A Novel Lens on Metacognition in Visualization

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Abstract

Metacognition, or the awareness and regulation of one's own cognitive processes, allows individuals to take command of their learning and decision making in various contexts. In tasks that require problem-solving and adaptive learning, individuals with heightened metacognitive awareness tend to outperform others, as they are better equipped to regulate cognition, leading to more effective processes. On the other hand, visualization research facilitates exploration and decision making with data. We posit that metacognitive frameworks that examine how individuals think about their own thinking processes can likewise enhance visualization processes. In this paper, we review metacognition literature from the cognitive and learning science to identify opportunities in visualization to improve people's ability to reason with data. We propose the use of a metacognitive framework, serving as a starting point to inspire future research to improve visualization practices and outcomes.

CCS Concepts

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

Keywords

Visualization, Metacognition

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1 Introduction

Interactive visualizations do more than just display data; they facilitate a dynamic dialogue between the user and the information presented. This interaction allows users to manipulate and probe into the data, encouraging a deeper engagement and understanding. Furthermore, there is a significant opportunity within this dialogue to integrate metacognition, defined as the awareness and regulation of one's own cognitive processes [29]. By enabling users to reflect on their own thought processes and decision-making as they interact with the data, we can promote a deeper level of cognitive engagement, fostering more insightful and informed decisions. In doing so, we can shift the passive data consumption into an active and reflective learning process.

Acknowledged as an essential component for effective learning, problem-solving, and cognitive development, metacognition has been extensively explored within the fields of education and psychology [28, 30]. In educational settings, teaching students to think metacognitively enhances their ability to learn and encode information [76], encouraging a deeper understanding of the material [19]. In fact, it has been shown in numerous settings that individuals with strong metacognitive skills can outperform individuals with stronger aptitude in academic settings [77, 94]. To leverage these benefits, educators incorporate metacognitive strategies into their teaching methods to help students assess their own learning processes, thereby improving academic performance [15, 73]. Similarly, in psychology, metacognition is key to understanding self-awareness and emotional regulation. It plays a significant role in cognitive therapy, aiding individuals in identifying and challenging negative thought patterns to promote mental well-being [106].

Despite its profound benefits, work exploring metacognition within visualization remains limited. We posit that metacognition can serve as a reflective layer for both visualization viewers and designers, analogous to the students and educators described previously. For visualization viewers (e.g., students), this means reflecting on their understanding of data encodings, trends, and insights, and altering their analytic strategies as needed to enhance their ability to interpret complex data. For visualization designers (e.g., educators, practitioners), this means reflecting on their understanding of what they have designed to support and guide viewers' interpretive processes (theory of mind) [75]. We contend that visualization designers should prioritize creating interfaces that facilitate metacognitive practices for end-users, encouraging users to pause, reflect, and adapt their strategies during data exploration. Visualization tools that are designed to support various metacognitive tasks such as reflection and regulation of data exploration, analysis, and interpretation stand to benefit significantly from the integration of these strategies.

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For instance, cognitive biases such as confirmation bias [66], which significantly influence decision-making, are of recent interest in visualization [27, 101]. While there are techniques aimed at reducing these biases through guidance and prescriptive interventions [33, 100, 103], their effectiveness largely depends on the accurate presentation of data, algorithms, and the user's intentions [17, 70, 79]. Metacognition, with its focus directly set on recognizing and correcting errors in our thought processes, can provide a self-driven approach to mitigating bias. This perspective suggests metacognition not as a standalone solution but as a reflective layer that enhances user awareness of their cognitive processes when interacting with visualizations. By fostering internal reflection alongside external aids, a metacognitive framework provides a holistic method to address human biases. We position this work as a starting point for ongoing theoretical development and practical application in this emerging area, inviting further exploration and refinement by the research community.

In this paper, we propose a novel metacognitive lens through which to view past and future work in visualization. Our contributions are multifaceted:

- We surveyed 293 visualization papers and synthesize findings from 21 of them, selected based on our inclusion and exclusion criteria, to provide a detailed exploration of how metacognitive practices may already be embedded within visualization research.
- We augmented the van Wijk model [99] to serve as a framework that integrates metacognitive components in the visualization process. We apply this model to analyze the design choices in two extant visual analytic systems.
- We identify gaps and opportunities for the novel metacognitive framework to inform visualization practices and research.

2 Related Work

We contextualize our work among areas of prior research in metacognition. In the following sections, we describe the essential components of metacognition and discuss investigations of metacognition in various settings.

2.1 Metacognitive Components

Metacognition refers to the cognitive processes involved in recognizing and controlling one's own thinking and learning [57]. This process can be separated into three distinct components: metacognitive knowledge, metacognitive skills, and metacognitive experiences [30, 31, 47].

Metacognitive knowledge includes declarative knowledge about cognitive processes, tasks, and strategies [47]. Consider an exam taker who uses their knowledge of test-taking to identify the scope of the exam and assess their personal familiarity with the topics involved. A strategic test-taker allocates their study time by focusing more on the subjects they find most challenging. By acknowledging their strengths and weaknesses, they can optimize their preparation approach, leading to improved learning outcomes. In the context of visualization, metacognitive knowledge helps users assess their understanding of data visualizations. For instance, a data analyst might evaluate the clarity of a chart and identify gaps based on their familiarity with different visualization techniques, allowing them to choose and adjust the chart for clearer, more effective data communication.

Metacognitive skills, also known as metacognitive monitoring or regulation, involves the ongoing assessment of one's understanding and control over the learning process [115]. For example, an exam taker engaged in effective monitoring might regularly test themselves on the material to gauge their mastery and identify areas needing further review. They could adjust (i.e., control) their study techniques based on these assessments – switching from passive reading to active practice questions, or varying their study environment to enhance concentration and retention. Metacognitive skills can also be applied when users continuously evaluate their understanding of visual data and their effectiveness in using it. For instance, a data analyst might periodically review their interpretation of a complex data visualization to assess whether their insights align with the data presented. They could adjust their analytical approach by seeking additional data, re-evaluating their visualizations, or using different visualization tools to improve clarity and accuracy. This ongoing self-assessment helps refine their analytical skills and enhances the quality of their data-driven decisions.

Finally, *metacognitive experiences* encompass the individual's conscious perception and emotional responses during cognitive activities [30, 115]. To continue with the example provided above, an exam taker might experience confidence upon mastering a difficult concept, encouraging them to tackle similarly challenging topics. Conversely, feelings of frustration or confusion might prompt them to seek additional resources or alter their study methods, perhaps by taking more breaks or discussing difficult material with peers. Similarly, in visualization, metacognitive experiences relate to users' feelings and perceptions of their data interactions. For example, a data analyst might feel satisfaction from successfully interpreting a complex visualization, motivating further exploration, while confusion or uncertainty may lead them to seek clarification, adjust the visualization, or consult colleagues. These emotional responses impact their approach and effectiveness in data analysis.

The relationship between metacognitive knowledge and experiences is reciprocal [30]. Metacognitive experiences can enrich metacognitive knowledge; for instance, the challenge felt during problem-solving can transform into a recognized understanding of one's difficulties with such tasks [95]. Conversely, metacognitive knowledge can come into play during metacognitive experiences. For example, recalling one's habitual struggles with problem-solving can intensify the feeling of difficulty faced during such tasks [95]. This interplay enhances our overall metacognitive awareness, allowing for more informed and adaptive cognitive engagements.

2.2 Metacognition and Learning

Advancements in metacognition research highlight the significant impact that self-awareness of cognitive processes has on enhancing learning outcomes. Research highlights that metacognition involves not just the execution of tasks but also the monitoring, evaluation, and planning of cognitive strategies, which are essential for effective learning [30]. This area of study delves into how students become aware of their own knowledge base and exert control over their learning experiences, thereby improving their ability to solve problems and think critically [90].

Several studies have explored metacognition within diverse educational settings, illustrating its significance in fostering essential academic skills. For instance, a review study by Wang et al. revealed metacognition to be the most powerful predictor of learning [104]. Furthermore, Veenman et al. demonstrated that metacognitive skills correlate strongly with academic performance, suggesting that these skills can be taught and enhanced through targeted educational strategies. Similarly, Romainville et al. observed that higher academic achievers not only exhibit enhanced metacognitive sensitivity but also excel in organizing their learning strategies more effectively [83]. To leverage these benefits, recent initiatives have aimed to incorporate metacognitive principles into educational systems. For instance, Azevedo et al. discussed the integration of metacognitive tools within learning environments to foster self-regulated learning through MetaTutor, which provides real-time feedback and visual cues to aid learners in adjusting their learning strategies [6]. Similarly, the nStudy software system supports the tracking and enhancement of self-regulated learning processes online, offering tools that enable learners to set goals, plan, monitor progress, and reflect on their learning process [108].

Although metacognitive concepts have been extensively studied within educational and cognitive psychology, their direct application to the design and interpretation of visualizations has not been thoroughly explored. This gap highlights a significant opportunity for research and development in this field, promising to enhance the functionality and impact of visual data representations.

3 Method

To understand the current research landscape of metacognition and visualization, we conducted a systematic literature search focusing on titles and abstracts to identify papers at the intersection of the two fields. We used the VitaLITy [63] paper corpus to collect papers from 6 visualization venues and extended the open-source scrapers to collect papers from 5 metacognition venues. Figure 1 depicts the paper selection process, which we describe in greater detail next.

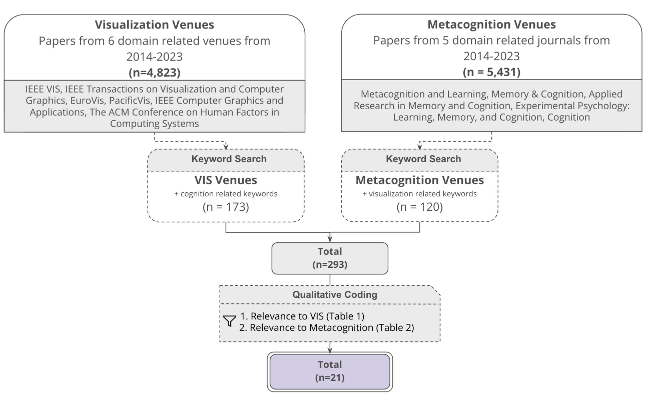

Figure 1: Summary of paper selection process.

Visualization Venues. We utilized the dataset from the VitaLITy system [5, 63] to collect titles and abstracts of papers from the past 10 years from six venues related to visualization research – *IEEE VIS, TVCG, EuroVis, PacificVis, CG & A,* and *CHI.* This search yielded a total of 4,823 publications from January 1, 2014, and December 31, 2023, inclusive. Inclusion was determined based on the publication year as listed in the dataset from the VitaLITy system [5, 63]. The first five venues are visualization-specific, hence we assumed all papers contained within this scope were relevant to visualization research. However, CHI covers more general human-computer interaction research, so we added an additional screening criteria to remove papers that did not contain words stemming from *"visual."* Next, we removed all papers that did not contain words stemming from *"metacognition"* or *"cognition,"* which yielded 112 papers from visualization-specific venues and 61 papers from CHI for further screening.

Metacognition Venues. We extended the open-source scrapers provided by VitaLITy [5, 63] to collect titles and abstracts of papers from the past 10 years from five venues related to metacognition research – *Metacognition and Learning, Memory & Cognition, Applied Research in Memory and Cognition, Experimental Psychology: Learning, Memory, and Cognition,* and *Cognition.* This search resulted in a total of 5,431 publications between 2014-2023, inclusive. For journal papers, inclusion was based on their formal assignment to volumes and issues published within this date range. Next, we conducted a keyword search using the term *"visual"* followed by a suffix (e.g., visualizations, visually) to filter out papers that merely mentioned the term "visual," such as those referring to "visual working memory," which do not pertain to our focus on data visualization research. This approach yielded 120 papers for further screening.

Inclusion and Exclusion Criteria. Our first round of screening was solely based on keyword search, resulting in a corpus of 293 papers. However, while papers at this stage may include words stemming from "visual" and "cognition" in the titles and abstracts, there are likely many papers within the corpus, e.g., that use visual stimuli without a focus on visualization research or study cognition without a focus on metacognitive factors. Thus, to determine if the papers were truly relevant to metacognition and visualization research, we conducted a comprehensive qualitative coding analysis. Initially, three authors independently read the titles and abstracts of 10 randomly selected papers from the corpus and determined their relevance as a binary "yes" or "no," then synthesized a set of inclusion and exclusion criteria for the papers. After discussing and agreeing on the relevance of these 10 papers, two authors repeated this procedure with another 10 randomly selected papers. From this process, we derived the following set of inclusion and exclusion criteria (Table 1 & 2) to guide our coding of the papers. Table 1 presents the inclusion and exclusion criteria specific to visualization, while Table 2 outlines the criteria specific to metacognition. Both sets of criteria are applied to each paper during the review process to assess relevance to both visualization and metacognition. Two authors then independently coded the remaining 273 papers for relevance. In case of disagreement, the two authors discussed and resolved the issue or, if it could not be resolved, referred it to a third author for a final decision.

Table 1: Relevance to Visualization

Criterion	Description
Inclusion	• The paper appears in a visualization related venue **AND** mentions "visual," **OR** • The paper involves: – The creation, implementation, or evaluation of visual representations, such as graphs, charts, maps, or other visual tools; **OR** – The use or development of visualization techniques for the purpose of data analysis, interpretation, or communication; **OR** – The studies or experiments focused on visual perception, visual cognition, or the effectiveness of different visualization methods.
Exclusion	• Papers that primarily focus on non-visual forms of representation (e.g., auditory, textual) where visualization is not a central component of the study or discussion, **OR** • Papers that mention visualization only in passing or treat it as a secondary aspect of the study, without examining the visualization techniques, processes, or outcomes, **OR** • Papers that involve the use of visualization software or tools but do not specifically focus on the visualization aspect (e.g., focusing on software usability or computational efficiency), **OR** • Papers that involve simple visual tasks (e.g., identifying colors, shapes, or basic patterns) with a purpose *other than* visual perception (e.g., many studies on response times using simple shapes as stimuli would fall under this exclusion criterion).

4 Findings

The authors mutually coded 21 papers as relevant to metacognition and visualization according to the inclusion criteria, achieving an inter-rater reliability among two independent raters using Cohen's Kappa of $\kappa = 0.51$, suggesting moderate agreement [60]. The two independent raters discussed any disagreements, having a third researcher weigh in as needed, until a consensus rating was achieved for all papers. Papers that were excluded at this stage included visualization papers that discussed or studied cognitive processes, such as perception (e.g., [26, 32, 42, 59]) and memory (e.g., [23, 45, 68, 88]), without any metacognitive reflection or regulation of those cognitive processes; or, metacognition papers that used simple visual stimuli (e.g., shapes or colors) as a mechanism to study performance metrics (e.g., completion time, accuracy) [43, 68, 88]. Among the 21 papers reviewed, 16 are from visualization-related venues, including 8 from *IEEE VIS*, 6 from *CHI*, and 2 from *TVCG*, as shown in Table 3. The remaining 5 papers are from metacognition-related venues: 3 from *Memory & Cognition*, 2 from *Metacognition and Learning*, and 1 each from the *Journal of Applied Research in Memory and Cognition* and *Cognition*. Table 4 shows an overview of the 21 reviewed papers, including visual stimuli used, types of metacognitive skills (adopted from [95]), methods used to measure these skills, and a brief description of the study context. We present a summary of our findings next, labeled **F1-F5** for future reference.

F1: Only two papers explicitly mentioned metacognition. A detailed examination of the 21 papers reveals a notable absence of the term "metacognition," with only two papers from metacognition venues explicitly including derivatives of *"metacognition"* in their titles or abstracts and none from visualization venues. One study investigated the impact of instructional visuals on students' metacomprehension accuracy and cue-use for different types of metacognitive judgments across four experiments [46]. Participants were randomly assigned to either a text-only condition or a text-and-image condition, where they made various judgments (test, explain, and draw) for each text and completed comprehension tests. They found that instructional visualizations (e.g., diagrams of biological processes) harmed relative metacomprehension accuracy, as evidenced by self-reported performance, e.g., participants' assessment of how well they felt they could draw the processes described in the text [46]. Another paper demonstrated that combining visualization with self-regulation metacognitive training – where students are trained to self-observe and self-assess whether they have accurately applied the visualizing strategy and to react appropriately in order to improve the accuracy and clarity of their drawings – effectively enhances learning from scientific texts [55]. The training involved three phases: self-observation, to recognize strategic actions; self-assessment, to evaluate visualization effectiveness; and reaction, to enhance visual clarity.

F2: Metacognition is not *explicitly* a focus in VIS. Our systematic analysis confirmed our intuition that metacognition is not explicitly a focus in the visualization community. Aside from the two papers that *explicitly* mentioned metacognition described previously, the remaining papers we reviewed indirectly addressed metacognitive concepts. For instance, Wall et al. introduced the concept of interaction traces, intended to promote user awareness of bias in their analysis processes [100, 102]. Baumeister et al. examined how different augmented reality display technologies influenced task performance with a focus on self-assessment of cognitive load [13]. Nowak and Bartram highlighted the need for data interfaces that encourage reflection and provoke alternative

Table 2: Relevance to Metacognition

Criterion	Description
Inclusion	• The paper appears in a metacognition related venue **AND** explicitly mentions "metacognition," **OR** • The paper involves: – Individuals stating their conscious understanding of cognitive aspects like their strategies (e.g., the optimality of solutions/strategies), reasoning abilities, decision-making, beliefs, or memory, **OR** – Individuals reflecting on their own performance or judgments (e.g., confidence levels or uncertainties in answers) by estimating probabilities for certain outcomes, **OR** – External tools or techniques that are designed to facilitate metacognition by influencing self-awareness (e.g., showing something such as interaction traces to the user about their own process or performance), supporting self-reflection and/or self-monitoring.
Exclusion	• Papers that elicit beliefs purely for gathering or measuring preferences or likelihoods (e.g., asking participants about product preferences or likelihood of purchasing) without follow-up on why they hold that belief or how confident they are, **OR** • Papers that center on characterizing automatic cognitive processes (e.g., object recognition, recalling positions, inhibitory control) without addressing how individuals are aware of, monitor, control, or reflect upon these processes, **OR** • Papers that assess the influence of visual representations on perceptual and cognitive biases affecting data interpretation or the impact of visualization techniques on performance metrics (e.g., completion time, accuracy) without addressing self-regulated learning or cognitive monitoring, **OR** • Papers that emphasize external factors such as immersive experience to increase cognitive engagement (e.g., memory, attention) without involving users reflecting on or controlling their cognitive processes, **OR** • Papers that mention interviewing or gathering feedback from the participants without involving self-reflection or self-monitoring of their cognitive processes.

Table 3: Distribution of 21 reviewed papers by venue. Visualization venues are highlighted with a gray background, while Metacognition venues are shown with a white background.

Venue	Count
IEEE VIS	8
CHI	6
Memory & Cognition	3
TVCG	2
Metacognition and Learning	2
Journal of Applied Research in Memory and Cognition	1
Cognition	1
Total	**21**

interpretations to support sensemaking in risk assessments [69]. Nevertheless, these studies do not explicitly adopt metacognitive terminology, signaling a low level of engagement with well-known work or established research in this field. Engagement with key theories about concepts such as "self-regulation" and "metacognitive strategies" could provide valuable frameworks for analyzing and enhancing the cognitive processes involved in visualization. We explore how adopting such a metacognitive lens could aid these efforts in Section 5.

F3: Presence of think aloud protocols. Among the 21 relevant papers, two studies mentioned using a think aloud protocol in their methodology, involving participants verbally expressing their thoughts in real-time, thereby potentially providing insights into metacognitive processes. The first study conducted a think aloud session to observe how participants interpreted three unfamiliar visualizations [54]. This research aimed to develop a model for novices' sensemaking in information visualization, which included five cognitive activities. Among these, two activities – constructing a frame and questioning that frame – specifically exemplify metacognition by involving reflection on and evaluation of one's own thought processes. Integrating seminal works on metacognition, such as Flavell's concept of "metacognitive knowledge" [30] or Schraw and Dennison's "Metacognitive Awareness Inventory," [90] could further enrich the analysis by providing structured frameworks to interpret the verbalizations in think aloud protocols. Another study explored how individual differences, experiences, and cognitive load impacted the effectiveness of the proposed "Soliloquy" interface. In this study, participants were asked to articulate their thought processes while interacting with the interface, providing insights into their cognitive engagement with the tool [80]. Papers such as Hacker, Dunlosky, and Graesser's work [38] on metacognition in educational psychology could provide additional theoretical underpinnings that explain how and why certain metacognitive strategies enhance learning and performance

Table 4: Overview of the 21 reviewed papers, focusing on the specified types of metacognitive skills we adopted from [95], as metacognitive experiences and knowledge are minimally involved. Papers marked with an asterisk (*) indicate those that did not involve a user study; thus, measurement methods are not included in the table.

	Visual Stimuli	Skill	Measurement	Description
Bancilhon et al. [8]	Icon arrays	Self-awareness	Self-rating	Users rate their effort in completing a task.
Baumeister et al. [12]	AR displays	Self-awareness	Self-rating	Users rate their mental effort after a task.
Groß et al. [37]	Representative icons	Confidence	Index estimate	Users estimate the sugar content of various food items both before and after given visual feedback.
Hall et al. [39]	Visual charts	Confidence, Task decomposition	Self-rating	Users rate their confidence on the previous task block. Users describe the strategies they used when completing the task.
Hatzipanayioti et al. [40]	Spatial scenes	Task decomposition	Post-study survey	Users describe the strategies they used after completing the task.
Jaeger et al. [46]	Instructional visualizations	Confidence	Judgment of performance	Users judge how well they perform.
Jung et al. [49]	Visual charts with alternative texts	Self-awareness	Think-aloud	Users verbalize their thought process during a task.
Karduni et al. [50]	Uncertainty visualizations	Confidence	Self-rating	Users rate their confidence in the judgment both before and after they view a data visualization.
Koonchanok et al. [52]	Vis tools	Task decomposition	Prompts	Users are prompted to incorporate their working knowledge more frequently in queries when performing exploratory analysis.
Lee et al. [54]	Visual charts	Task decomposition	Think-aloud	Users reflect on the frame which they form to make sense of a given visualization.
Leopold & Leutner. [55]	Visualized scientific texts	Task decomposition	Self-regulated learning	Users receive metacognitive self-regulation learning training to study scientific texts.
Loksa et al. [58]	Progression visualization	Task decomposition	On-demand prompts	Users reflect on their strategies when seeking help from instructors.
Nowak & Bartram [69]	Vis tools	Self-awareness	Think-aloud	Users verbalize their thought process and explanation of actions taken in a task.
Robb et al. [81]	Imagery feedback	Task decomposition	Interview	Users describe their interpretation of the given feedback and how it inspires them to change their designs.
Robey & Riggins. [82]	Pictures	Confidence	Self-rating	Users rate their confidence in their judgments.
Risha et al. [80]	Vis tools	Task decomposition, Self-awareness	Pop-ups	Enhancing users' understanding of poetry by exposing them to a visualized think-aloud of an expert reading poetry.
*Sacha et al. [87]	Vis tools	Task decomposition, Self-awareness	–	Authors recommend developing systems that enable or encourage analysts to reflect on their analysis afterwards.
Shi et al. [92]	Vis tools	Self-awareness, Confidence	Self-rating, Post-study survey	Users rate their confidence in the final decision and write down their reasons for the final decision.
Wall et al. [102]	Vis tools	Self-awareness	Interaction traces	Users are aware of their analysis process by viewing interaction history in real-time while exploring data.
Wall et al. [100]	Vis tools	Self-awareness, Metacognitive flexibility	Interaction traces	Users gain an awareness of their analytic process and biases by viewing the visualized interaction sequences.
Zhao et al. [113]	Visual feedback	Self-awareness	Interview	Users describe their preferences with explicit reasons after completing the task.

in such settings. By referencing these metacognitive frameworks, researchers can specifically analyze how participants monitor and adjust their thinking during think-aloud sessions, leading to a more detailed understanding of cognitive processes. This application could reveal subtle cognitive strategies or errors, allowing for more precise data interpretation and the development of targeted interventions to enhance cognitive performance.

While only these two papers were identified from our inclusion and exclusion criteria, a broader search for *think aloud* among the entire corpus of 10,254 papers, disregarding other inclusion criteria, yields 56 papers in total that mention use of this protocol in the title or abstract. While these papers may contain further insight on metacognitive processes and visualizations, we opted not to include them all in our detailed review because many of the papers did not primarily focus on metacognitive processes but rather mentioned the protocol in differing contexts that may not directly align with the core scope of our survey. For instance, some papers identified in the broader search discussed the use of the think-aloud protocol in assessing user interaction with a new tool [48, 56, 78, 85]. While they provide valuable insights into user behavior and cognitive processes while interacting with the tools, their focus was primarily on usability testing rather than exploring metacognitive processes in visualization. Hence, the insights from those papers, although relevant in a broader cognitive context, do not align closely with the core objective of the present survey centered on metacognition in visualization.

F4: Related papers mention confidence and strategy. Although most of the related papers are not explicitly grounded in metacognition, they frequently mention specific keywords that hint at metacognitive elements through secondary measures. A particularly significant keyword found across 5 out of 21 studies is 'confidence.' In these studies [39, 46, 50, 87, 92], participants are asked to self-report their confidence levels regarding their judgments or analyses, e.g., by using a slider on a 0–100 scale during a post-survey. This recurring emphasis on confidence may imply an underlying appreciation for self-awareness in evaluating analytical processes and outcomes, which is a core aspect of metacognitive monitoring. Incorporating Narens' model of metacognition, which details the formation of metacognitive confidence judgments, can clarify the specific mechanisms by which these judgments influence cognitive monitoring and control [64]. By understanding the criteria and processes that underlie confidence assessments, researchers may discern how confidence levels serve as indicators of the effectiveness and reliability of one's cognitive monitoring, thereby providing a more robust theoretical basis for interpreting these self-assessments.

Additionally, although not numerous, four papers mention 'strategy.' For instance, some studies such as [39, 40, 81] required participants to report their strategy or reasoning behind their choices after completing tasks, intended to provide insights into the decision-making behaviors of the participants. Another study develops an intervention that involves displaying a flow chart of six problem-solving stages, designed to prompt learners to reflect on their strategies when seeking help from instructors in the context of programming education [58]. To more effectively bridge these discussions with metacognitive frameworks, referencing papers such as Zimmerman's work on self-regulated learning [114] would be beneficial. Zimmerman's model, which emphasizes planning, monitoring, and evaluating as essential skills of self-regulation, could provide a valuable lens for analyzing how strategies reported in these studies relate to metacognitive control processes. This theoretical framework can explain why incorporating metacognitive prompts in study methodologies could enhance learning outcomes by fostering more effective self-regulation among learners.

F5: Studies seldom complete the feedback loop. Although some relevant studies have analyzed participants' self-reported strategies, e.g., investigating the effects of personal differences on interpreting various visual charts [39] or examining the influence of sensorimotor encoding on participants' reasoning about spatial scenes [40], they typically conclude without "closing the loop" by providing the opportunity for users to view, interact with, and adjust their strategies accordingly. A notable exception includes the work by Wall et al., which displayed real-time interaction traces by coloring points in a scatterplot that users had interacted with. This approach prompted reflection after decisions were made by comparing the distribution of user interactions with the underlying data distribution, thereby enabling participants to revise their decisions accordingly [102]. Similarly, Robb et al. provided 12 designers with feedback in response to their visualization designs and conducted interviews to explore how visual feedback, as opposed to text feedback, inspired changes in their designs [81]. The benefit of closing the feedback loop is well-documented in educational and metacognitive research. For example, Butler and Winne's paper on feedback and self-regulated learning emphasizes the importance of timely and specific feedback in enhancing metacognitive awareness and improving learning outcomes [20]. This process helps learners adjust their cognitive and metacognitive strategies in response to new information, which is critical for effective learning. We explore the promising potential of integrating similar feedback mechanisms into visualization studies in Section 7, highlighting how such practices could significantly enhance user engagement and learning.

5 Metacognitive Model of Visualization

In the field of visualization, understanding how users interact with and make decisions based on visual data is crucial [61, 105]. Established cognitive frameworks, such as the decision-making models proposed by Padilla et al.[71], and their recent applications by Bancilhon et al.[7], have modeled these interactions effectively. Van Wijk's model [99] underscores the iterative nature of visualization, where understanding evolves as the user interacts with the data. Furthermore, the sensemaking process described by Pirolli and Card [74] models how individuals transform raw data into actionable insights. However, these frameworks primarily focus on cognitive aspects without considering the critical layer of metacognition, which involves self-awareness and self-regulation of these cognitive activities. Integrating metacognition into visualization processes can facilitate a deeper understanding of user interactions with visual data, emphasizing how users monitor and regulate their cognitive processes. It provides insights into the users' awareness of their own thought processes and their ability to adjust strategies in real time, enhancing the design and utility of visualization tools.

In this section, we explicate how metacognitive components can be integrated into the van Wijk operational model of the visualization process. We chose to expand the van Wijk operational model for its comprehensive approach to capturing the dynamic relationship between perception, knowledge, and interaction [99]. Unlike other models that may focus more narrowly on specific aspects of visualization, such as data representation or user interaction in isolation [14], van Wijk's model encompasses the entire cycle of visualization interaction, from data processing to knowledge formation and back to data interaction. This cyclical and iterative nature aligns closely with the principles of metacognition, which emphasize continuous monitoring, evaluation, and adaptation of cognitive processes. Additionally, we outline several metacognitive strategies designed to improve users' interpretation and decision-making with visual data, as shown in Figure 2. By embedding metacognitive strategies into this model, we aim to provide a framework that not only describes how users interact with visual data but also how they reflect on and regulate their own thinking during these interactions.

This discussion is intended to join metacognitive concepts with an existing operational model, marking a progressive step in understanding holistic human cognitive processes. Our goal is to show how a metacognitive lens can inform and improve visualization design, which we discuss further in Section 7.

5.1 Expanded van Wijk Model

Van Wijk conceptualizes the 'user' in terms of Perception and Cognition (P), Knowledge (K), and Interactive Exploration (E). The user perceives the image (I) and engages with the visualization through various available manipulation techniques, referred to as the specifications (S) in Figure 2. Green et al. [36] have expanded this model by adding two directional arrows, depicted in green in Figure 2. The arrow from P to E underscores the critical role of perception and perceptual logic in facilitating active exploration, while the arrow from E to K highlights how an iterative interaction cycle enriches knowledge and reasoning. As users explore and learn, this new knowledge shapes and directs further exploration, integrating Perception, Knowledge, and Exploration as interdependent cognitive processes. We further augment this model with metacognitive components, depicted in blue.

When the user perceives the image (I), early cognitive and perceptual (P) processes such as selective attention and categorization are activated [36], potentially triggering *metacognitive experiences* (Figure 2, (a)). These experiences can include subjective feelings like a sense of familiarity or the realization that one has misunderstood a visualization. Additionally, they may involve implicit cues that inform us about our cognitive processes, such as 'processing fluency' cues that indicate how swiftly a memory is recalled [1, 67, 95]. A self-loop labeled with dM/dt to metacognitive experiences represents changes in metacognitive experiences over time, indicating how users' reflections and reactions to the visual data evolve as they interact more deeply with the content.

The perception process enriches the user's knowledge base (K), which encompasses both the initial knowledge and insights gleaned from the image [99], along with new knowledge generated through reasoning and problem-solving [36]. This involves *metacognitive knowledge* (Figure 2, (b)) – an understanding of their cognitive strategies and processes. This knowledge includes recognizing the types of cognitive tasks at hand and understanding which cognitive strategies might be most effective in navigating them. For example, a viewer might identify that analyzing complex data requires a strategy of breaking information into smaller, manageable parts. As viewers acquire metacognitive knowledge from initially perceiving and interpreting visualizations, this foundational understanding paves the way for deeper engagement. Just as with *metacognitive experiences*, there is a self-loop for *metacognitive knowledge* labeled with dM/dt that indicates continual adjustments and refinements in the viewer's metacognitive knowledge over time, emphasizing its dynamic development through interaction with visual data.

As users accumulate knowledge, they might decide to adjust the visualization's specifications to explore the data further, engaging both P and K in a dynamic cognitive process [36]. During this phase, viewers may likewise utilize sophisticated *metacognitive skills* (Figure 2, (c)) such as monitoring and controlling their own thought processes as they interact with the visualization. Monitoring and control are pivotal metacognitive abilities that enable individuals to evaluate and steer their own cognitive processes [95]. Monitoring involves assessing one's own thinking, encompassing skills like self-awareness and adjusting confidence levels. In contrast, controlling cognitive processes involves actively regulating and directing one's thoughts, decisions, and behaviors to achieve specific goals. This often includes managing attention, inhibiting distractions, and applying strategies to optimize problem-solving or task performance.

For instance, cognitive monitoring in visualization might entail recognizing one's mental state and how it influences their cognitive processes, crucial for setting clear goals and intentions such as, "What insights do I hope to gain from analyzing this dataset?" This awareness is critical as viewers interact with visualizations to understand data deeply and control the output of that thinking to achieve specific goals. Confidence relates to assessing one's capability in handling tasks [109], such as determining, "How confident am I that my interpretation is correct?" Properly calibrated confidence helps objectively evaluate performance and align it accurately with one's abilities. For example, they may evaluate how well they understand the information presented and whether they are able to draw accurate conclusions based on the visual data. A self-loop labeled with dM/dt indicates the ongoing development of *metacognitive skills* in this framework.

5.2 Metacognitive Strategies

We briefly discuss a few metacognitive strategies, depicted in orange in Figure 2 within the expanded van Wijk model. While this is not an exhaustive list, these strategies, when effortfully engaged by visualization viewers, can be used to enhance the way they interpret and make decisions with visual data.

Self-explanation. Learning involves the integration of new information into existing knowledge. Generating explanations to oneself, known as self-explaining, facilitates this integration process. Self-explanation has been extensively studied in the fields of learning and cognitive sciences, and considerable research underscores its effectiveness in enhancing understanding and problem-solving skills [2, 21, 22, 107]. For instance, a study by Chi et al. [22] demonstrated that students who explained concepts to themselves understood better than those who did not. This benefit could be equally significant for viewers of visualizations. In a practical scenario, an analyst reviewing a line graph showing changes in consumer behavior over time could use self-explanation to enhance their understanding. As they identify trends or outliers, they could self-explain such as "I think this pattern exists because there is an underlying relationship between spending on marketing in general and web traffic," or "I think this peak represents a significant impact from a recent promotional campaign" based on their knowledge of recent market changes or promotional campaigns. This practice could encourage deeper engagement with the data and help solidify learning. It can also foster critical thinking by requiring the viewer to justify their interpretations, which can lead to more accurate and insightful data analysis.

Self-questioning. Different from self-explanation, which focuses on articulating what one already knows or believes, self-questioning is oriented towards exploring unknowns, challenging existing knowledge, and seeking new information [35]. This approach is

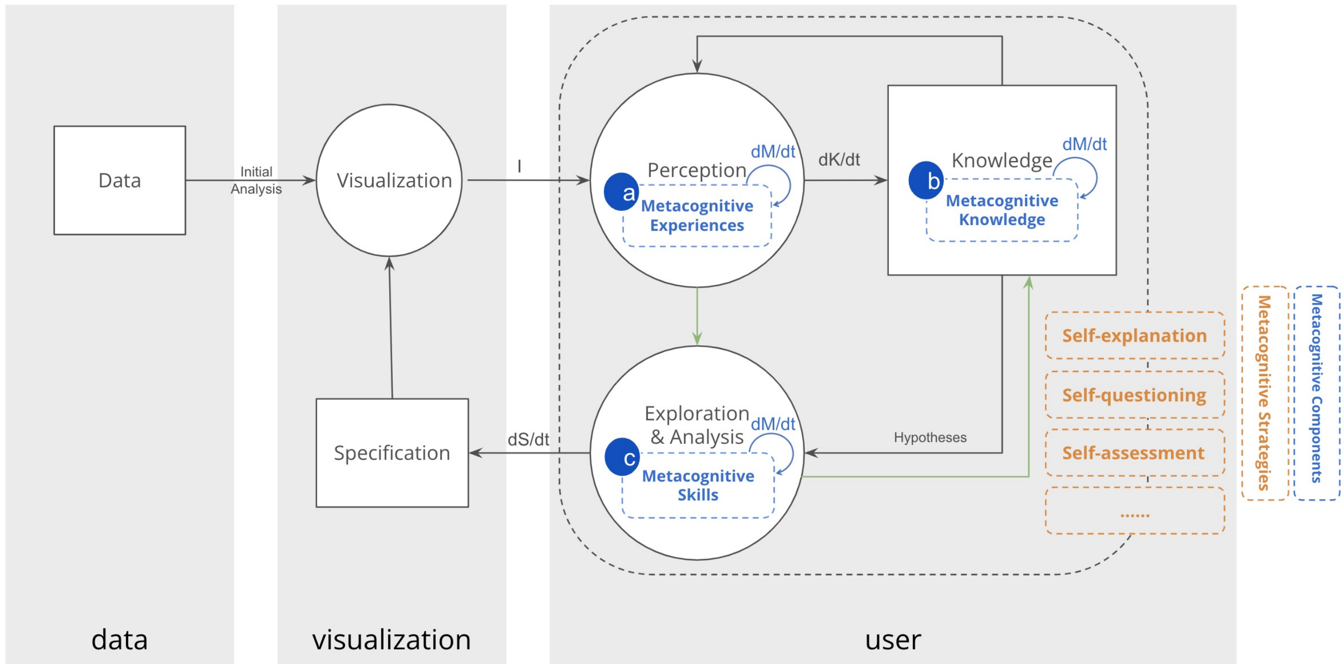

Figure 2: An adaptation of the visualization process defined by van Wijk [99], augmented with metacognitive factors.

well-supported in the educational context, where questioning strategies have been proven to promote deeper understanding and enhanced learning outcomes [51]. In the realm of data visualization, self-questioning could play a crucial role by encouraging viewers to actively formulate questions that guide their exploration of visual data. As viewers interact with a visualization, they might pose questions such as "What anomalies are present in the data?" or "What might be causing this trend or anomaly in the data?" Such inquiries not only have the potential to provoke deeper engagement with the data but also drive the discovery of insights that might not be immediately apparent. By continuously posing and addressing these questions, viewers can ensure a comprehensive examination of the data, thereby enhancing the quality of their analyses and the validity of their conclusions. This dynamic process of questioning and reevaluating may help to foster a critical mindset, crucial for effective data-driven decision-making.

Self-assessment. Self-assessment, or self-evaluation, has been demonstrated to contribute significantly to academic success, especially when compared to students who do not practice it, supported by findings in educational psychology [18, 34, 84]. Unlike strategies such as self-explanation and self-questioning, which focus on articulating and querying one's understanding, self-assessment emphasizes evaluating the reliability of one's own conclusions. In the field of data visualization, self-assessment can enables analysts to critically assess their interpretations and the underlying data. As viewers navigate through data visualizations, they can regularly assess how certain they feel about the accuracy and reliability of their interpretations. For instance, after identifying a trend or anomaly in the data, a viewer might rate their confidence in their explanation or prediction related to that observation, asking themselves questions like, "How confident am I in the conclusions I am drawing from this trend?" or "What is the likelihood that my interpretation of this data is accurate?" If they find their confidence level is low in certain areas, they might decide to revisit the data, consider alternative interpretations, or consult additional sources. This practice may help to validate data analysis accuracy and enhance understanding of personal biases and limitations. Effective self-assessment can strengthen analytical skills, improve decision-making reliability, and support professional growth by fostering continuous critical reflection and adaptation to complex information [84, 93].

6 Examples

In this section, we demonstrate how the expanded van Wijk model from Section 5 can be used to provide a novel lens with which to assess extant visual analytic systems. We analyze the ways in which two systems, Lumos [62] and Soliloquy [80] integrate metacognitive concepts using the expanded van Wijk model. Metacognitive strategies are highlighted in orange, and the specific metacognitive components associated with these strategies are indicated in blue, in line with Figure 2. We chose to analyze Lumos [62] (the system used in experiments by Wall et al. [102]) and Soliloquy [80] from our set of coded papers as they both provide visual analytic interfaces that can demonstrate a breadth of metacognitive techniques.

6.1 Lumos

While it does not use the language of metacognition, the Lumos [62] system is designed to enhance metacognition through the lens of *bias awareness* by fostering active self-monitoring and self-reflection of a user's interaction traces. This system leverages both in-situ and ex-situ visualization techniques to foster continuous metacognitive engagement and reflection.

In its in-situ configuration, Lumos tracks how users interact with visual data representations such as bars, lines, points, and strips. It leverages the unused visual channel of color on a gradient from white to blue to visually represent the frequency of interactions with data, with a darker blue indicating more frequent interactions, and white indicating none. This immediate visual feedback is crucial for promoting the *metacognitive skill* (Figure 2, (c)) of real-time *self-monitoring* For instance, a mouseover on a visualization element in the visualization canvas (Figure 3, (E)) highlights this point with a corresponding shade of blue, depending on the interaction intensity. This feature enhances the *metacognitive skill* (Figure 2, (b)) of *self-awareness*, by making users conscious of their focus areas, as well as encouraging a balanced approach to data analysis by visually cueing areas of potential neglect or overemphasis. Similarly, the Attribute Panel uses the same white-to-blue color scale to indicate the level of interaction with different data attributes (Figure 3, (B)). This consistent visual coding across different components of the interface supports users in developing an intuitive understanding of their analytic behaviors over time, supporting another critical *metacognitive skill* (Figure 2, (c)) known as *self-assessment*. This enables users to evaluate their engagement and adjust their analytical focus dynamically, ensuring more effective data exploration and decision-making processes.

In addition to these in-situ mechanisms, Lumos incorporates ex-situ visualizations to further enhance metacognitive processes. The Distribution Panel (Figure 3, (G)) allows users to compare their interaction patterns against a set of predefined target distributions, such as Proportional, Equal, or Custom baselines. For example, in a dataset of job applicants with diverse gender identities (e.g., 50% identifying as male, 40% as female, and 10% as nonbinary), a proportional target might reflect the actual demographic distribution, encouraging users to align their interactions accordingly. Lumos visually contrasts the observed user behavior with these target distributions, using a color-coded system (red to green) on the attribute cards to signify how closely user actions match the expected distribution. Redder hues indicate significant deviations, prompting users to engage the *metacognitive skill* of *self-reflection* on potential biases or oversights. This acts as a trigger for *self-assessment*, encouraging users to critically evaluate their performance. Conversely, greener hues suggest alignment with the target distribution, reinforcing effective analytic practices. This setup not only aids in the development of *metacognitive skills* (Figure 2, (c)) like critical thinking and adaptive learning but also enhances *metacognitive knowledge* (Figure 2, (b)) by providing users with feedback that informs them about their analytical efficacy and areas for improvement.

By providing multiple layers of feedback, Lumos effectively integrates metacognitive components into the data exploration process. This design not only aids users in becoming conscious of their interaction patterns but also empowers them to self-regulate and adapt their analytical strategies in response to real-time insights about their behavior. This approach is fundamental in helping users develop deeper metacognitive skills, such as self-awareness and self-regulation, which are essential for effective and unbiased data analysis.

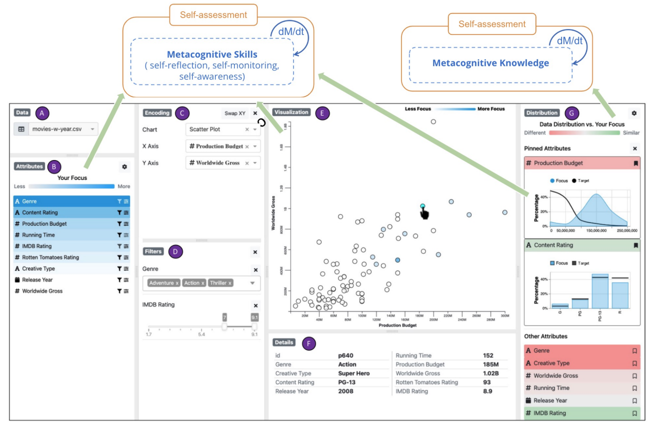

Figure 3: An example of Lumos adapted from [62], shows a user's interaction traces using both in-situ ((B) Attributes Panel, (E) Visualization Canvas and (F) Details View) and ex-situ ((G) Distribution Panel) visualization techniques.

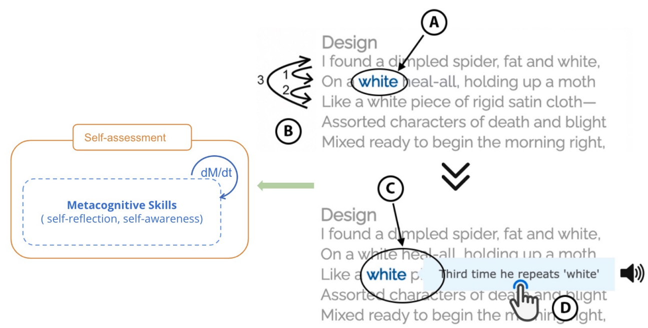

Figure 4: An example of Soliloquy adapted from [80], features (A) shading to denote current attention of the expert reader, (B) ordering of lines to illustrate recursive reading patterns, (C) highlighting of specific words or phrases that trigger thoughts, and (D) verbalized thought displayed as popups with optional audio playback.

6.2 Soliloquy

Risha et al. present Soliloquy, an interface designed to visualize the thought processes of an expert as they read and interpret a poem to novice readers, aimed at enhancing their understanding of expert cognitive strategies to improve their comprehension of poetry [80]. Soliloquy is inspired by the think-aloud instructional strategy commonly used in educational settings, where an instructor or student vocalizes while performing a task, such as reading a poem, to model the process and provide a worked example for others.

It begins simulating the think-aloud process by bolding each word to indicate the expert reader's current focus, guiding novices on how to pace their reading and what to emphasize (Figure 4, (A)). Furthermore, Soliloquy incorporates text shading animations

(Figure 4, (B)) to simulate recursive reading patterns, which are typical of experienced literature and poetry readers who often reread sections, posing questions, and forming connections [80]. This recursive approach helps novices understand that deeper reading involves revisiting and reflecting, not just linear progression through the text.

Critical moments of insight, such as forming an idea, posing a question, or making a connection, are captured in popups (Figure 4, (D)) which convey the expert reader's thought. The word or phrase that triggers the thought is highlighted, linking the text to the thought process visually (Figure 4, (C)). This feature promotes *self-reflection* as novices compare their thoughts with the expert's, enhancing the *metacognitive skill* (Figure 2, (c)) of *metacognitive awareness.* By observing the expert's insights, novices are encouraged to engage in *self-assessment*, evaluating their own understanding and identifying areas where their interpretations may differ, thus recognizing gaps in their comprehension.

The integration of metacognitive components is a key aspect of Soliloquy's design. This interface actively involves novices in developing metacognitive skills by enhancing their awareness of their own reading processes. As novices observe the expert's focused and recursive reading, they are introduced to effective reading techniques, learning to monitor their own comprehension and adapt their strategies accordingly. By allowing novices to witness the real-time cognitive processes of an expert, the popups serve as triggers for metacognitive engagement, prompting novices to reflect on their understanding of the poem and how their thoughts align or differ from the expert's. This reflection is essential for developing the *metacognitive skill* (Figure 2, (c)) of *self-awareness*. Soliloquy thus improves poetry comprehension and serves as a powerful tool for teaching and reinforcing metacognitive strategies within an educational context, helping learners to become more reflective and effective readers.

Overall, by explicitly highlighting metacognitive features in systems like Lumos and Soliloquy, we demonstrate how visual analytics tools can go beyond facilitating task performance to actively fostering self-awareness, reflection, and adaptive learning in users. These examples illustrate the transformative potential of incorporating metacognitive components, enabling users to become more thoughtful and effective in their analytical or interpretive processes. This focus underscores the importance of designing systems that not only support task-specific outcomes but also cultivate broader cognitive and metacognitive skills.

7 Next steps: how is a metacognitive framework helpful for future visualization research?

In this paper we posit that the exploration of metacognition in visualization can profoundly enhance our understanding of how users interact with visual data. This insight is particularly beneficial for designers who create these visualizations, and researchers who evaluate effects of visualization techniques. In section 5.2, we outlined metacognitive strategies. Here, we expand on actionable methods for researchers and designers to enhance users' metacognitive abilities. Designers may rely on intuition when making decisions; however, our model can elucidate why certain design choices are effective and help designers make informed decisions that are grounded in a deeper understanding of user interactions and cognitive processes. By integrating these guidelines, designers can better predict how users will interact with and benefit from visual data, ensuring that visualizations are both functional and insightful. For researchers, these guidelines offer a framework for investigating the impact of metacognitive strategies on visualization efficacy. By exploring how these strategies influence user behavior and cognition, researchers can contribute to a more nuanced understanding of the relationship between user and visualization, ultimately driving advancements in visualization technology and methodology.

7.1 Metacognition for Visualization Designers

In this section, we discuss some strategies that visualization designers might use when designing systems that promote metacognitive engagement. Building on Section 5.2 and Figure 2, a designer's goal should be to slow down the analysis and decision making processes, promoting self-reflection. How might systems support strategies like self-explanation, self-questioning, and self-assessment? In this section, we demonstrate example metacognitive interventions that visualization designers might consider.

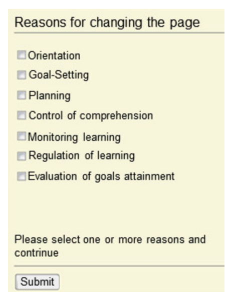

Figure 5: An example of prompts in Bannert and Menglkamp's work [10].

Prompting Users to Check Their Work. Prompting is a form of instructional scaffolding designed to support self-regulated learning in educational settings [72]. This is typically achieved by asking learners relevant questions or providing explicit instructions [9]. Enhancing reflection in visualization should similarly involve strategically prompting users to examine their own thought processes, decisions, and strategies when appropriate. This could range from simple features that prompts users by asking "Are you sure?" to prompt reflection before finalizing a data-driven decision, to more complex interventions. For instance, in Bannert and Menglkamp's work [10], prompts were provided after each navigation step students made in a hypermedia learning environment about operant conditioning. The learning environment included both relevant and irrelevant pages for the learning goal. Students were prompted to select one or more reasons for their page changes in a pop-up window, which included options like orientation, goal-setting, planning, and control of comprehension, as depicted in Figure 5 from [10].

While these interventions can foster deeper cognitive engagement, it is equally important to balance them with the natural exploratory flow of the users. Overly frequent or poorly timed prompts could disrupt user focus, causing frustration or breaking the continuity of thought. One solution is self-directed prompts, as developed by Bannert et al. [11]. When configuring self-directed prompts, learners can decide when to receive the prompts during the learning process and decide the sequence of reasons for their learning activities when being prompted (e.g., planning, goal specification, and orientation) [72], which supports feelings of autonomy [25, 86]. When implemented thoughtfully, these features can encourage more deliberate analysis and prevent oversight, ultimately fostering cognitive growth over time. By embracing both reflective practices and user autonomy, visualization tools can evolve beyond mere data interpretation aids to become platforms for sustained cognitive development.

Figure 6: An example of degraded fonts in Hullman's work [44].

Inducing Visual Difficulties. Interacting with an information visualization is akin to engaging in a learning process, where drawing inferences from the visualized data is part of a broader activity of assimilating new information and integrating it with existing knowledge. Typically, the evaluation of visualization effectiveness is guided by the cognitive efficiency model, which measures how well a graph enhances the speed and accuracy of pattern recognition, as noted by Larkin and Simon [53]. However, a substantial body of psychological research on learning from graphs and diagrams suggests that introducing desirable visual difficulties – tactics designed to stimulate more intense cognitive activity through specific alterations in the visual representation – can significantly enhance learning [16]. This approach is supported by Hullman et al., who argue that such challenges promote crucial elements of learning, specifically the active processing of information and engagement with the content [44].

Active processing involves additional cognitive operations aimed at deepening understanding, as depicted in the complementary metacognitive container on the right in Fig. 2. Hullman et al. highlighted two primary forms of active processing: *self-explanation* and the manipulation of *internal visualizations*. Some prior work supports the integration of visual difficulties that prompt *self-explanation* within visualization. For example, Natter and Berry [65] conducted two experiments on the active processing of risk information graphs. In these studies, participants engaged in reflective tasks such as representing risk sizes on a bar chart and answering reflective questions, which not only increased their satisfaction with the information but also led to more accurate judgments and estimates. To implement self-explanation facilitation, textual or task prompts have proven effective in reliably inducing self-explanation when interacting with visualizations [24]. On the topic of *manipulating internal visualizations*, cognitive psychologists emphasize the importance of this technique in aiding comprehension. Trafton et al. [97] observed that experts who formed and compared schematic internal representations with external visualizations were better able to identify gaps in their knowledge. Engaging viewers with internal visualizations can be effectively facilitated by asking them to predict the workings of a visualized process before they examine the actual visualization [44]. This metacognitive strategy, similar to using reflective thinking prompts for self-explanation, promotes a more profound understanding by encouraging viewers to reflect and question actively the visual data presented. This method fosters a metacognitive environment where viewers are not just passive recipients of information but are actively involved in the cognitive unraveling of the data, thereby enhancing their learning and retention of complex information.

Another approach to implementing visual difficulties is grounded in disfluent learning experiences, which stem from the metacognitive judgment of fluency. This judgment falls under metacognitive knowledge in the Fig. 2, specifically within the category of knowledge about one's cognitive conditions. Fluency is defined by psychologists as a metacognitive judgment that assesses how smoothly information processing seems to occur [3]. For example, a previous study found that while degraded fonts (e.g., as described in Figure 6 from [44]) are perceived as more effortful to read, they can actually enhance comprehension and memory, by prompting viewers to avoid mental shortcuts and heuristics [4]. Additionally, introducing perceptual disfluency, such as using complex graph legends, can benefit graph viewers by heightening their awareness of the effort they are exerting [91]. This is because perceived disfluency encourages viewers to engage in systematic, analytical reasoning instead of relying on automatic or heuristic processes [4]. This concept is similar to how introducing "difficulties" into graph comprehension tasks can make viewers aware of gaps in their mental models, motivating them to invest more effort into understanding the information [44].

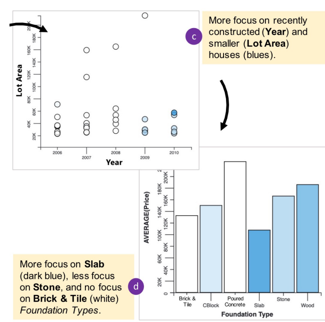

Figure 7: An example of using color encoding to indicate interaction intensity in Lumos [62], promoting awareness of potential biases.

Closing Feedback Loops in Vis. From the perspective of metacognition, an incomplete feedback loop (**F5**) represents a missed opportunity for deeper metacognitive engagement, which is critical for nurturing an environment of continuous learning and improvement. Specifically, the failure to provide feedback prevents participants from reflecting on and refining their strategies based on their self-assessments. Offering such feedback in visualization tools could significantly enhance participants' understanding of their cognitive processes, elevate self-reflection, and sharpen critical analysis skills. For instance, Wall et al. enabled participants in a controlled study to revise decisions after viewing interaction traces that showed how they allocated time and attention across the data, which can promote conscious reflection of one's analysis process [102]. Similarly, Loksa et al. observed increases in productivity and programming self-efficacy by enabling learners to adjust their strategies based on explicit and on-demand prompts for self-reflection when seeking help from instructors [58]. Systems can be designed with these features in mind, such as Lumos [62], which provides real-time feedback by capturing and displaying users' interaction history with data by using the color channel in the visualization to promote awareness of potential biases in the data exploration process as depicted in Figure 7. This practice can not only improve task performance but also evolve individuals' learning processes over time, contributing to more effective and insightful visual data exploration and interpretation.

However, it is important to recognize that the necessity and impact of such feedback loops can vary depending on the nature of the research or the objectives of the visualization tool. In some contexts, such as studies exploring the effects of personal differences on interpreting various visual charts [39] or examining the influence of sensorimotor encoding on spatial reasoning [40], the immediate closure of feedback loops may not be essential. Here, the primary goal may be to observe and measure natural cognitive and behavioral responses without the influence of feedback, to understand baseline performances and intrinsic processes. For more discussion on how metacognition might influence researchers' goals, see Section 7.2.

7.2 Metacognition for Visualization Researchers

The novel lens of metacognition in visualization opens up a number of promising avenues for future research. We envision some potentially fruitful outcomes could include improved decision-making accuracy and efficiency by better understanding and leveraging how users become aware of and manage their cognitive processes during data analysis. Furthermore, as with metacognitive skill training in the learning sciences [110], the development of metacognitive skills in visualization may lead to transferable skillsets. Here we outline key future research opportunities that explore these aspects.

Adaptations to Existing Evaluation Methods. Integrating metacognitive measures into existing evaluation methods in visualization has potential to enhance the effectiveness and relevance of these assessments. By incorporating metacognitive elements, researchers can gain deeper insights into the cognitive strategies that users employ, the decision-making processes they follow, and the biases that may influence their interpretations. One possible adaptation is the incorporation of metacognitive prompts within the evaluation framework. These prompts can be strategically placed during tasks to encourage users to reflect on their thought processes as they interact with visual data. For example, after presenting a complex graph or chart, evaluators might ask participants to describe what strategies they used to interpret the data and what information they found most or least reliable. This approach not only helps in understanding how users process visual information but also in identifying areas where their understanding may falter. Similarly, researchers might consider the use of think-aloud protocols (**F3**), where participants verbalize their thought processes while engaging with visualization tools. By analyzing these verbalizations, evaluators can identify patterns in how different types of users approach problem-solving and decision-making in real-time, adjusting their strategies based on the feedback they receive from the visualization. Additionally, the integration of metacognitive assessment could be tailored through pre- and post-task questionnaires that measure changes in understanding and approach. These questionnaires should also gauge users' confidence (**F4**) in handling the visual tasks, assessing how users' perceptions of their own knowledge and abilities evolve as they interact with visual data. These questionnaires can assess how users' perceptions of their own knowledge and abilities evolve as they interact with visual data. This data could be invaluable for designing visualizations that are not only informative but also tailored to improve user competence and confidence.

Development of Adaptive Visualization Systems. Future research could examine the role of metacognitive flexibility [95] in visualization – the ability to change one's cognitive strategies based on new information or feedback. In educational and cognitive sciences, tools such as the Metacognitive Awareness Inventory (MAI) have been used to measure aspects of metacognitive awareness and control that could inform adaptive system design. For example, Schraw and Dennison's MAI could be adapted to assess how users reflect on and regulate their cognitive activities while interacting with visualizations [90]. This insight could directly influence development of adaptive visualization systems capable of modifying visualizations in real-time, tailored to a user's metacognitive state. Previous work has already laid the groundwork for adaptive systems in visualization. For instance, Zhang et al. introduced AdaVis, an adaptive visualization recommendation system that utilizes machine learning techniques to suggest one or multiple appropriate visualizations based on data context [111]. Additionally, Toker et al. have advocated for adaptive information visualization systems that personalize displays according to individual user needs such as perceptual speed and personal preferences [96]. Building on this foundation, integrating metacognitive concepts into the design of adaptive visualization systems could monitor how a user interacts with a set of visualizations and detect patterns such as prolonged engagement without progress or frequent switching between data points without drawing conclusions. If such patterns are recognized, the system could intelligently suggest a shift in visualization – for instance, changing from a complex scatter plot to a simpler bar chart or from a static graph to an interactive one that allows for manipulations like zooming or re-scaling. By integrating the concept of metacognitive flexibility, this adaptive approach ensures that visualization tools are not only more responsive but also more intuitive, enhancing user engagement and insight generation from the data. This approach ensures that visualization tools cater directly to the evolving needs of their users, promoting efficient data exploration and more informed decision-making.

Integrating Metacognition for Cognitive Bias Mitigation. Future research could study the usage of metacognition to combat cognitive biases, such as confirmation bias or anchoring, which can significantly affect the outcomes of data analysis by leading analysts to make decisions based on skewed perceptions rather than objective data [98]. By increasing metacognitive awareness, users can become more conscious of their own thoughts and biases, prompting users to self-correct their initial assumptions. Promoting metacognition can possibly be a simple yet effective method to reduce users' biases. Wall et al. observed increased awareness of potential unconscious biases, by enabling view interaction history in real-time while exploring data and in a summative format after a decision has been made in an interactive scatterplot-based visualization tool [102]. This approach not only highlights biased patterns in data interaction but also prompts users to reconsider their analytical strategies. In a related study, the author proposed metrics to quantify behavioral indicators of bias, such as data point coverage metric which measures the user's attention to the data points, that could be integrated into visualization systems to help users recognize and adjust for cognitive biases during their analyses [100].

This integrated approach, where metacognitive practice is coupled with effectively designed visualization tools, enhances the reflective capabilities of users, making them more adept at recognizing and correcting biases. Thus, while metacognition alone may not solve all issues related to bias in data analysis, it serves as a vital component in a multi-layered strategy that includes good design practices and appropriate tool support. These elements collectively contribute to a more informed and unbiased analytical process, underscoring the value of metacognition as part of a comprehensive solution.

Collaborative Metacognitive Strategies in Vis. Collaboration in visualization is fundamentally a social process that involves efforts in parallelization, discussion, and consensus building [41]. Incorporating collaborative metacognitive strategies in visualization can significantly improve this process by enhancing the effectiveness of distributed teams working on complex data analysis tasks. For example, the work by Sarvghad et al. [89] highlighted a common challenge in collaborative data analysis: understanding the scope of investigation already covered by team members and identifying what still needs to be explored. Traditional visualization histories, often presented as sequential lists, do not sufficiently convey the depth and breadth of analysis, especially in complex datasets with multiple dimensions. This limitation can hinder effective collaboration and strategic planning in distributed teams. To address this, they introduced a "dimension view" to visualize the history of data exploration from a dimension coverage perspective. This strategy allows analysts to see not just what has been done, but how it relates to the entire dataset's dimensional structure. By providing a visual representation of which dimensions have been explored and to what extent, this view supports a more strategic and informed approach to further analysis. Such integration in visualization fosters a more synchronized and reflective approach to distributed data analysis, which not only enhances the efficiency and effectiveness of collaborative efforts but also deepens the analytical acumen of the team as a whole.

8 Limitations

We scoped our review to work done in the last ten years from a total of 11 metacognition- and visualization-related venues. This search is limited in at least three ways: (1) the scope of time and venues, (2) searches were limited to titles and abstracts only, and (3) the initial keyword-based search strategy can miss relevant work. While we believe our review covers a broad and deep enough space to provide useful insights in this paper, we emphasize that this framework is intended as a starting point for further exploration rather than a definitive model. A more thorough future review could include full text search of all 38 visualization venues covered by the VitaLITy corpus [5, 63] and explore a similar scope of metacognition venues.

Older and upcoming research was excluded from scope but may nevertheless help fill in the gap of research at the intersection of visualization and metacognition. For instance, certain pivotal studies, like the 2011 paper on visual difficulties to engage users in cognitively demanding activities such as self-explanation to facilitate their ability to monitor and evaluate their understanding [44], were excluded from our current corpus due to the constraints on the year range.

Similarly, our keyword-based search covered cognitive and metacognitive keywords, however, relying solely on titles and abstracts introduces two potential limitations. Firstly, papers might seem relevant by mentioning terms such as "confidence assessment" in their abstracts without engaging with discussion of self-rating in the full text (e.g., [50]), and secondly, some papers may have relevant content in the full text of the paper, but not in the title or abstract fields, or may have used other types of keywords which were scoped out of our review. For example, the KTGraph system by Zhao et al [112] describes an interface that aids analysts in externalizing their investigations. It features capabilities like tagging any element of the graph to embed meta-information about their thoughts, such as highlighting promising areas for further investigation or noting tasks to complete, thereby enhancing analysts' awareness of their analysis coverage.

9 Conclusion

In this paper, we introduced a novel metacognitive lens through which to consider visualization research and practice. From a large corpus of papers from both metacognition-related and visualization-related venues, we identified 21 relevant papers that lie at the intersection of the two fields. We observe that among these papers, (i) they rarely explicitly mention *"metacognition"* (**F1** and **F2**), (ii) instead integrating some metacognitive measures into study designs, e.g., by having users reflect on confidence and strategies (**F4**) or using think aloud protocols (**F3**), and (iii) seldom "close the loop" by providing insights back to users in a way that can influence their analysis process (**F5**). We finally synthesize a framework of visualization that explicitly integrates metacognition and use it to stimulate future research directions. We offer this augmented framework as a next step in advancing the dialogue on metacognitive integration within the visualization community. We hope that this paper can inspire a research agenda that begins to explicitly grapple with metacognitive theories and frameworks. We believe this has potential to transform visualization into a field that focuses on deep iterative learning and reflection.

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