize evaluative and relational judgments. To make structured elicitation techniques more expressive while maintaining efficiency, visualization researchers have extended them into **visual elicitation methods** [50] that demonstrate at least two key benefits: (1) by incorporating visual representations that are more intuitive than raw numbers (e.g., bar heights, line slopes), it can help participants more easily grasp what each value means and connect it to their own attitudes and beliefs; and (2) by adding interactions such as dragging, clicking, or sliding, it enables people to engage with visualizations in a meaningful way so that people can observe granular changes in visual representations in response to their interactions and stop when it best matches the beliefs or attitudes they hold. For instance, Kim et al., visualized the process of eliciting subjective proportion parameters by depicting the allocation of a certain number of balls into a set of bins. Users could adjust the number of balls in each bin by clicking icons above these bins[37]. Similarly, Heyer et al. used an interactive bar chart, allowing users to drag and adjust bar heights to express their prior beliefs as percentages before they viewed data in bar charts. Their findings suggest that externalizing prior beliefs in this way enhances participants' ability to acquire new information from data-driven storytelling by highlighting the deviation between their prior beliefs and the actual data [28]. More recently, Karduni et al. and Koonchanok et al., utilized lines with slopes that could be adjusted by dragging to elicit correlations to help people better reason with scatterplots [36, 39, 40].

Despite these elicitation methods in visualization and the broader HCI community, many of these techniques have not considered how people mentally represent their attitudes and beliefs without relying on predefined icons or scales, thus raising questions about the effectiveness of these elicitation techniques in capturing an individual's attitudes and beliefs. To address this gap, we ask the following research questions:

RQ: How do people visually externalize their attitudes and beliefs when unconstrained by predefined visual scales? What design insights does this provide for future visual elicitation techniques?

To answer these questions, we conducted a two-round qualitative study where we asked 41 US-based participants to express their attitudes and beliefs in a visual form. Specifically, we use the most expressive form of visual elicitation, analogous to open-text responses—free-form drawing. We provided participants with a canvas interface to externalize their attitudes and beliefs. We use the drawings to gain insight into the elements and strategies used by participants' when asked to express their attitudes and beliefs visually. To complement this, we also incorporate the textual channel as natural language to allow us to interpret their drawings, and for participants to clarify and supplement details that may be otherwise constrained by their drawing abilities.

We conducted a thematic analysis on both visual responses and textual responses. In this paper, we focus on how US-based participants **visually** represent their attitudes and beliefs, and we aimed at using the findings to inform the design of future visual elicitation techniques that balance two needs: enabling participants to produce expressive depictions that reflect their mental representation of attitudes and beliefs, and ensuring that the resulting data remain sufficiently structured and analyzable for researchers. While textual responses were also compelling, we primarily utilized them as a channel for interpreting and contextualizing participants' sketches. Our analysis of the drawings revealed three basic elements that participants used to represent attitudes and beliefs: (i) Pictorials, (ii) Facial Expressions, and (iii) Directional Symbols. These elements appeared either individually or in combination, allowing participants to express attitudes and beliefs in visual form ranging from simple to complex; we describe these in more detail in section 4. Inspired by the strategies participants used to visually convey their attitudes and beliefs in our study, we conclude with a design exploration. We present three alternative visual elicitation methods and underscore the need for future research to expand and validate these approaches.

Rather than seeking definitive structural conclusions, our qualitative study serves as an exploratory effort to inspire visualization researchers to advance structured elicitation methods by incorporating visual representations that better align with the internal representation of human attitudes and beliefs. Beyond elicitation methodologies, our findings also provide valuable insights for researchers and professionals developing survey instruments to better understand people across a variety of topics.

2 Related Work

2.1 Drawing & Diagramming Mental Constructs

Researchers across arts and social science disciplines have been designing visual representations of mental constructs from basic concepts to complex structures. In the 1920s, Homeberg attempted to gain insights into how individuals mentally form fundamental concepts like "I", "another person", "good", and "bad" by instructing participants to visually represent these concepts through abstract shapes[31]. The study also revealed how participants associated attitudinal concepts with the shapes and colors used in their abstract drawings. Positive concepts, such as "Good/Active," were often represented with warm colors and compact shapes, while negative concepts like "Bad/Passive/Weak" were depicted with cold colors and jagged shapes. Similarly, Hunter and Farthing utilized drawing as a tool to visualize teenagers' mental constructs of complex concepts such as "Nation", "Heritage" and "identity"[32]. The researchers observed that visual elements in teenagers' drawings acted as metaphors to convey intricate narratives, and explaining the symbolism behind each choice enriched the depth of their responses. For instance, one participant drew a fruit bowl filled with various flavors, shapes, and sizes to symbolize the concept of "culture", with the decay of the fruits representing the diminishing of cultures. These insights suggest a broader applicability: visualization and HCI tools can benefit from leveraging semantically resonant visual mappings as cognitive supports that align with how users already express meaning through visual form. For example, Schloss and colleagues demonstrated that color–concept alignments (e.g., darker colors representing “more” or “higher magnitude,” and culturally grounded color–food associations such as mango or watermelon hues) lead to more accurate and faster judgments in perceptual tasks [69, 70]. Similarly, Bartram et al.'s work on color–name and semantic matching in visualization contexts shows that aligning linguistic and perceptual associations improves interpretability and visual reasoning [2], which created the visualization specifications that underlie the industry-leading tool of Tableau. However, these approaches also carry limitations: color–form associations are context dependent, interpretive rather than quantitative, and often non-generalizable across cultures and user groups. Consequently, while informative for visualization design, these studies focus on how individuals represent their internal attitudes rather than on developing visualization systems or tools per se.

Therefore, visualization researchers have developed visualization tools that leverage the power of drawings, adopting sketching as a method for exploring and generating data representations. Walny et al. conducted an exploratory study in which participants sketched visualizations of a small dataset [82]. Their analysis revealed a continuum of sketches, ranging from highly numeric forms (e.g., countable dots) to highly abstract pictorial and narrative representations, illustrating the diverse ways individuals externalize data understanding through free-form drawing. Extending this notion into a more artistic domain, Sturdee et al. introduced data painting, where participants used precise volumes of paint to map data values, enabling complete freedom in visual expression [73]. This study highlighted how expressive representations can foster memorability, creativity, and personal engagement with data. Complementing these approaches, Walny et al. analyzed 82 workplace whiteboards to examine spontaneous visualizations as sketches [81]. Their findings revealed how people naturally combine text, diagrams, and graphical elements to support ideation and communication, suggesting directions for visualization design—such as incorporating ellipses or combining words and diagrams to support reasoning. Together, these studies motivate our use of free-form drawing as a design probe for exploring visual representations of attitudes and beliefs in future visual elicitation techniques.

2.2 Elicitation with Interactive Visualizations

Visual elicitation techniques have garnered increasing attention in visualization research as effective methods for uncovering individuals' mental constructs and perceptions. For instance, Koonchanok et al. demonstrated that participants who used a graphical slider to express their prior beliefs about the strength of relationships between variables were more successful in making accurate inferences about the relationships presented in subsequent data visualizations [40]. Similarly, Karduni et al. assessed a visual elicitation technique "line + cone" designed to capture beliefs about linear correlations and their uncertainty through a set of slopes [36].

Building on this work, Koonchanok et al. introduced an innovative exploratory visual analytic system, articulating their beliefs by sketching expected trend lines prior to encountering new data, thereby prompting users to scrutinize disparities between the incoming data and their preexisting beliefs [39]. Meanwhile, the VIBE framework [50] envisioned a design space for visual belief elicitation in the context of data journalism, offering high-level considerations for designing elicitation strategies based on user characteristics such as graphical literacy, statistical literacy, and domain expertise. VIBE aimed to provide tailored elicitation designs that cater to the diverse needs of users, ensuring engagement and comprehension. These efforts collectively provide some specific elicitation techniques [36, 40] and guide design efforts [50], helpful for contextualizing elicitation strategies by user characteristics. While these systems demonstrate the potential of drawing and visualization for eliciting beliefs, they are primarily applicable in data literacy and analytic reasoning contexts. They are limited by their dependence on structured visual interfaces rather than open-ended expressive representations. We build on this work to explore how individuals *freely* represent their attitudes through drawing. We revisit a foundational characteristic inherent to these efforts: namely, we explore 'what' attitudes/beliefs people can represent visually and textually and 'how' people employ different strategies to represent these attitudes and beliefs.

2.3 Alternatives to Visual Elicitation

Our paper focuses primarily on visual elicitation; however, there are other non-visual strategies that researchers use. Historically, many classic experiments in psychology utilized structured interviews or questionnaires to glean insights into individual attitudes and beliefs. The Bogardus Social Distance Scale questionnaire, developed by Emory S. Bogardus in the 1920s, was designed to elicit people's willingness to engage in contacts of 19 racial descents, employing a 7-level Likert scale for measurement. This scale provided insights into eliciting attitudes and beliefs towards different racial and ethnic groups, revealing deep-seated societal beliefs and biases [3]. Similarly, the early versions of the Minnesota Multiphasic Personality Inventory (MMPI) employed an array of true/false questions designed to diagnose mental disorders and map personality attributes, revealing individual beliefs and attitudes [52].

Furthermore, psychological research has proposed diverse methodologies to gain insights into cognitive processes, attitudes, and beliefs. For instance, one notable approach is the use of projective tests. These tests, such as the Rorschach Inkblot Test and the Thematic Apperception Test (TAT), presents ambiguous stimuli to participants, prompting them to project their unconscious beliefs and emotions to interpretations [54, 65]. Such methods aimed to elicit beliefs and emotions that might not surface in more structured or direct questioning formats.

3 Qualitative Study Methodology

3.1 Study Motivation

Cognitive psychologists have long been debating how people represent information internally, led by two prominent figures in this area: Stephen Kosslyn and Zenon Pylyshyn. Kosslyn and colleagues believe that information is spatial and depictive, therefore pictorial in nature [42], while Pylysyn and colleagues argue that information is propositional, language-like, symbolic internal representations [59, 61]. While this debate is far from being conclusive, more recent visualization research has emphasized the equal importance of text and visualization in information communication[27]. This research further highlights the preferences of a minority who favor text-only information, underscoring the importance of acknowledging text as a standalone factor in the assessment of data visualization designs.

In light of this discussion and recognizing the importance of both visual and textual mediums for communication, we conducted a two-round qualitative study to understand how people mentally represent attitudes and beliefs through *both* (i) free-form drawing responses using a canvas interface on tablet devices (ii) typing out open-ended responses in natural language. The first round focused on collecting a diverse range of visual and textual representations of attitudes and beliefs to develop a comprehensive codebook. The second round, following the same structure as the first but using different topics to elicit responses, was conducted to validate the robustness of the existing codebook and to identify any emerging patterns based on different topics that could inform the addition of new codes. Our goal was to understand the characteristics and preferences among visual and textual representations of attitudes and beliefs. We next describe our rationale for focusing on drawing.

Drawing Perceptions. Attitudes and beliefs are immaterial and complex, often influenced by cultural environments and personal experiences[22, 80]. To gather these nuanced representations visually and synthesize their commonalities for broader understanding, we use drawing as a free-form technique to externalize the visual mental constructs of attitudes and beliefs.

Drawing is more often used in research studies involving children, as researchers have been concerned that cultural standing and willingness to engage may significantly affect adult drawings[49]. However, drawing remains an effective channel for articulating perceptions and can be greeted with pleasure among adults as well[6]. Research studies have used drawing to investigate differing opinions on abstract concepts (e.g., what is energy, what is information)[6, 25, 26]. These studies found that drawing returns participants to their youth, inspiring beautiful and insightful drawings for compositional interpretation and thematic analysis. This approach explores how concepts are culturally constructed, such as when participants drew light bulbs, sockets, and batteries to represent "energy," connecting the concept to more than just heat or electricity. Therefore, to thoroughly explore the mental constructs of attitudes and beliefs, we use drawing to connect participants to their social and cultural worlds, accessing their tacit knowledge and unconscious perceptions[49, 68].

3.2 Participants

We recruited $N_1 = 20$ participants in the first round (10 women and 10 men) and $N_2 = 21$ participants in the second round (11 women, 9 men and 1 non-binary individual) from the crowdsourcing platform Prolific [57]. Participants were asked to report their age group, and most fell within the 25–44 ranges, with 11 participants each in the 25–34 and 35–44 groups, while the 18–24 (8 participants), 45–54 (6 participants), and 55+ (5 participants) groups were less represented. Participants were also generally well educated, with most holding a Bachelor's degree (17) or High School equivalent (12), followed by smaller groups with an Associate's degree (5), Master's degree (2), Ph.D. (2), Professional degree (1), Technical Certificate (1), or another specified qualification (1).

Our eligibility criteria included participants who were at least 18 years old, have an approval rate above 95%, located in the United States, fluent in English, and able to complete the study using a *tablet device*, as required by the study protocol. Participants who completed the first round were ineligible to complete the second round. Studies were conducted via Qualtrics [71]. Across the two rounds, we paid a flat rate of $3.35 to complete the study, which took median times of 17.62 and 22.02 minutes respectively.

3.3 Conditions: Visual and Textual Attitudes/Beliefs

To compare visual and textual responses, participants expressed their attitudes or beliefs about each topic by drawing (visual) and typing (textual). For the textual response, participants were provided an essay text box in Qualtrics, with a character limit set at 20,000 (participants provided responses ranging from $min = 5, max = 2146, \mu = 226.62$ characters). For the visual response, participants were provided a 1000×600 pixels canvas with basic drawing tools to adjust pen size (from 1 to 72 pixels), a color picker, and an eraser tool. Participants could use this canvas to draw a response, or they could draw elsewhere and upload an image file. Participants primarily used the digital canvas to create their drawings; an upload option was provided only for cases where a device did not support on-screen drawing (used by 1 of 41 participants). At the end of both visual and textual tasks, participants may optionally add comments to clarify their responses. The language used in the visual and textual conditions is summarized in Figure 2b.

3.4 Study Design and Procedure

After obtaining informed consent and prior to the formal study, participants completed a warm-up task that involved (i) typing about and (ii) drawing their favorite fruit, designed to familiarize them with the canvas interface and study procedure. As shown in Figure 2, both rounds of the formal study followed the same structure. Each participant was asked to express their attitudes or beliefs about two topics. Topics were selected to represent a diverse set of domains, some triggering strong attitudes (vaccination, generative AI) and others triggering strong beliefs (education spending, bicycle transportation) to enable us to observe varied forms of visual and textual responses. We also sought a range of topic familiarity; participants rated their familiarity with each topic on a 0–10 scale (0 = "have never heard of it," 10 = "know it well"). Familiarity was highest for vaccination and public health (M = 7.10, 95% CI [6.20, 8.00]), followed by education spending and academic outcomes (M = 5.35, 95% CI [4.23, 6.47]) and generative AI and its applications (M = 5.05, 95% CI [3.95, 6.14]). Bicycle use and traffic safety was the least familiar topic (M = 4.38, 95% CI [3.05, 5.72]). In the first round, participants (i) described their attitudes toward "Vaccination" ("What are your attitudes towards vaccination?") and (ii) articulated their beliefs about "Education Spending" ("What are your views on the relationship between education spending and academic achievements?") (Figure 2a). For each topic, participants completed both the visual and textual tasks described in Conditions (Figure 2b). Afterward, they reported their preference between visual and textual responses and indicated which modality they felt more accurately reflected their attitudes and beliefs (Figure 2c). Based on the first round, we developed a codebook that captured the key themes in the responses. The second round mirrored the procedure of the first but focused on two new topics: attitudes toward "Generative AI" ("What are your attitudes towards generative AI?") and beliefs about "Bicycle Usage" ("What are your views on the relationship between the use of bicycles and the occurrence of traffic accidents?"). This round allowed us to examine the robustness of our coding framework and to identify emerging patterns across different topics. In both rounds, the order of attitude versus belief tasks and of textual versus visual tasks was randomized. At the end of each round, participants completed a short questionnaire covering demographics, the role of drawing and writing in lives, and how much they like these activities. The study plan was reviewed and approved by the authors' university ethics board.

Note that we operationalize **attitude** as the perceived likelihood that something is viewed as positive or negative, and **belief** as the perceived likelihood that certain attributes are associated with the topic or object of discussion [85]. We chose four topics where participants are likely to hold strong opinions, aiming to elicit more pronounced attitudes and beliefs. Our focus is exploring the visual representations participants use and how these visuals convey their perspectives. To achieve this, we intentionally framed our instructions to be vague to avoid biasing participants, allowing for a wider range of user interpretations to obtain a broader sample of responses.

3.5 Thematic Analysis

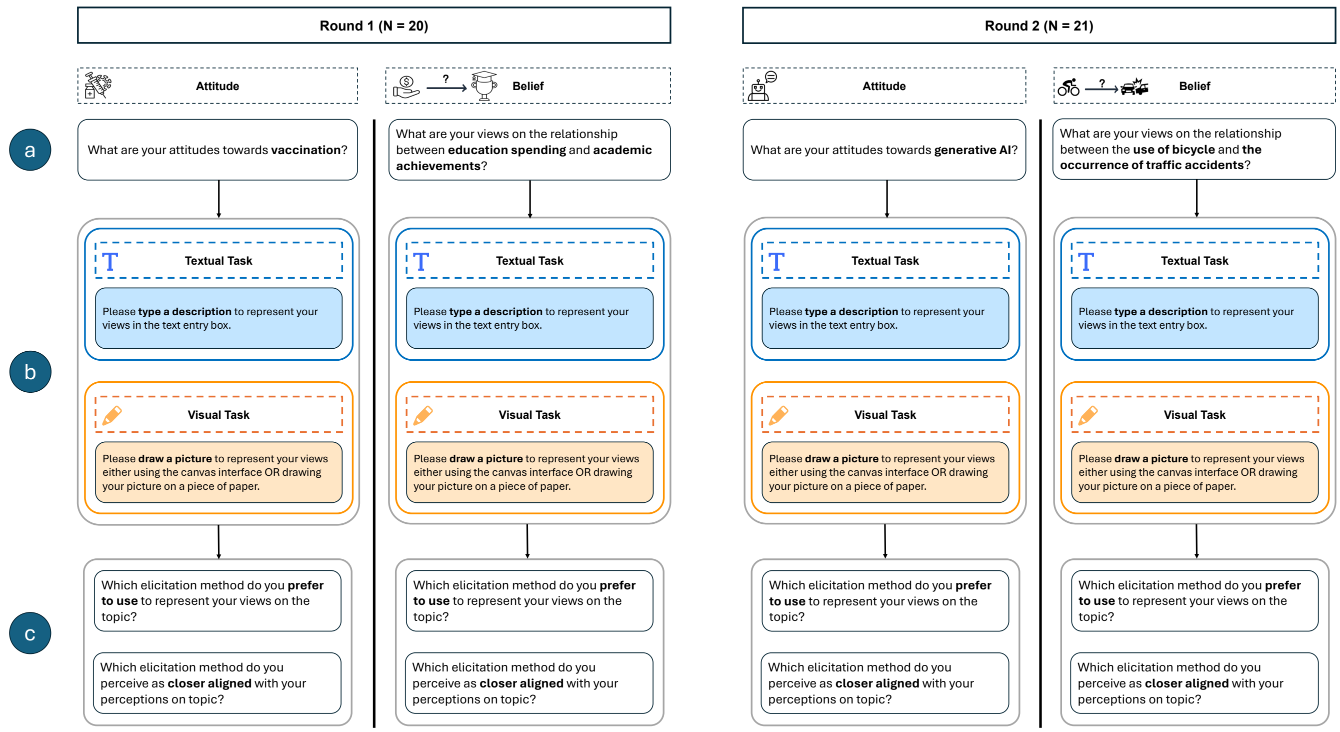
After the first round of the study, two authors independently conducted a thematic analysis [7] to derive a preliminary set of codes each for the visual and textual responses. The resulting codes had significant overlap and were ultimately combined together to produce a codebook after discussion with all authors. Two different authors then independently coded the results from the first round, achieving an inter-rater reliability using Cohen's kappa [13] of 0.79, indicating moderate agreement. Subsequently, all disagreements were discussed and resolved to achieve consensus labels.

After the second round, the authors discussed the disagreements and introduced new codes to better capture nuances in the data. These included textual codes for Personal Experiences (using personal experiences to rationalize a belief) and Conditional Beliefs (depict a belief under specific condition). The data from both rounds were re-coded using the updated codebook. For the second round, the two authors achieved a final inter-rater reliability score of 0.44. The lower inter-rater reliability resulted from two factors: (1) different interpretations of the code Belief in the textual responses, and (2) the introduction of new data and emerging textual codes in round 2, which required further adjustments to the codebook. Specifically, the Belief code was intended to capture expressions of belief only for questions explicitly asking about beliefs (Topic "Education Spending", "Bicycle Usage"). However, one author also applied this code to rationales for attitudes in attitude-related questions (Topic "Vaccination", "Generative AI"). To address this, the authors discussed and resolved all disagreements collaboratively and established the final codebook. The final codebook and all coded data are provided in the Supplemental Materials.

4 Findings

Our final code books for characterizing visual and textual responses are presented in Table 1 and Table 2, respectively. Both code books include a description of each code and its prevalence, as well as an example. The codes are not mutually exclusive, i.e., a response can fit multiple codes. When responses (text or drawings) were

Figure 2: The study procedure for round 1 and round 2.



ambiguous, we utilized the optional explanatory comments provided by participants at the end of the task to disambiguate our interpretation.

In the forthcoming sections, we will discuss visual and textual data across both rounds together. As outlined in section 1, we devote greater detail to the visual responses, beginning with three basic elements of attitude/belief expression identified in participants' drawings and then examining how these elements are combined into compositions to depict attitudes and beliefs. While we also conducted a thematic analysis on textual responses, our discussion of text is more concise, drawing attention to themes that illuminate how textual expressions may complement and inspire the visual representations of attitudes and beliefs.

4.1 Visually: *What* is in People's Attitudes and Beliefs–*Basic Elements*

In this section, we introduce the theme: Basic Elements–individual, atomic visual elements that participants used on their own without other components, often to convey simple and directional attitudes and beliefs. In total, we identified five Basic Elements: (i) Pictorials, (ii) Facial Expressions, (iii) Posture, (iv) Text, and (v) Symbols. In this section, we describe our findings on Pictorials, Facial Expressions, and Symbols, and we defer discussion of Posture and Text to Supplemental Materials.

4.1.1 *Pictorials.* 

Most of our participants included Pictorials in their drawing as an indication of objects related to the topics at hand (N = 60). In some cases, these Pictorials functioned as a component of structured objects, where their arrangement conveyed relationships that express attitudes or beliefs. For example, participant P19 drew a syringe connected to a ✓ mark with an = sign, forming an equation to indicate a positive attitudes towards vaccination, consistent with the textual response: "I believe that vaccinations are incredibly important for safeguarding public health." In other cases, we identified 11 sketches that depicted only the topic without revealing any clear attitudes or beliefs. We labeled these cases as Topics Only in the visual codebook (Table 1). However, even in these cases, participants conveyed explicit attitudes or beliefs in their complementary textual responses. For example, participant P10 drew only a syringe in the visual response, but the accompanying textual response clearly articulated a positive attitude: *"Vaccinations are usually injections meant to prevent once deadly or very harmful illnesses or conditions."* Such cases suggest a tendency among these participants to rely on text rather than visuals to communicate their attitudes and beliefs.

4.1.2 *Facial Expressions.* 

Sometimes participants utilized Facial Expression as a channel to convey attitudes and beliefs (N = 31). As one of the most powerful non-verbal communication channels, Facial Expressions can convey a wide array of emotions and intentions [17]. For example, P14 utilized a smiling faces to indicate a positive attitude towards vaccination, reinforced by the textual response: "*I like they are happening*.". In contrast, P22 depicted a frowning face to express concern about Generative AI; the stance was also echoed in the textual response: "*I think Generative AI is strange and unknown to me so I'm a little afraid of it.*" Similarly, participant P16 also used a frowning face to express confusion about vaccination, which was validated by the textual response: "Unsure, confused." One notable case is participant P27, who drew a smiley face with a frown to communicate mixed feelings about Generative AI. This visual response captured the uncertainty about the advantages and drawbacks of using AI. This tension was expanded upon in the textual response: "*I am unsure about generative AI. I think it may have some positive benefits, but I want to think that the human element needs to be considered.*"

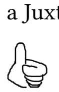
4.1.3 Directional Symbols. 

Beyond Facial Expressions, participants also conveyed their attitudes through simple Directional Symbols, indicating a positive, negative, or uncertain stance towards the topic (N = 14). As an example, participant P12 used only a ✗ mark to represent the attitudes towards vaccination in visual form, and the accompanying textual attitude was equally straightforward: "*I'm against any type of vaccination.*" Similarly, participant P15 used the hand-sketched word "yes!" in drawings to signify a positive attitude towards vaccination, further reinforced by the textual response: "*Vaccination is important in controlling and/or eradicating serious diseases.*" Additionally, participant P35 also employed a 👍 symbol to signify a positive attitude towards Generative AI, but unlike P12 and P15, the accompanying textual response revealed a more hedged attitude: "*I think it's interesting and useful, but for now isn't good enough to have lots of uses.*" Finally, participant P12 drew a ? mark to convey an uncertain attitude towards Generative AI, with accompanying textual response clarifying this stance: "*I have never used generative AI.*"

4.2 Visually: *How* do people convey attitudes/beliefs?–*Compositions*

Next, we share how participants combined the aforementioned visual elements to articulate varying attitudes and beliefs. We subdivide these Compositions into Simple (Juxtapositions and Superimpositions) and Complex (Stories, Diagrams, Equations, and Visualizations).

4.2.1 Simple Compositions. Some participants communicated their visual attitudes or beliefs using a combination of text, symbols, and pictorial representations, which we refer to as 'Simple Compositions' (N = 14). These simple compositions depict two objects either as a Juxtaposition (N = 8) or Superimposition (N = 6).

  **Juxtaposition with Symbols**. The first Simple Composition strategy we identified combines a Topical Pictorial and a Direction Symbol in juxtaposition (N = 8) to express attitudes. Participants following this approach typically used one Pictorial to symbolize the main topic and paired it either with a Facial Expression (N = 6) or a symbol (N = 2) to communicate their attitudes towards the topic. For example, participant P3 drew a smiley face next to a syringe to indicate a positive attitude towards vaccination, consistent with the accompanying textual response: *"I think vaccinations are necessary for a healthy and successful society. The positives of them far outweigh the negatives.*". Similarly, participant P38 sketched a 👍 symbol alongside a laptop to signify a positive attitude towards "*Generative AI", echoed in the textual response: "Generative AI can be used to help advance other technologies beyond our current ability and comprehension.*"

 **Superimposition of Pictorials**. Another arrangement of Simple Composition combines a Topical Pictorial and a Directional Symbol through Superimposition (N = 6). In these cases, participants often embedded the Pictorial within the shape of the attitudinal Symbol, a strategy that may have been influenced by the visual metaphor of street signage, where pictorial and symbol are merged to communicate stances on the topic. Most of the Superimposition responses appeared to Convey Attitudes (N = 5). For instance, participant P9 sketched a syringe enclosed within a heart shape to express a strongly positive attitudes, as elaborated in the textual response: "*Vaccination is a scientific miracle...*" Conversely, participant P6 drew a syringe within a crossed-out circle symbol to signify distrust of vaccination, as validated in the textual response:"*I don't trust certain vaccines.*" The remaining case from participant P29 stood out: a crossed-out circle containing "30mph" alongside another circle with "15mph", reflecting an experience-oriented belief that slower driving reduces accidents, as explained in the textual response: "*Where I am from, there are few bicycle accidents. In fact, drivers drive slower and give more space.*"

4.2.2 Complex Compositions. Beyond Simple Compositions, participants utilized tangible stories, diagrams, equations, and data visualization to build complex structured compositions that convey more nuanced attitudes and beliefs (N = 46).

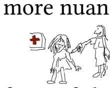
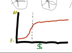
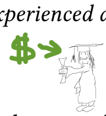
 **Stories.** Story is a commonly employed composition form of sketch to visualize participants' attitudes or beliefs about a prompt in a way that's tangible and vivid to them (N = 28). Different from Simple Compositions, a story typically depicts a scene to represent the *interactions* between objects related to the topic. We note that the story form of Complex Composition is mostly employed to depict beliefs as relationships between the use of bicycles and the occurrence of traffic accidents (N = 14). This may be because transportation plays a role in people's everyday lives and is therefore natural to mentally represent as a story. For instance, participant P41 depicted a car and a bicycle each in their respective lanes. "*I think bicycles have little role in road accidents. Due to their lanes along the road they do not create much interruptions on the road.*" From the textual response, it is clear that participant P41 intended to convey no relationship between bicycle usage and traffic accident frequency. When conveying an attitude visually through a vivid Story (N = 9), participants tend to provide clear attitudes in the visual response while unfolding more detailed rationales in the textual responses. For instance, participant P20 illustrated a relieved patient finally receiving protection from COVID-19 by getting vaccinated, thereby expressing a clear positive attitude toward vaccination. Participant P20 further expanded on this in the textual response, where the same message was expressed but with more in-depth rationale (excerpted for length): "*Vaccines have **greatly***

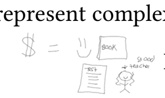
Table 1: The Final Codebook: Visual Codes.

Theme	Code	Description	Example	Prevalence (#/82)
Basic Elements	Pictorials	Depicts items that are not people or faces		60
	Facial Expression	Depicts a face, likely showing emotion		31
	Posture	Depicts the posture of a human body		26
	Text	Depicts words written or typed out		23
	Symbols	Depicts symbols such as hearts, stars, or ✗ to convey an attitude		14
Compositions	Story	Depicts a scene that indicates relationships between objects		28
	Diagram	Depicts a schematic diagram, possibly using arrows to indicate relationships; may suggest a causal relationship		8
	Juxtaposition	Depicts a directional symbol or facial expression placed beside a topical pictorial to convey an attitude toward that topic		8
	Superimposition	Depicts containment or modification of an object to change its meaning (e.g. an object enclosed in a crossed out circle)		6
	Equation	Depicts a mathematical relationship between entities		6
	Visualization	Depicts a chart or other form of abstract data visualization		4
Miscellaneous	Conveys Attitude	Conveys attitude or opinion towards a topic		46
	Topics Only	May describe the topic, but does not indicate the user's attitude/beliefs towards it		11
	Unintelligible	The drawing cannot be deciphered on its own due to complexity, penmanship, etc.		4
	Non-traditional	Indicates non-traditional responses such as searching the web for images rather than drawing them		1

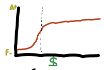
***improved** the health and welfare of people... More recently, the vaccines that were **tested and marketed** in response to the COVID-19... I was open to receiving the COVID-19 vaccine and it's follow up boosters, and I never, to my knowledge contracted COVID-19. I also never experienced any notable side effects from the vaccine.*"



Diagrams. Unlike Stories, Diagrams depict schematics and are employed, often with arrows, to illustrate causal relationships or attitude transitions (N = 8). Overall, Diagrams are primarily used in response to the questions asking for beliefs (topic: "Education Spending" and "Bicycle Usage") (N = 5). For instance, when expressing a belief about relationship between education spending and academic achiement, participant P20 sketched a green dollar sign connected by an arrow to a smiling student wearing a graduation cap. This illustration suggested a belief in a positive correlation, which was also articulated in the textual response: "*I believe there is a positive correlation between education spending and academic achievement because an institution that is well-funded is more likely to have better resources for students which can help them learn and develop interest in the subject matter being taught.*" Apart from causal relationships, diagram also appeared as a way to express transition in attitudes. Participant P26, for instance, drew a smiley face linked by an arrow to a surprised face, signaling their current satisfaction with AI while underscoring future uncertainty, as reflected in the textual response:"*I have really enjoyed using it for work. It is very impressive what it can create in a matter of seconds. I am a little concerned down the line what this will mean for creatives.*" From participants' reflection on the role of drawing in their lives, we observed that the majority of those who used Diagrams did not consider drawing to play a role in their lives. These findings could imply that Diagrams may serve as an intuitive and efficient way to represent complex attitudes and beliefs.



Equations. We also observed participants use Equation as a visual form to express attitudes and beliefs in mathematical terms (N = 6). The majority of the Equations were in response to questions related to beliefs (N = 4); namely, the topics for "Education" and "Bicycle usage" were framed as beliefs about relationships. Participants tended to construct complex equations that incorporated multiple factors related to their beliefs. For instance, participant P15 illustrated "woman in dress + cash + computers," linked by an = sign and finally pointing to a doctoral hat, to signify that education spending can contribute to academic achievement but also requires good teachers and educational facilities. This interpretation also aligned with the accompanying textual response: "*Schools where more money is spent per student tend to produce better-educated students who score well on standardized tests. This is likely due to the fact that **such schools offer teachers better pay, and have up-to-date computers and books to facilitate learning**.*" The remaining two sketches (participant P17 and P19), expressing attitudes toward vaccination, were more concise and direct. Both drawings included a sketched syringe and a ✓, connected by an = sign, to convey a favorable stance on vaccination.



Data visualizations. While most previously introduced compositions featured pictorials to represent objects in the topic, a subset of participants abstracted these objects as lines or bars in the form of Data Visualizations (N = 4). Specifically, We observed participant P13 drew a bar chart to illustrate the belief expressed in the textual response: "*Academic achievements are good but attention to what's being spent and or towards is very important.*" In this drawing, each bar represented funding allocation among different categories. The other three participants created line charts to depict beliefs as relationships (in response to questions about Education and Bicycle usage). For example, participant P9's line chart represented education spending as a temparory booster of academic achievement – showing achievement rising with increased spending but leveling off after a threshold. This was further elaborated in the textual response: "*It's complicated; education spending is no doubt a necessary yet not sufficient component of academic achievement.*" Under the same topic, participant P11 drew an almost horizontal line to suggest no connection between education spending and academic achievements, and expanded on this view in the textual response: "*I think academic achievements are largely not related to education spending. High achievers come out of poorer school districts all of the time.*" Finally, participant P39 drew a curve that first rises and then falls to represent the relationship between bicycle usage and occurrence of traffic accidents. The rationale is further explained in the textual response: "*Traffic accidents will first increase along with bicycle numbers due to more chaotic. But then it will decrease when the average speed went down.*" The participant believed that while greater bicycle use may initially create more disorder, it ultimately lowers travel speeds and reduces accidents. Collectively, these examples show how participants appropriated familiar visual forms such as bar and line charts to express beliefs about correlational and conditional relationships in ways that go beyond simple pictorial representation.

4.3 Textual: How do people *articulate* attitudes/beliefs?

In order to enrich our interpretation of the visual data and uncover attitudes and beliefs that may not have been fully captured due to limitations in participants' drawing abilities, we applied the same thematic analysis to their textual responses. In this section, we discussed three codes under the theme Articulating Views–Attitudes, Beliefs, and Hedging. Similar mental constructs of attitudes and beliefs emerged from the textual responses as from the visual responses. Most Attitudes (N = 41) and Beliefs (N = 27) were clearly articulated through textual responses. An illustrative example comes from participant P9, *"Vaccination is a scientific miracle; it's a public good that has reduced or eliminated a tremendous amount of what used to be inevitable suffering, pain, and death."*

Textual responses allowed participants to express *complex* attitudes and beliefs. For instance, Hedging was a recurrent feature observed in participants' textual responses (N = 17). Hedging characterizes responses that introduced uncertainty, caveats, or exceptions to attitudes and beliefs. Participant P4 provided a telling example: *"I suppose the more spent on the infrastructure, the more opportunity exists for students to achieve academically. But correlation doesn't imply causation."* This nuanced stance clarified that the participant did not intend their beliefs to be construed as causation.

Interestingly, after identifying the textual pattern of Hedging, we looked to the sketches to see how this textual observation manifested in visual form. For instance, participant P4 utilized ≈ symbol to signal a distinction between correlation and causation in the "Education Spending" topic. Similarly, participant P27 employed a face combining smiles and frowns depicted mixed feelings, such as cautious optimism about Generative AI. Furthermore, the analysis of textual responses revealed that the content of participants' sketches varied based on the importance of their hedged concerns. For significant issues depicted in the textual response such as participant P1's statement: *"I think vaccination is necessary for some illnesses. But I do not think babies should be over-vaccinated."* had a corresponding visual response depicting detailed imagery including a crying baby alongside a syringe—to convey concern about over-vaccinating infants, even though the textual response reflected a partially positive attitude towards vaccination. Conversely, for minor concerns within the textual responses (participant P35: *"I think it's interesting and useful, but for now isn't good enough to have lots of uses."*), participants portrayed their overall stance, like using a 👍 symbol to signify general positivity towards Generative AI, relegating Hedging to the textual description only.

4.4 Textual: How do people *elaborate* attitudes/beliefs?

While the previous subsection focused on how participants stated their Attitudes and Beliefs directly–whether clearly or with Hedging–we also observed cases where participants elaborated on those views in more complex ways. In this section, we concentrate on three codes in particular–Rationales, Math, and Wishes–because they go beyond simple statements to offer reasoning, formalized relationships, or forward-looking expectations. Our focus on these codes reflects the primary goal of this paper: to use insights from textual responses to guide the design of future visual elicitation techniques, and we will later show how each of these connects to opportunities for designing visual elicitation techniques. In the remainder of this section, we illustrate how each code points to specific design opportunities. Additional responses coded under Elaborating Views are provided in the Supplemental Materials.

The most common method of elaborating attitudes and beliefs observed in the textual responses was Rationale (logical basis or justification) for attitudes (N = 18) and beliefs (N = 14). For instance, participant P30 provided a Rationale to their belief about the relationship between bicycle use and traffic incidents, stating, *"I think bike riders do not pay enough attention and cause accidents by thinking they rule the road."* In most of these cases, participants only expressed more complex rationale through text rather than visuals (N = 30). For example, P33 described, *"Generative AI is mostly a bad thing since it uses public data without getting the consent of the person that put the data online. It also could end up giving bad advice or information that could have disastrous effects on the technology that relies on them. They are also still in their infancy stages and are undergoing updates and could cause more harm than good. The fact*

Table 2: The Final Code Book: Textual Codes.

Category	Code	Description	Example	Prevalence (#/82)
Articulating Views	**Attitude**	Conveys attitude or opinion towards a topic	*"I'm against any type of vaccination"*	41
	Belief	Conveys a belief in a trend or relationship	*"I believe money does help you be better educated."*	37
	Hedging	Describes caveats to the belief, often includes the use of the word "but" to affirm exceptions	*"I think vaccination is necessary for some illnesses. But I do not think babies should be over-vaccinated."*	37
Elaborating Views	**Rationale**	Provide details or rationale, often includes the use of word "because" to provide explications	*"The use of bicycle reduce traffic accidents because less people are on the road."*	32
	Speculation	Speculates reasons for a relationship	*"Education spending is likely to provide the latest technological advances for students"*	18
	Math	Uses language around mathematical relationships such as plus, equals, linear, etc.	*"More dollars = more achievement."*	16
	Relationship	Describes a relationship between two concepts or entities, often causal in ture	*"I feel the more they invested in education spending, the more achievements will be achieved"*	11
	Uncertainty	Indicates lack of knowledge or sense of unpredictability	*"I have never used generative AI"*	10
	Conditional belief	Describes a relationship between two concepts or entities, often causal in ture under specific conditions	*"When rules are not followed by automobiles on the road and bicycles accidents happen."*	9
	Morality	Invokes morality; may use phrases such as "should" or "should not", "right" or "wrong", etc.	*"I think it (Generative AI) is terrible for humanity in general. It has no real benefits and should be banned."*	8
	Wishes	Describes a future preference	*"I think people should be more careful with bicyclists because they are normally hard to see."*	8
	Figures of Speech	Uses metaphors , analogies, or colloquial expressions	*"I think it (Generative AI) can be a big timesaver and make jobs more automated."*	8
	Emotion	Indicates an emotional response to the topic such as happiness, fear, or disgust	*"I think Generative AI is strange and unknown to me so i'm a little bit afraid of it."*	6
	Personal experience	May use personal experiences to make a point	*"In my city, I do not think bikes have an effect on traffic accidents."*	4
	Data	Mentions references to historical data or past studies	*"They have a proven track record of preventing the spread of infectious diseases"*	1

more people are becoming reliant on technology like chat bots is also not a good thing since it means that less people will be knowledgeable and will rely too heavily on chatbots which are not foolproof nor 100% reliable." This individual began by describing data privacy concerns using generative AI and then transitioned to speculations about the broader risks of over-relying on still-evolving technology. Such in-depth perspectives can be challenging to depict solely via sketches. This case illustrates the limitations of sketches in fully reflecting complex thought processes, and how textual responses can bridge this gap by providing a richer context. In this example, we can infer the participant's primary concern: the outweighing of risks over benefits with the advent of Generative AI. This stance could theoretically be symbolized by a simple Equation, "Risks > Benefits," offering a glimpse into the participant's visual beliefs.

We also observed the use of mathematical language (the code Math) in textual responses (N = 18). For example, some participants mentioned likelihoods (e.g., P15: *"The higher the number of people vaccinated, the* ***more likely*** *that a given population will develop herd immunity to serious diseases."*), and some described correlation (e.g., P32: *"I believe that there is a* ***positively correlating relationship*** *between use of bicycles and occurrence of traffic accidents."*) in their response. Such expressions suggested the potential for representing these beliefs through data visualizations, such as line charts, to depict relationships between variables.

Additionally, a pattern emerged wherein participants often concluded their textual responses by expressing their Wishes for the future (N = 8). For instance, P28 wrote, *"We as a society need to find a better way to incorporate people who ride bicycles because as it stands now they pretty much get in the way."* This observation suggests a valuable additional mental construct of beliefs that visual elicitation techniques can explore: allowing participants to separately articulate their ***future expectations*** as part of their feedback, distinct from the elicited beliefs. For instance, in discussing bicycle use and its impact on traffic, participants could visually depict their concern by placing a bicycle close to a car to symbolize a concerning distance as their ***current belief*** and then place another bicycle at a safer distance to represent their ***future expectation***.

4.5 Visual Representations of Attitudes versus Beliefs

Our exploration revealed strategies that individuals naturally use to express their attitudes and beliefs visually. We observe that participants often relied on visual representations that fit the nature of the constructs better. Specifically, *attitudes* were often straightforward and most frequently conveyed through visual representations that afford encoding directionality of attitudes such as **Facial Expressions** (N = 18), occasionally through Directional Symbols (N = 9) or by sketching a topical Pictorial alone (N = 4), to reflect support, concern, or ambivalence. In contrast, *beliefs* were structural and most frequently expressed through vivid visual Stories (N = 19). These story-based sketches depicted scenes, interactions, or scenarios that helped participants communicate complex (often causal) relationships. Some participants also conveyed more abstract beliefs, such as Diagrams (N = 5) or Equations (N = 4) to highlight specific **causal relationships**. Within these abstract visuals, participants commonly used Pictorial symbols to represent the topic objects, arrows, or = signs to illustrate the directions of relationships, and occasionally employed symbols like ≠ sign to explicitly indicate the absence of a relationship.

While these broad patterns distinguish how participants visualized attitudes versus beliefs, the specific topics within each category further shaped the visual strategies they adopted. As shown in Figure 3, the two belief topics diverged substantially. Bicycle Usage sketches overwhelmingly took the form of Story compositions (14/20), indicating that participants relied on concrete, lived scenarios to express beliefs about safety and risk of bicycle usage. Education, in contrast, showed a more balanced distribution – Story (N = 5), Diagram (N = 2), Equation (N = 1), and Visualization (N = 3) – suggesting that participants drew on both narrative scenes and abstract structures when reasoning about education spending. The two attitude topics – Vaccination and Generative AI – showed broadly similar strategy patterns, with no single strategy dominating either topic. Both attitude topics showed similarly dispersed patterns. Responses on the Vaccination topic distributed across a range of mid-frequency strategies – Story (N = 4), Superimposition (N = 3), Face Only (N = 3), with all remaining strategies appearing only once or twice. Generative AI displayed a nearly parallel spread – Story (N = 5), Superimposition (N = 2), Topics Only (N = 2) – again with the rest occurring at very low frequencies. In both cases, counts per strategy remained low and relatively even, indicating that attitudes were expressed through a wide variety of visual forms rather than converging on a single preferred representation.

5 Discussion

5.1 Eliciting Other Mental Constructs

In this paper, we focused exclusively on exploring visual representations aligned with mental constructs of attitudes and beliefs. However, we hypothesize that our qualitative findings could also be valuable for other types of mental constructs. For example, previous research has used drawing to elicit *emotions* such as happiness in various scenarios, where participants often associate a happy face with visual depictions of leisure activities [47]. This aligns with our findings, where participants frequently use pictorials to depict their environment and faces to convey attitudes. Furthermore, structured diagrams such as tree maps, flow charts, and mind maps could be employed to elicit more structured abstract constructs, like *knowledge*, by offering a framework for organizing complex information [18]. Together, these insights underscore the potential of applying our findings to capture a wider array of mental constructs, highlighting further exploration within the visualization community.

5.2 Going Beyond Textual Preferences

From our two-round qualitative study, we found that in 84.1% of the topic-level responses, participants indicated that the textual channel more accurately reflects their mental constructs of attitudes and beliefs compared with the visual channel[1]. Motivated by this strong preference, we revisited the textual responses to identify aspects of attitudes and beliefs that were more readily expressed through language but omitted or underrepresented in the visual responses. Our goal was to uncover the strengths of textual articulation and explore how these insights could inform the design of more effective visual elicitation methods.

Internal representations of attitudes and beliefs are often complex and influenced by multiple factors such as personal observation, social influence and reasoning from other beliefs [20, 48, 66]. Through textual responses, we identified two common **layered structures** of attitudes and beliefs that were often missing from participants' visual representations: *attitudes articulated through hedging* and *beliefs conveyed through conditional reasoning*. For attitudes, as discussed in section 4.3, hedging was a frequent strategy used to convey nuance, appearing in 17 out of 84 textual responses. However, 7 of the corresponding visual responses only partially represented the hedged attitude. For instance, participant P28 stated, *"AI is simply a new tool that we created in order to benefit us; it can have both negative and positive effects on society,"* but drew only a smiling robot face—highlighting the positive attitude while omitting the expressed ambivalence. For beliefs, layered structures often took the form of conditional statements that describe relationships between concepts under specific circumstances. Among 9 textual responses conveying Conditional Beliefs, 7 expressed the condition only textually, not visually. For example, participant participant P39 wrote, *"Traffic accidents will first increase along with bicycle numbers due to more chaotic. But then it will decrease when the average speed went down."* Yet the accompanying visual response depicted only the trend of accidents rising and falling, omitting the speed-related condition that contextualized the belief.

We speculate that this asymmetry in textual and visual representations of hedging and conditional reasoning could be two-fold: first, representationally, participants may find it *more natural* to convey these complexities through language and difficult to represent through sketching. Specifically, visual elicitation can make it more effortful to encode conditional logic or multi-layered arguments, since expressing contrastive or causal conditions (e.g., "if…, then…") demands specialized visual conventions such as arrows, branching diagrams, or annotations that not all participants are familiar with. Second, cognitively, when people are asked to "draw what they think," they may first externalize a core or gist-level attitude—an affective stance that is faster to access and easier to visualize—rather than a nuanced position that integrates exceptions or contingencies. This pattern is consistent with prior work on sketching, which shows that drawings tend to schematize thought by conveying salient conceptual structure while omitting less relevant or detailed information [76]. In our context, participants might visually externalize what they perceive as most central to their mental representation rather than fully reproducing all verbally articulated content. This tendency further aligns with dual-process theories [19], which suggest that intuitive or affective evaluations are more readily expressed through imagery, whereas analytic qualifications require verbal reasoning. Future elicitation techniques could bridge this gap by incorporating structured visual affordances—such as multi-branch sliders or diagrams—that explicitly invite users to externalize exceptions and conditions, which we explore in Section 5.3.

[1]Each participant completed both visual and textual tasks for two topics, yielding 82 topic-level responses. The 84.1% figure reflects 69 of these 82 responses in which participants selected "description" (textual responses) for the question, 'Which elicitation method do you perceive as more closely aligned with your perceptions on this topic?', as shown in Figure 2C.

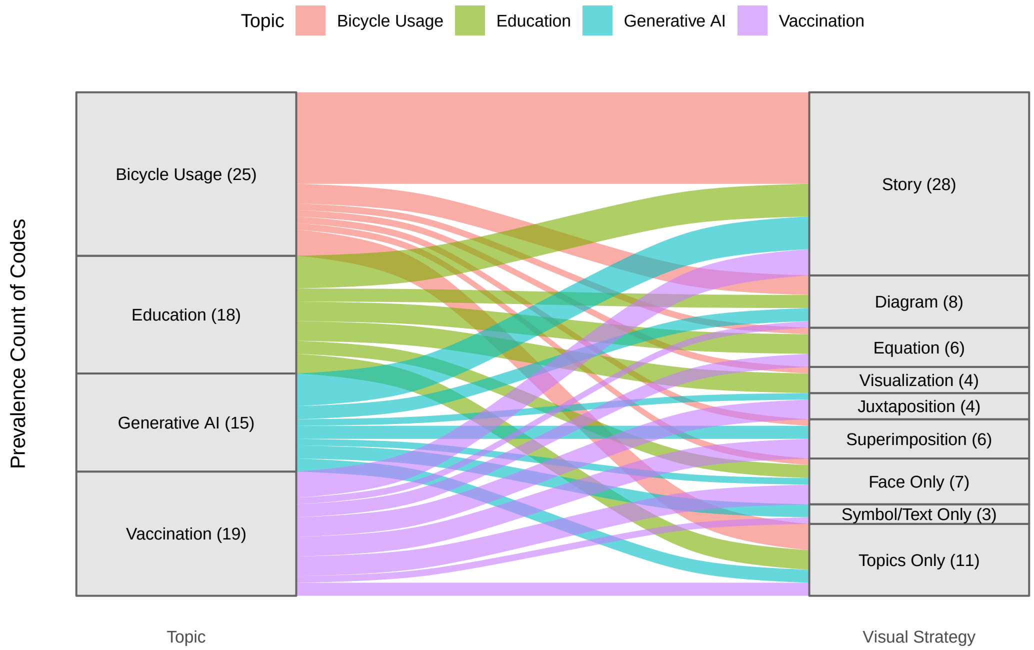


Figure 3: Sankey diagram showing how participants' sketches map from the four study topics—Bicycle Usage, Education Spending, Generative AI, and Vaccination – to the six visual strategies identified in our codebook (Story, Diagram, Equation, Juxtaposition, Superimposition, Visualization). The width of each flow reflects the number of sketches that used a given strategy for a given topic. Note: A sketch may contain multiple strategies. We also include three additional strategies – Face Only, Symbol/Text Only, and Topics Only – to capture sketches that relied solely on basic visual elements described in Section 4.1.

5.3 Provocation: How Might Future Visual Elicitation Techniques Look?

Building on the expressive patterns and gaps identified in participants' visual and textual responses, we now consider how these insights can inform the design of future visual elicitation techniques. The findings from our qualitative study suggest that while participants readily used visual forms like Facial Expressions, Symbols, and causal Diagrams, these often lacked the layered complexity present in their textual articulations.

We approach these observations from our qualitative study **not as fixed templates but as a way to imagine what alternative visual elicitation techniques could look like**. Our goal is to demonstrate how participants' intuitive visual strategies can be used to design structured techniques that are both expressive and analyzable, positioning them near the midpoint of the axis in Figure 1. In doing so, we explore three directions that emerged as both prevalent in participant responses and promising for design. These concepts are to be taken as speculations on future expanded visual elicitation techniques and require further validation before being employed as elicitation devices:

- First, given the widespread use of Facial Expressions to convey affective attitudes, we propose using face-based visual elements to elicit **emotional attitudes**.
- Second, we view the absence of Hedging and layered nuance in many visual responses as *an opportunity* to expand the expressive potential of visual elicitation. To address this gap, we propose multi-slider interfaces that draw on the strengths of textual articulation, enabling participants to more precisely express **hedged attitudes** in a structured and analyzable form.
- Third, building on participants' use of arrows, symbols, and occasional equations to represent cause-effect relationships, we explore using Diagrammatic structures to capture **causal beliefs**.

While the techniques we propose are grounded in naturally occurring participant responses, we encourage future research to further evaluate the expressiveness and accuracy of them.

5.3.1 Using faces to elicit emotional attitudes. Studies show that faces not only communicate basic emotions but also convey complex social and moral information [75]. Similarly, facial expressions represented as emojis in instant text messaging could enhance both the processing speed and the comprehension of textual contents [5]. Additionally, researchers have explored how facial features can serve as visual representations of multivariable data, allowing for nuanced interpretations of meaning. For instance, the technique known as Chernoff Faces encodes data points using facial features—such as the mouth, eyes, and eyebrows—so that viewers can detect anomalies through distinct facial characteristics [12]. Collectively, these findings underscore the potential of faces to serve as powerful, multidimensional tools for encoding complex attitudes.

As a potential channel for eliciting emotional attitudes, previous psychological research suggests that a face with an adjustable grin may capture attitudes more accurately by eliminating the need to translate subjective feelings into textual responses [45]. However, this study also identified only a weak positive correlation between mouth curvature and subjective attitudes, suggesting that other facial features may also play significant roles in conveying emotions. This finding also aligns with research work by Boucher et al., who demonstrated that different facial regions contribute uniquely to the perception of specific emotions [4]. For instance, the brow and forehead are more strongly associated with sadness and surprise, while the cheeks and mouth are stronger indicators of happiness and disgust. More recent research has further explored how humans perceive emotional signals in terms of both their category and intensity [11]. Specifically, the research revealed that facial movements used to classify different emotions are highly distinct, whereas those that intensify emotions tend to be more similar across categories. For instance, happiness is uniquely signaled by a smile, surprise by raised brows, fear by a stretched mouth, disgust and anger by an upper lip raise, and sadness by a lowered brow and raised chin. In contrast, intensifiers of emotions—such as mouth stretch—are shared across several emotions including surprise, fear, anger, and disgust, while cheek raising serves to intensify both happiness and sadness. These patterns suggest that emotional categories are differentiated by specific facial signals, whereas emotional intensity is conveyed through a common set of facial movements.

Building on these insights, future visual elicitation techniques could leverage the expressive potential of specific facial regions to more intuitively capture participants' attitudes. Prior research has introduced several pictorial approaches for emotion elicitation, including emoji-based surveys that use fixed icon-style faces for quick affective judgments [34], SAM's stylized figures for rating valence, arousal, and dominance [53], and pictorial rating scales that rely on pre-drawn facial illustrations to convey discrete emotional levels and reduce survey ambiguity [64]. Additionally, existing survey platforms such as Qualtrics and SurveySparrow also support discrete graphic sliders incorporating facial expressions ranging from anger to happiness, while SurveyMonkey and QuestionPro also provide facial expression-based Likert scales [1, 63, 74, 83]. However, these approaches all operate through a small set of pre-defined facial states or single-axis adjustments, limiting participants' ability to express subtle variations in expression. Moving beyond these constraints, we envisioned and implemented an interactive face where users **continuously** adjust features such as mouth curvature, brow position, and cheek elevation to visually articulate a broad range of emotional attitudes (Figure 4). At the same time, researchers could also apply the emotion classifiers and intensifiers discussed earlier to interpret both the type and intensity of the expressed attitude, enabling richer and analyzable representations of participant responses.

5.3.2 Incorporating textual structure to elicit hedged attitudes. Text allowed participants to articulate the underlying rationale behind their hedged attitudes, frequently referencing personal experiences, sensory impressions, social norms, and other internal or external factors [20, 66]. Recent visualization research also highlights the importance of considering user preferences for text in information communication. Demographic differences, including variations in age, eyesight, and spatial skills, can impact visual information comprehension and shape the preferences for text vs. visuals [27, 72]. These preferences may also relate to how individuals form and express attitudes, which are often complex and layered [20]. Attitudes can be represented as networks of various evaluations on a given object [35]. Structured text elements, such as paragraphs and clauses, support the articulation of these layered perspectives by allowing individuals to logically develop and communicate nuanced arguments [38, 44], minimizing the cognitive load to map complex perspectives onto visual representations. Thus, while directional and emotional attitudes might be effectively represented through simple visuals such as facial expressions, conveying complex attitudes including hedging may require more sophisticated visual representations.

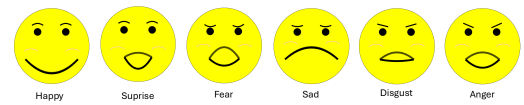


Figure 4: A face with adjustable eyebrows grin, and cheeks to elicit emotional attitudes (accessible in supplemental materials).

Building on this connection between structured text and attitude expression, future visual elicitation tools could explore ways to incorporate text-like structure into visual representations to better capture complex attitudes. As shown in Figure 5, we implemented a set of interactive sliders as one such approach – designed to express both overarching attitudes and the caveats that contribute to hedging, in a manner analogous to how structured paragraphs support layered expression in text. This interface enables users to specify both positive and negative dimensions of a complex attitude. By editing the title of the main slider, users can express their primary attitude toward the topic. They can also add and then title additional sliders to represent sub-attitudes that serve as rationales supporting their main attitude. For instance, a user could create a main slider labeled "Vaccination" to capture positive attitudes as the main stance related to disease prevention, alongside an additional slider labeled "Over-vaccinating Babies" to express potential concerns. Since each slider is coded from "Strongly Negative" to "Strongly Positive", uncertainty is indicated by placing the relevant slider at its midpoint, allowing users to express unclear or ambivalent views for both the main stance and any sub-attitudes. This structure allows researchers to analyze the individual components of a hedged attitude—using the text labels and corresponding slider values—or to compute an overall attitude by averaging the slider values. This approach balances expressive attitude reporting with analytical clarity, producing datasets that capture diverse sub-attitudes within each participant while remaining systematically comparable across participants, In this sense, responses can also be viewed as multi-attribute rankings: each participant's overall stance is not a single value, but a summary that integrates several underlying dimensions, much like in LineUp where an item's rank reflects the combined influence of multiple attributes rather than any one attribute in isolation [21].

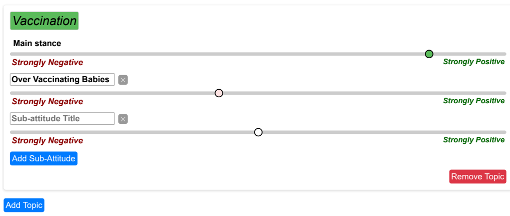


Figure 5: A multi-slider technique to elicit hedged attitudes. (accessible in supplemental materials)

5.3.3 Using pictorial diagrams to elicit causal beliefs. Unlike textual communication, Pictorial language is universally effective because it communicates meaning directly through visual forms rather than relying on specific linguistic conventions [78]. Through our study, we observed that participants frequently used concrete pictorial items, which we refer to as pictorials in our code book, to depict attitudes and beliefs (N = 60). This contrasts approaches taken in another popular form of visual communication – data visualizations, where designers prefer representing concrete objects in datasets using abstract encodings like shapes and lines [86]. This finding suggests that such abstract encodings may not naturally align with how people perceive their surroundings. Instead, it suggests a deeper consideration for incorporating more concrete images, such as isotypes and pictographs [9, 24], in visual communication to better reflect people's beliefs.

In our visual responses, pictorials are primarily used to convey complex attitudes and beliefs through vivid visual Stories (N = 28), which highlight the value of pictorials in visualizing complex mental constructs due to their flexibility and expressiveness. However, as researchers, eliciting attitudes/beliefs through visual stories can pose challenges, such as (i) difficulties incorporating them into more structured elicitation techniques and (ii) potential ambiguity in interpretation during subsequent analysis. To balance expressiveness and analyzability, we explored participants' frequent use of Diagrams as a more structured format for depicting causal relationships. Diagrams retain some expressive qualities of pictorials while also reducing the cognitive load associated with abstraction through drawing beliefs [79]. Given that beliefs often involve relationships between certain entities, diagrams might be particularly suitable for eliciting them, as they naturally support this relational structure, and enhance clarity in subsequent analysis [51].

Diagrams use literal and metaphorical conventions to convey meaning in multiple ways, with pictorials, spatial arrangements, and relationships between components all helping participants translate their mental constructs of beliefs into a visual format [15]. Because diagrams have also been shown to support mathematical reasoning [14], they may similarly help participants express beliefs that involve quantitative or relational structure. To maximize the effectiveness of utilizing diagrams, researchers should iteratively refine the diagrams, considering participants' visual literacy and anticipating how they might interpret the visual representations within [15]. For instance, in our collected data, we observed that participants frequently used arrows in Diagrams to depict causal relationships between entities in a given topic (N = 8). This usage aligns with the structure of argument maps, which support individuals in articulating complex reasoning by visually linking claims and subclaims through directional connectors such as arrows [77]. Another example is the use of directed acyclic graphs (DAGs), which represent variables as nodes connected by arrows to illustrate assumed causal relationships [16]. Building on these insights, we envisioned and then implemented a pictorial diagramming tool–illustrated in Figure 6–to further support the elicitation of beliefs as relational concepts. In this example, participants could use arrows to indicate whether an increase in one variable might lead to an increase or decrease in another. Unlike traditional argument maps or DAGs, this technique could be composed with others for richer elicitation techniques; e.g., as depicted in Figure 6, a slider could be used to adjust the strength of these relationships, visually showing the impact of one variable on another. As part of an iterative design process, further testing and refinement are needed to validate this tool's effectiveness and generalizability across a broader range of users.

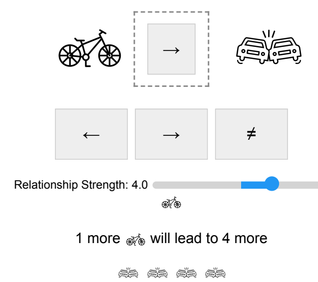


Figure 6: An interface to express the relationship between the use of bicycles and the occurrence of traffic accidents. (accessible in supplemental materials)

6 Limitations and Future Work

6.1 Impact of Drawing Skill, Graphical Literacy, and Task Order on Visual Responses

According to the demographic questionnaire completed at the end of the study, 26 out of 41 participants reported they had no significant prior experience with drawing. We observed that participants with more advanced drawing skills tended to create more expressive Stories to communicate attitudes and beliefs. In contrast, participants with limited drawing abilities tended to produce simplified or occasionally ambiguous sketches, leading to difficulties in data interpretation. The skill level of participants in drawing thus influences the clarity of their visual responses and might introduce bias in our thematic analysis. In future research, this challenge could be addressed by providing participants standardized drawing templates and several types of example sketches. The templates would give them clearer structure for their drawings, while the examples would demonstrate different ways of visually expressing attitudes and beliefs. Together, these aids could enhance participants' ability to communicate their ideas through drawings, particularly for individuals with limited drawing experience.

Similar to drawing ability, participants' broader graphical literacy may also have influenced our results. We did not measure familiarity with structured visual forms – such as flow charts or schematic diagrams – which could enable some participants to produce more organized or conceptually rich sketches. Future work could incorporate measures of graphical literacy to better understand how these competencies shape the nature and richness of elicited visual representations [46, 58].

Finally, the ordering of our tasks may have influenced participants' visual responses. We placed the textual task first because written descriptions allow participants to articulate the propositional and nuanced aspects of their attitudes and beliefs – content that is often more difficult to convey visually, which tends to capture more spatial or depictive elements [41, 42, 62]; had we placed the visual task first, participants might simply have verbalized whatever they drew, reducing the independence and richness of the textual data. However, completing the textual task beforehand may have shaped how some participants approached their visual responses, as their drawings could reflect the specific wording they had already chosen. Future work may explore experiment designs that introduce brief buffer tasks between modalities to minimize cross-modal influence [56].

6.2 Differences in Visual Attitudes/Beliefs Across Cultures.

> *Meanings belong to culture, rather than to specific semiotic modes. And the way meanings are mapped across different semiotic modes, the way some things can, for instance, be 'said' either visually or verbally, others only visually, again others only verbally, is also culturally and historically specific.*
> - Kress et al, 2020 [43]

While we identify recurring visual elements and composition strategies in our study, these patterns should be understood as culturally situated rather than universal. Our study focuses on participants recruited exclusively from the United States, which may result in a relatively homogeneous cultural perspective rooted in Western values. This limitation is important because mental constructs such as beliefs and attitudes can vary significantly across cultural contexts. For example, while facial expressions such as smiles or frowns were commonly identified by our U.S. participants as effective means to convey attitudes, research has shown that the interpretation of these expressions differs across cultures [33]. Specifically, East Asian cultures may emphasize emotional intensity conveyed through the eyes, whereas Western cultures often prioritize the mouth when interpreting emotions. This cultural specificity suggests that the findings of this study may not be universally applicable and highlights the need for caution when generalizing across diverse populations. Cultural differences also affect how individuals engage with elicitation tools. Studies on cross-cultural variations have found that East Asian participants are more likely to select the midpoint on scales, while North American participants tend to choose more extreme values [10]. This pattern has been linked to the Confucian principle of moderation, where East Asians may seek to avoid standing out and align more with group norms, in contrast to the individualism often emphasized in North American cultures. Such differences in response tendencies could skew data distributions in cross-cultural research, leading to biased conclusions. Thus, the taxonomy presented here may reflect visual literacy patterns that are prevalent in a U.S. cultural context rather than general cognitive tendencies. We do not claim universality; rather, we present this work as an empirical grounding for how attitudes and beliefs may be visually externalized within a Western cultural frame. Future work should examine how these representational strategies differ across cultural backgrounds, communication traditions, and languages, and may require adapting or re-designing elicitation techniques rather than applying them uniformly.

6.3 Validation of the Elicitation Techniques.

Evaluating the effectiveness of elicitation techniques is essential for both their design and selection [29]. However, the existing work in evaluating the effectiveness of leveraging visualization to elicit attitudes and beliefs remains limited [50]. One notable example is the work by Karduni et al., who assessed a visual elicitation technique designed to capture beliefs about linear correlations and their associated uncertainty [36]. Specifically, they compared the elicited belief distributions obtained through this technique with those generated using the Markov Chain Monte Carlo with People (MCMC-P) method [67], a widely used approach in cognitive science for eliciting subjective beliefs and estimating belief distributions. The evaluation strategy employed by Karduni et al. offers a valuable model for future work, particularly in assessing the **analyzability** of visual elicitation techniques by benchmarking visually elicited data against distributions derived from structured, iterative methods such as MCMC-P.

Equally important is evaluating the **expressiveness** of visual elicitation techniques: the degree to which they allow participants to communicate nuanced, multi-faceted perspectives. Researchers could utilize the Elicitation Interview technique to gather and understand participants' experiences, such as their emotional reactions to the topic and the personal meaning it holds when expressing attitudes and beliefs through visual elicitation techniques [30]. By explicitly asking participants to what extent the visual elicitation method helped them express these rich insights, researchers can gain a deeper understanding of the technique's expressive capacity.

6.4 Dependence Between Visual and Textual Meaning

While our analysis focused on participants' visual representations, we acknowledge that the interpretability of drawings sometimes depended on accompanying textual descriptions. In several cases, the visuals communicated meaning on their own; in others, text clarified ambiguous or abstract elements. This interplay underscores a limitation of open-ended drawing elicitation: such methods capture rich, expressive data but also introduce variability and ambiguity in interpretation. Prior work in visualization perception shows that even structured graphics can yield divergent interpretations depending on visual arrangement and context [84]. While drawings effectively express participants' intent, those accompanied by brief textual descriptions tend to be the richest and most interpretable. Future work could explore more structured or multimodal elicitation formats that balance expressive freedom with improved reliability and standalone interpretability.

7 Conclusion

We presented findings from a two-round qualitative study involving N = 41 participants. The study examined how participants mentally construct attitudes and beliefs and how they intuitively externalize them across both visual and textual channels. Our thematic analysis revealed basic elements that serve as the building blocks of participants' responses, as well as a spectrum of compositions through which these elements were combined to visually convey attitudes and beliefs. Based on these findings, we envisioned alternative visual elicitation prototypes, which could inform the design of future survey instruments. By offering a broader range of expressive options–both textually and visually–researchers and designers can create more intuitive, engaging, and effective interfaces for capturing and understanding user attitudes and beliefs.

Acknowledgments

This work was supported by the National Science Foundation under grants IIS-2311574.

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