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Survey Paper

Guiding through uncertainties in visual analytics: A survey☆

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ABSTRACT

Several uncertainties emerge in each component of the visual analytics (VA) cycle that hinder the user's ability to make efficient and effective decisions, e.g., through missing data, model approximations, or visual mappings. Well-known VA strategies aim first at making users aware of these uncertainties, often through visual means. When visuals alone are insufficient to accurately quantify or communicate uncertainties, VA designers may rely on guidance to support users' understanding of these uncertainties throughout the VA cycle. While prior VA research has attempted to conceptualize guidance, the ability and mechanisms for guidance to comprehensively address different sources of uncertainties remain an open question. In this survey, we characterize the relationships between uncertainties and guidance in VA literature. Our key contribution is a taxonomic framework that relates uncertainty sources to relevant guidance strategies and their respective profiles, i.e., roles, scopes, and features. Through this taxonomy, we discuss how guidance addresses uncertainties, identify research gaps, and promote a more comprehensive understanding of guidance strategies to support effective design for uncertainty in VA. Our survey underscores the effectiveness of guidance in navigating uncertainties with context-aware and multi-scope strategies. We highlight challenging opportunities for further research in this space, especially in the adjacent areas of accessibility and onboarding, and suggest new research areas, such as *narrative* and *persuasion guidance* to support uncertainty awareness in VA.

1. Introduction

Visual analytics (VA) supports users in deriving knowledge and insights in interactive sense-making loops to make more informed decisions [1–3]. However, uncertainties throughout the VA cycle are responsible for knowledge gaps. These gaps impede users' trust in the system, their analysis, and their decision-making [4–6]. Sources of uncertainty can be encountered in all four main components in the VA cycle introduced by Keim et al. [7] as illustrated in Fig. 1: (1) data, (2) visualization, (3) hypothesis/model, and (4) insight. Yet, these sources of uncertainty may be interconnected, accumulating, and propagating through the entire VA cycle [8,9].

Recent research proposes guidance strategies to help users navigate, interpret, and manage interconnected sources of uncertainty [6,10,11]. The Oxford English dictionary defines *guidance* as "advice or information aimed at resolving a problem, difficulty, etc." [12, p. 629]. In VA, Ceneda et al. [13, p. 112] define *system guidance* as "a computer-assisted process that aims to actively resolve a knowledge gap encountered by users during an interactive visual analytics session". In this work, we employ the generic dictionary definition to enable a broader perspective on guidance in VA while considering guidance strategies for visual data analysis as an essential building block of VA [14]. *Our interest is to examine guidance provided at any* ***component*** *of the VA cycle — not exclusively in the "insight" component — and focus on the* ***advice or information*** *the VA system provides*. These strategies can be of different **types**, such as explanations or recommendations, and ultimately help address uncertainties in the VA cycle and their corresponding knowledge gaps.

In our state-of-the-art report (STAR), we focus primarily on system guidance strategies [15] that support users in disentangling, understanding, or acting upon uncertainties. These strategies reflect the growing trend in the literature toward user-centered solutions. Our working definition for *system guidance in VA under uncertainty* is *a system* ***intervention*** *that aims to help or advise the user in resolving a* ***knowledge gap*** *generated by an* ***uncertainty*** *event in the VA cycle*. This

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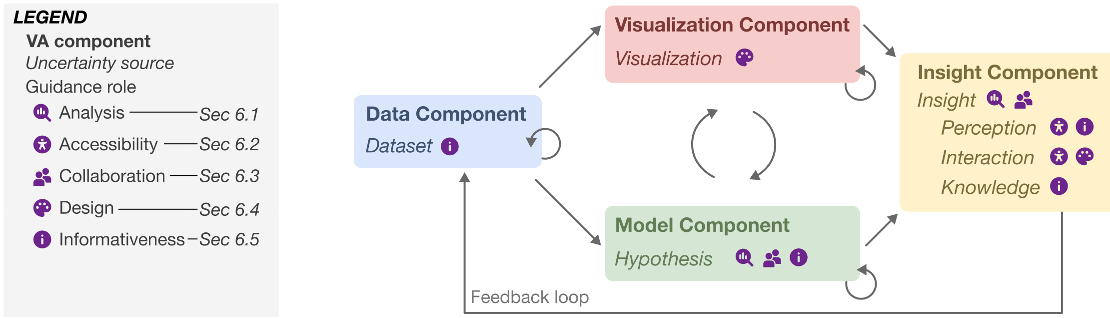

Fig. 1. Depiction of how uncertainties spread within the VA cycle, highlighting the four VA components and their respective uncertainties in different colors [8]: **data**/dataset, **model**/hypothesis, **visualization**/visualization, and **insight**/insight/perception, interaction, and knowledge. Around the VA process, we integrate the five guidance roles proposed in our taxonomy, showing how they contribute to addressing uncertainties. The full list of papers reviewed in this state-of-the-art report — classified by guidance role, guidance scope, and source of uncertainty — can be found in Supplementary Table 1.

definition implies that work qualifying as guidance for uncertainty should incorporate the intervention as *auxiliary* or an *extension* to the system, and *not as an essential* component for the system to function. For example, a vehicle GPS helps the driver navigate the roads. The GPS is an auxiliary element, as the driver can still fully operate the vehicle without it. Thus, the GPS is a guidance tool. On the other hand, the braking system helps the driver stop and control the vehicle's speed. The driver cannot fully operate a vehicle without the braking system. Thus, the braking system is not considered a guidance tool. Without guidance, a user should be able to complete tasks afforded by the system, although possibly with less efficiency, effectiveness, precision, or accuracy [13].

System guidance can be produced, for instance, by an expert system that employs *explicitly-programmed* rules, operations, or *inferences derived* from intelligent strategies such as machine learning [16]. Recommender systems are also well-known examples of guidance that provide personalized suggestions based on the user's past interactions, preferences, and the context of the analysis. For instance, a recommender system can use inference models to suggest possible interactions to the user in the VA system [17].

Research questions and contributions. In this work, we explore how guidance mechanisms have been used in literature to address uncertainty in diverse VA scenarios. We examine how these strategies enhance decision-making processes by providing support to manage and interpret uncertainties effectively despite the additional (and often competing) layer of complex information that uncertainties may introduce into the VA process.

In summary, we respond to three main research questions:

1. *What* ***role*** *can guidance take w.r.t. the* ***VA cycle*** *in the presence of uncertainties?*
2. *To what extent can* ***uncertainties*** *(not) be addressed with the help of different types and combinations of guidance?*
3. *Which scope (strength and subtleness) of* ***guidance*** *appears most valuable in a given context of uncertainty-aware VA?*

To answer these questions, we systematically review the literature and propose a comprehensive taxonomy of guidance strategies that support users in addressing uncertainties introduced throughout the VA cycle in Fig. 1. In our discussion, we present gaps and rich areas of research. In addition, we map suitable guidance strategies to possible uncertainties in the VA cycle. Finally, we suggest future directions for research on guidance strategies to support users in addressing uncertainties in VA. In summary, we contribute to the literature by:

1. *classifying* system guidance strategies based on the guidance role and uncertainty source they address;
2. *proposing* whether and how guidance can address specific sources of uncertainty in VA; and
3. proposing vital research areas *solidifying* guidance strategies in uncertain VA scenarios to support the user.

2. Uncertainty in the VA cycle: Background

Uncertainty refers to the ambiguity, variability, or lack of confidence in data, hypotheses/models, and interpretations generated within the cycle of VA [18,19]. The presence of uncertainty challenges decision-making and interpretation across numerous fields. Among those, medicine and climate science are two prominent examples where uncertainty can significantly affect outcomes. In medical imaging, for instance, uncertainty might arise from inaccurate or noisy data, such as positional deviations in a CT scan due to patient movement [20], impeding diagnosis and treatment. In climate science, approximations in model predictions can hinder accurate forecasting or decision-making [21]. When looking at the general VA cycle (see Fig. 1), uncertainty may originate from various sources [8]. Understanding, categorizing, and addressing these uncertainties is, therefore, critical for improving the robustness and reliability of the generated insights [22,23].

According to Griethe et al. [24], uncertainty can be defined as *error* (outlier or deviation from a true value), *imprecision* (resolution of a value compared to the needed resolution), *subjectivity* (degree of subjective influence in the data), and *non-specificity* (lack of distinction for objects). Conversely, Tannert et al. [25] distinguished between *epistemic* and *aleatoric* uncertainties. The former stems from a lack of knowledge about the data or processes, while the latter relates to inherent variability or randomness [25]. Uncertainty has been extensively studied, leading to diverse categorizations [8,20,25–29]. Potter et al. [21] and Bonneau et al. [26] focused on uncertainty visualization in weather forecasting and simulation scenarios, while Gillmann et al. [20] and Ristovski et al. [29] discuss medical imaging and visualization, respectively. Sacha et al. [19] further emphasized the role of human factors in uncertainty, such as perception and interpretation errors. Specifically, we selected Gillmann et al.'s taxonomy [8] as a starting point for this survey, being one of the few that directly link uncertainties to the VA process. While other taxonomies primarily focus on uncertainty from a philosophical or application-specific perspective, Gillmann et al.'s classification emphasizes how uncertainty *emerges* and *propagates* through the analytical pipeline of VA. The taxonomy divides uncertainty into four components — namely derived from the dataset, hypothesis, visualization, and insights — to facilitate systematic identification and mitigation across the VA cycle. Gillmann et al. refer to the origin of uncertainty in these four component as an *uncertainty event*. These events are dependent on each other as they propagate throughout the VA cycle. In their work, Gillmann et al. use the concept *uncertainty event* to characterize the arise of uncertainties in the VA cycle. In the remainder of this survey, we use consistently the color scheme to indicate, respectively, the aforementioned uncertainty components (see also Figs. 1 and 2).

Dataset Uncertainty Data forms the foundation of any analysis, and uncertainties here can significantly affect subsequent sources. According to the aforementioned definition of uncertainty by Griethe [24] and Tannert et al.' s [25] categorization, examples of uncertainty here include aspects such as missing data points, limitations of the granularity of measurement tools, non-representative or biased sampling methods, and observational variability. Specific uncertainty events include those that primarily correspond to aleatoric uncertainty in Tannert et al.'s work:

- *Data Incompleteness:* Entire records or key attributes are absent from the dataset, causing incomplete evidence for analysis.
- *Measurement Resolution:* Values are captured with limited resolution or instrument precision, limiting reliability.
- *Non-representative Sampling:* The dataset systematically excludes relevant data points, distorting the analysis outcome.
- *Variations in Observations:* Fluctuations in repeated observations that introduce aleatoric uncertainty.

Hypothesis Uncertainty The hypothesis source involves developing models or theories based on the dataset, which implies that, in this source, we encounter epistemic uncertainties. Epistemic uncertainties include model incompleteness, where limited knowledge or computational constraints often result in models that fail to capture complex phenomena. This category also includes modeling approximations or assumptions, as well as uncertainties due to parameterizations [29,30]. Determining the optimal set of parameters and their subsequent fine-tuning is a challenging topic that often introduces variability. Specific uncertainty events in this category include events that map to epistemic uncertainties in Tannert et al.'s categorization:

- *Model Incompleteness:* Simplifications or omitted factors in a model due to computational or theoretical limitations.
- *Parameter Uncertainty:* Unknown or imprecisely estimated model parameters that affect predictive power.
- *Incompleteness of Measurand:* Underlying model structures (e.g., assumptions) that might not fully capture reality.
- *Model Approximation:* Numerical or algorithmic shortcuts made to enable tractability, at the expense of precision.

Visualization Uncertainty Visualization translates data and hypotheses into interpretable visual representations. This translation stage introduces several sources of uncertainty [31,32], which, in our view, largely relate to the threats addressed by Munzner's nested model [33]. While all levels in Munzner's nested model can contribute to uncertainty, we mainly focus on the data/abstraction (i.e., poor mappings between data and tasks) and visual encoding levels (i.e., ineffective representations). Although algorithm levels and the domain situation may also introduce uncertainties, they deal with the efficiency of an algorithm and understanding the target users' problem context, goals, and tasks, respectively. Thus, they could be considered less central to the interpretability of a visual representation in this context. Specific uncertainty events include events that primarily affect how users interpret the visualization, regardless of the underlying data quality. Examples thereof include, but are not limited to [34]:

- *Mapping Uncertainty:* Ambiguities or inaccuracies in how data attributes are mapped to visual elements (e.g., axes, color scales), which can lead to misinterpretation.
- *Integration Uncertainty:* Errors or approximations that arise when combining multiple data sources or types into a single visualization, potentially introducing inconsistencies.
- *Interpolation Uncertainty:* Inaccuracies introduced when estimating unknown data values between known points, often necessary in continuous visual representations like surfaces or curves.

Component	Event
Dataset	• Incompleteness of data • Finite instrument resolution • Non-representative sampling • Variations in observations
Hypothesis	• Incompleteness of model • Parameter uncertainty • Incompleteness of measurand • Approximation of model
Visualization	• Mapping uncertainty • Integration uncertainty • Interpolation uncertainty • Shading model
Insight	
Perception	• Perceptual uncertainty • Memory uncertainty
Interaction	• Usage uncertainty • Thinking uncertainty
Knowledge	• Decision-making bias • Incomplete knowledge • Ignorance

Fig. 2. Taxonomy of uncertainty events for each of the four VA sources, adapted from Gillmann et al. [8].

- *Shading Model Uncertainty:* Variability or inaccuracies in the rendering process (e.g., lighting, shading) that can distort depth perception or visual salience, particularly in 3D visualizations.

Insight Uncertainty The insight generation source involves user interpretation of data, hypotheses, and visualizations (see Fig. 1). Here, uncertainties arise from human factors, such as perception issues, interaction variability, or gaps due to a lack of domain knowledge [19]. One further aspect to consider through the VA cycle is that uncertainties at different sources are not isolated—they interconnect and propagate [34]. For instance, incomplete data can lead to flawed models, producing misleading visualizations and erroneous insights. Specific uncertainty events in this category highlight the role of human interpretation in generating potentially flawed conclusions [34]:

- *Perceptual Limitations:* Difficulty in accurately perceiving or recalling visual encodings, especially in complex charts.
- *Interaction Limitations:* Differences in how individual users manipulate or explore the interface may lead to divergent insights.
- *Knowledge Gaps:* Users lack the domain expertise or knowledge to draw correct conclusions from the presented data.

3. Scope, positioning, and methodology

We present a survey of guidance strategies by identifying the uncertainty they address, see Fig. 2. We also describe the potential scopes of each guidance role, described in Section 4, and its typical features. In this section, we clarify our scope and outline our methodology, see Fig. 4. We also present the inclusion and exclusion criteria that define our literature corpus, also outlined in Fig. 3.

3.1. Relevance of our work

Guidance objective. The topic of guidance, i.e., providing system support to users for various tasks, is not new and has gained importance over the years. Silver [35,36] studied the importance of incorporating *decisional guidance* into information systems. Several papers recently proposed design frameworks for adequate guidance during an analytical session [37–41]. Pérez-Messina et al.'s [42] typology proposes

Papers included

- Guidance throughout VA cycle
- Guidance to support analysis
- User maintains agency in decision-making
- Guidance as a mixed-initiative system
- Maps with our working definition of guidance
- Does not contradict Oxford dictionary's definition of guidance [Haw91]

Papers excluded

- Non-visualized AI
- Only user-initiative described
- User guiding system
- Entire visualization as guidance
- Automated approaches
- Not auxiliary intervention
- Contradicts Ceneda et al.'s [CGMMSST17] definition of guidance

Fig. 3. Outline of the inclusion and exclusion criteria for our survey.

a helpful task-driven classification of guidance strategies during the VA session. Also, Lee et al.'s [43] recommendation taxonomy offers helpful strategies to design guidance. Moreover, a few recent papers reviewed guidance strategies during an interactive VA session. Ceneda et al. [44] presented a comprehensive survey of guidance strategies in VA, showing how they can be used to support a variety of analytical tasks. Another objective of the survey by Ceneda et al. [44] is to improve the efficacy of human–computer collaboration. Conversely, the objective-oriented review of Collins et al. [45] outlines the user's input into the guidance and the knowledge output of the employed guidance strategy. Similarly, Yanez et al.'s [41] taxonomy also emphasizes the importance of adapting guidance to users' contexts and needs, by surveying interventions as co-adaptive models in the VA cycle. Finally, in their review of 13 knowledge-assisted visual analytics (KAVA) systems, Böck et al. [46] investigate how explicit knowledge can be used to guide user analysis in industrial manufacturing. They position KAVA as the root of guidance. In contrast to previous surveys, ***our work aims to explicitly demonstrate how system guidance can play a critical role in explicitly resolving or mitigating uncertainties throughout the analytical process***. By focusing on the intersection of uncertainty and guidance, we uncover how existing system guidance solutions address uncertainties and the corresponding knowledge gaps, as well as where they fall short. This perspective enables us to highlight key challenges, emerging research opportunities, and design considerations for developing more adaptive, context-aware, and uncertainty-resilient guidance mechanisms in VA.

Guidance strategies. Domova and Vortsou [47] review automation techniques to guide the VA process. Additionally, Enge et al. [48] only partially address guidance in VA when reviewing STAR work on integrating sonification and visualization strategies, where the audio channel serves as a guiding tool to VA. Similar to these works, our survey also considers all modes of audiovisual guidance equally as long as the sound takes a supporting role in handling uncertainties in the VA cycle, i.e., the guidance is provided through sound. In other words, we exclude work that presents the audio channel as an essential analytical tool, not an auxiliary guiding tool. Although our work builds upon all these previous surveys, ***we intend to expand the categorization of guidance based on the role it takes to aid the user in resolving uncertainties, specifically***. This aspect represents the first dimension of our taxonomy. Perpendicular to this dimension, we further classify uncertainties addressed by guidance strategies throughout the VA cycle components: dataset, hypothesis, visualization, and insights.

Considering guidance in a broader sense, our work also intersects with three surveys [49–51] that address guidance in an earlier component of the VA cycle: the *visualization* design. Zhu et al. [49] survey semi-automatic and automatic strategies that recommend data-driven and knowledge-based visualizations to the user. Soni et al.'s [50] survey addresses a similar topic focusing on multi-view dashboards. Lock et al.'s [51] survey is narrowed to urban dashboards. While we consider guided visualization design strategies, we review them from a new perspective. First, we only consider strategies that *recommend* visualizations for the user of a VA system, excluding automatic strategies that do not allow the user to make the final decision on the design. Second, we describe each guidance role's potential scope and features as outlined in Section 4.

In summary, guidance and uncertainty in VA is a fast-developing research area. Thus, a comprehensive survey and a broader guidance classification are needed to integrate guidance tools into the VA cycle effectively. We expand and shape the knowledge of guidance roles based on our analysis of the recent literature on guidance. We propose the guidance roles and define them with examples. Analyzing the literature, we demonstrate how each role in the literature addresses uncertainties in the VA process. Demonstrating how guidance addresses the various uncertainties in the VA cycle can expand the breadth of uncertainty visualization methods and address some challenges in the domain, such as the complexity of the accumulated uncertainties. To allow the practical application of the roles, we define *three guidance scopes* and *six guidance features*, which we analyze for each guidance role to demonstrate how the guidance can address the uncertainties.

3.2. Search strategy and filtering

We followed a multi-stage process to select and filter the literature corpus, as outlined in Fig. 4. We reviewed the literature of the leading conferences and journal databases, such as IEEE Xplore, Wiley, and Eurographics Digital Library, through TU Bibliothek CatalogPlus (). We collected work published since the publication date of the last guidance survey in 2019 [44], i.e., our literature corpus includes work published from January 2019 through December 2025. However, as mentioned, in contrast to the existing surveys, we expanded our scope to include a broader definition of guidance to address different types of uncertainties. We queried keyword combinations from two sets. The first set (Set 1) includes *visual data analysis* and *visual analytic** to ensure we narrow down results to the field of interest. We searched for the exact keyword from Set 1 in *any field*. In combination, we queried a keyword from Set 2 in *publications' titles*. Set 2 includes roots of words and synonyms connected to *guidance*: predict*, anticipat*, forecast*, expla*n*, aware*, mediat*, communicat*, guid*, recommend*, suggest*, prescrib*, interven*, sense*, support*, boost*, facilit*, feedback, validat*, verif*, accesib*, disab*, *blind*, *impair*, sonif*, group decision, collabor*, participat*, decision support, *aid, steer*, assist*, direct*, spatial decision, and automat*. To compile the keywords of Set 2, we brainstormed terms that can describe guiding in VA and its context based on our knowledge of the domain. We also extracted terms from key literature on guidance as described in Fig. 5.

The initial query yielded 3500 papers. After filtering the duplicates, we screened 3351 titles to eliminate irrelevant work during the search, yielding 778 unique publications. Then, one of the authors reviewed the abstracts and introductions for eligibility. We identified 92 relevant papers, after which the same author snowballed more recent papers from the citations of selected relevant papers, yielding a total of 171 papers. Then, a second author independently reviewed the abstracts and introductions of the papers based on the exclusion and inclusion criteria described in Section 3.3, also outlined in Fig. 3, and classified the papers based on the taxonomy of guidance roles described in Section 4. This process yielded 152 relevant papers.

3.3. Survey scope

Inclusion. The inclusion criteria are outlined in the left column of Fig. 3. Our survey reviews guidance strategies that *support the user* throughout the *VA cycle*. The implication is that the guidance tool should play a *supporting role* to a self-standing VA system, and the

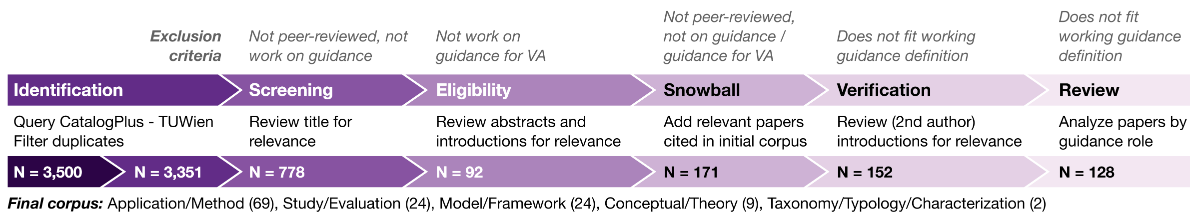

Fig. 4. Methodology flowchart: The literature search and filtering process of this survey, as conducted in seven stages (including filtering of duplicates during the initial identification stage).

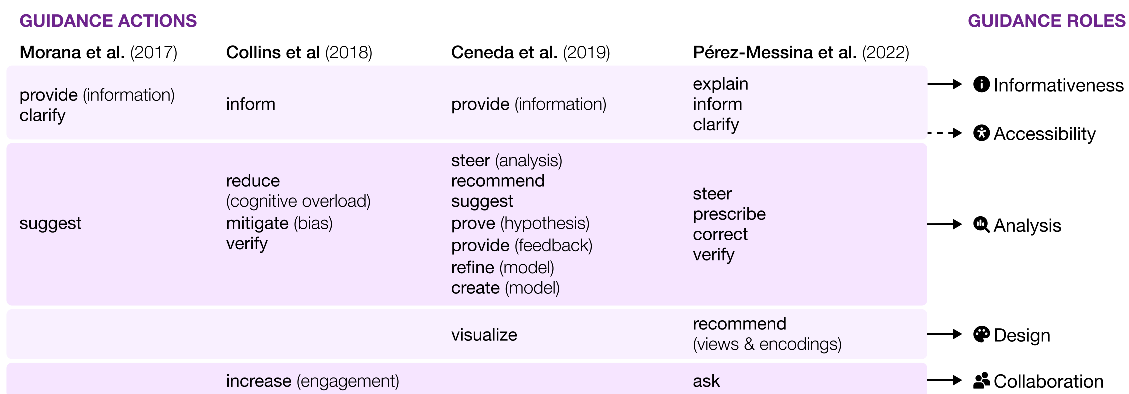

Fig. 5. We deduce guidance roles from actions that describe guidance function in key literature [42,44,45,52]. *Accessibility guidance* is a role that can be indirectly inferred, hence the dashed arrow to *Accessibility*.

user maintains the agency when making decisions. Guidance is a mixed-initiative system where a system supports the user and the user guides the system, e.g., with appropriate feedback [13]. However, in this paper, we focus only on the guidance provided by the system to the user (and not vice versa), i.e., system-initiative guidance [15]. The reviewed papers describe guidance *provided by the machine* to the human as an *auxiliary* to a VA system. The system can *guide the user at any component of the VA cycle*. Thus, our survey also includes guidance strategies for supporting the design of visualization.

Exclusion. The realm of guidance expands with the introduction of intelligent agents [53], i.e., AI strategies can be used to generate the guidance necessary for the user. However, this expansion also overlaps with AI strategies that automate domain decisions, which would not typically be considered guidance in VA [13]. Almost one-third of the excluded papers encompass work where intelligent agents (IAs) are proposed to address knowledge gaps in VA with *automated* solutions. These strategies preclude humans from the process, even if they incorporate visual aspects. We also excluded papers describing works that propose visualization and VA to guide decision-making and intelligent models that are typically *not visualized*. We also excluded strategies where *only user-initiative guidance* is described. When reviewing mixed-initiative systems [54], we include the paper in our classification but focus on the system guidance aspect of the work as reflected in our working definition stated in Section 1. More than half of the excluded papers focus on *users guiding* intelligent agents through VA and visualization tools. These papers also included developing VA and visualization to guide decision-making in various domains, such as tools to explain intelligent agents to humans.

Finally, based on the criteria stipulated in this section, the authors conducted an additional check of the exclusion criteria during the analysis stage, yielding the exclusion of an additional 24 papers from the analysis, for a final sum of 128 reviewed papers. **Three** papers were excluded because they did not address guidance. **Seven** papers use visualization to guide analysts in analyzing big data to address usage and thinking uncertainties. Since their methods use visualization to guide data analysis, not visual data analysis, the papers are excluded based on the first exclusion criterion. We also excluded **two** collaboration papers where all system features are integral to the proposed system. Moreover, based on the third criterion, we excluded **five** papers that *do not present a guidance strategy auxiliary* to a visualization or VA system. Finally, based on the fourth criterion, we excluded **seven** papers that propose either a *fully-automated* intervention or *strategies to offload user tasks* instead of guiding the user in the task. These strategies can take agency from the user in the analytical process.

3.4. Analysis methodology

To construct the taxonomy, we follow a hybrid deductive–inductive approach. In the two-stage process, the first author reviewed the literature on guidance (i.e., its conceptualization, typologies, and surveys [42,44,45,52]) to systematically extract meaningful categories from the literature, as seen in Fig. 5. We then pivoted inductively by deriving possible guidance roles that we map to uncertainty components in the VA cycle.

To resolve disagreements in constructing the categories and coding the literature, we followed a systematic qualitative process to ensure the conceptual credibility of the design-space analysis. The categories and definitions were discussed and refined as we coded the literature corpus. Thus, we allowed the taxonomy to shape organically by the literature corpus. In the coding stage described in Section 3.2, we started with a dyadic negotiation between the two coders. Then, we transferred remaining disagreement to the bigger group for a consensus resolution and tie-breaking by senior co-authors. During the process, we assume that disagreement is due to conceptual rigor. Thus, we refine our conceptual boundaries in a formative process of taxonomy design space revision. Finally, in the analysis stage, authors conduct a final layer of strict negative case filtering protocol. The results of this protocol is described in Section 3.3.

We review the 128 surveyed papers in three main sections. Through the lens of our proposed taxonomy, Section 5 discusses the papers (35) that conceptualize guidance and propose frameworks to design it. In Section 6, we start by discussing the uncertainties addressed by application and method papers (69). We primarily base our analysis on the uncertainty components and events in Gillmann et al.'s [8] uncertainty taxonomy, as shown in Fig. 2. We explicitly characterize the uncertainty present in these papers and map their source(s) to guidance role(s). Where uncertainty events fulfills no or multiple descriptions in Gillmann et al.'s taxonomy, we decided the best fit among the authors. We highlight potential gaps in the uncertainty taxonomy in Section 8.4. Then, we discuss the potential scopes afforded by each guidance role and how the different scopes have been utilized to address uncertainties and describe the features in the reviewed guidance techniques. Finally, in relation to our proposed roles, Section 7 discusses papers (24) that presents guidance evaluation methods and studies.

4. Multidimensional taxonomy

In the following, we present our taxonomy of guidance strategies, seen in Fig. 6, focusing primarily on their **roles** in resolving or mitigating **uncertainty events**. We map each guidance role to the uncertainty component(s) it addresses, as seen in Fig. 1. Throughout the text, we highlight specific words based on the color map in Fig. 1. We also discuss two additional aspects of guidance, which we describe later in this section: its scope and multiple guidance features.

Guidance roles. A role emphasizes the overall *motivation* of a tool, as opposed to the goal [44], which describes the measurable targets of a tool. Each guidance tool may fulfill multiple roles depending on the context of the application to help and advise a human on performing a task. In our taxonomy, we see the **guidance role** as the pattern of behavior expected to achieve a goal. The patterns of behavior of each role manifests in each role's scopes, as discussed below and described in Fig. 7. Meanwhile, the goal a guidance tool aims to achieve manifests in the addressed uncertainty, and the features of guidance that allows the fulfillment of the role. Thus, although *analysis guidance* can be seen as a higher level role that parents other roles, it can be distinguished through the pattern of behavior (*scopes*), uncertainty addressed, and guidance *features*. We identified five guidance roles:

Analysis: This role supports users during sense-making or decision-making when a need arises. This role refers to the original characterization of guidance in VA [13]. *Analysis guidance* strategies can address uncertainties in **insight**, such as recommender tools [55] or sensory guidance [56]. It can also provide validation on exploratory decisions addressing uncertainties in **hypothesis**, such as feedback [57].

Accessibility: This role guides users with disabilities in using a visualization/VA efficiently and effectively. This role is present in contexts where the system remains usable by all users but not equally efficient or effective. Typically, these strategies address uncertainties in **(insight-)perception** or **(insight-)interaction**, such as using sonification strategies [58].

Collaboration: This role augments knowledge from multiple users to support the analysis. The uncertainty addressed by this type of guidance is correlated to **hypothesis** or **insight** generation, such as using provenance to bridge the gap between experts and novices [59].

Design: This role supports users on the most effective visual design given the data. The uncertainties addressed by these strategies are in the **visualization** or **(insight-)interaction** components of the VA cycle, such as recommending a visualization [60].

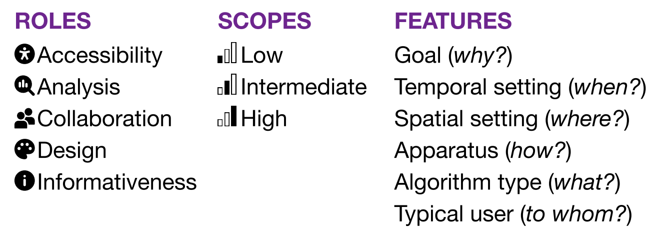

Fig. 6. Proposed taxonomy diagram for uncertainty-aware guidance. We classify five roles, three scopes, and six features.

Informativeness: This role aligns knowledge between users and the system by providing additional information. These guidance strategies address uncertainties in the **data(set)**, **hypothesis**, **(insight-)perception**, or **(insight-)knowledge** components, such as explanations [61].

Guidance scopes. The scopes describe the guidance's strength and subtleness in fulfilling its role. Our understanding of scope is primarily inspired by the concept of guidance degrees [13], which describe the extent to which guidance supports analysis (i.e. when it takes an *analytical role*). However, we extend and abstract this concept to apply it across the additional roles we include in this survey. Additionally, we incorporate elements of Morana et al.'s *content type* [52], influencing how guidance is conveyed to the user. Thus, we describe three guidance scopes, highlighting how different guidance scopes are presented in the various guidance roles.

The scope can be **low**, **intermediate**, and **high**. A *low scope* refers to a weaker and more subtle guidance that does not provide direct or explicit actions to move forward. This scope is a less involved strategy that improves the users' orientation and empowers them to find more appropriate actions for efficient and effective analysis. An *intermediate scope* is expected to be the basis of the guidance and the most common scope. It refers to guidance explicitly presenting multiple options or evaluating multiple assumptions to guide the user. The guidance is more substantial (stronger) and direct (less subtle). Finally, a *high scope* refers to guidance that provides actionable step-by-step advice. It is more assertive and direct than the intermediate scope as it offers precise steps for only one, not multiple, path options, and it builds the recommendation on one assumption or hypothesis. It reflects more system certainty in the best analytical path. Having described the abstract concept of scopes, we now describe how the three scopes are instantiated for each guidance role.

Analysis: With a *low scope*, *analysis guidance* facilitates the analytical process indirectly with hints to improve the user's orientation, for example, assessing images in an image selection task [62]. In an *intermediate scope*, the system provides multiple suggestions to support the analysis, for example, highlighting multiple areas of interest in the visualization [62]. Notice that the guidance becomes more explicit when suggesting options. However, with a *high scope*, proposing a specific step-by-step analytical path is more assertive [63]. The guidance is more involved, but the agency remains with the user to accept the suggestion.

Accessibility: In the *accessibility* role, a *low-scope* guidance improves the user's mental map to make a task easier without getting directly involved, for example, mapping encodings to natural sounds [58]. An *intermediate-scope* guidance includes strategies that assist users with disabilities during the VA process by presenting multiple inferences, such as ranked chart insights [64]. With a *high scope*, *accessibility guidance* presents

GUIDANCE SCOPES	Low	Intermediate	High
Accessibility	Enhance mental map	Direct with multiple inferences	Assertive with one inferred summary
Analysis	Subtle without options	Direct with multiple options	Assertive with one step-by-step advice
Collaboration	Subtle reference	Direct with multiple options for augmenting knowledge	Assertive with one option for augmenting knowledge
Design	Add without altering design	Alter visual encodings	Suggest an entire design
Informativeness	Subtle without new information	Explicit explanation of new information	Assert explication implication

Fig. 7. The criteria that distinguish each scope level, i.e., low, intermediate, and high, for each of the five guidance roles.

a higher form of involvement. The system integrates the guidance into the analysis process to direct the user into one precise analytical step. For instance, presenting an inferred summary of a chart that could be useful to complete a task (notice the increasing level of assertiveness of the guidance) [65].

Collaboration: With a *low scope*, the *collaboration* guidance coordinates the analysis between multiple users with an indirect augmentation of knowledge. The user is better informed by knowledge extracted from other users, but is not offered explicit recommendations on moving forward. Other users' knowledge remains a reference to the user without recommending specific analytical paths or altering the underlying hypothesis. For example, when the system allows the user to explore dashboard states from different stages of multiple user analytical provenance [66]. With an *intermediate scope*, the guidance allows users to cooperate by suggesting multiple options to augment the knowledge and improve the analysis and underlying hypothesis. For instance, the guidance can present multiple analysis options based on multiple user provenance [67]. Here, the guidance is more explicit by offering options. Conversely, *collaboration guidance* presents *high-scope* guidance when consolidating knowledge from multiple users into one entity. For example, the system can propose precise analytical steps based on analytical provenance from multiple users [68]. This strategy is more assertive.

Design: This guidance can enhance the design at a *low scope* by proposing additions to the current visualization or VA system without altering existing encoding or views [69]. This scope is subtle as it only enhances the existing design. With *intermediate-scope* guidance, the system recommends modifying existing encoding and views or replacing some of the views [70]. Notice here that the guidance is more involved in replacing components than adding to them. Conversely, a *design guidance* can recommend a complete visualization design with a *high-scope* guidance [70]. This more assertive and involved strategy proposes a design that impacts all future analytical steps for the user.

Informativeness: In a *low-scope* context, the *informativeness* guidance clarifies presented information without adding new information to the user, for example, clarifying underlying parameters [71]. This strategy is subtle as it does not provide new information to direct the user's actions. Informativeness can be more assertive and explicit by offering an *intermediate-scope* guidance that explains the model or visual system components with more specific new information, for example, unlocking the black box of the model [71]. In a *high-scope* context, informativeness becomes more assertive by presenting an explication, explaining the importance of something and its implication on the analytical process [72]. This strategy directs the user's analytical thinking in a specific direction as it connects the explanation to future implications, for example, explicating the impact of a specific analytical path [73].

Guidance features. The roles and scopes described above illustrate the different ways in which guidance can manifest in VA. However, regardless of the specific role or the scope of involvement, each form of guidance can be further characterized by common underlying features. Inspired by past surveys [44,47,48], we adopt six features that consistently apply *across all roles and scopes.* These features, derived from prior characterizations [42,44,45,52,74], enable designers and researchers to systematically identify the nature of the guidance being provided, compare strategies, and position their work in the literature. We describe them as follows:

- **Goal (Why?)**: is the measurable target for providing guidance, such as boosting confidence or improving decision-making efficiency. It refers to the goal of providing guidance, not the goal of the analysis. This can relate to the target and intention [52], goal [45], objective [44], intent [42], and purpose [74].
- **Temporal setting (When?)**: is the instance at which the guidance is provided. The guidance can be continuously presented, or it can be displayed on-demand or on-gap identified. This can relate to the invocation and timing [52], analysis phase [42,45], and the needed moment [74].
- **Spatial setting (Where?)**: is the position where guidance appears in relation to the visualization, such as the margins or as a pop-up. This can relate to the location [74].
- **Apparatus (How?)**: is the tool and form used to construct the guidance, such as verbal or audio. This can relate to the format and directivity [52], modalities [45,74], and interaction methods [42].
- **Algorithm type (What?)**: is the computer-based process and rules used to construct, such as AI-based or explicitly programmed algorithms. We also outline the input and the output of the method. This can relate to the mode [52], computing steps [45], guidance inference [44], and input and output [42].
- **Typical user (To whom?)**: is the characteristic of humans to whom the guidance is intended, concerning their knowledge, such as users with domain or visualization knowledge gaps. This can relate to the audience [52] and target user [74].

5. Theorizing guidance

This section connects conceptualizations of guidance in the nine theory-related surveyed papers to our guidance role taxonomy and uncertainty components. The mapping grounds abstract models in a common vocabulary, letting us compare otherwise heterogeneous proposals. It also reveals coverage and gaps in the design space, as presented across 26 model and framework-related papers. Section 5.1

summarizes the main conceptual lines that support effective guidance in VA. Section 5.2 shows how these models can be used to address uncertainties in practice. In this section, we do not present a new conceptualization for guidance. However, we collate the definitions and conceptualizations in relation to the taxonomy introduced in Section 4. Section 5.2 is thematically-structured to describe the anatomy of the design models.

5.1. Guidance conceptualization and theory

Across the literature, we identify one dominant role that aligns with our taxonomy: *analysis* [75]. The *analysis* guidance provides insights that directly address the user uncertainties, driving the VA knowledge generation process, aligning with the main goal of VA [75]. Sometimes the guidance is seen as an arrangement where humans and guidance are both agents interacting within a VA environment. This proposes a useful conceptualization where uncertainty is linked to the user's behavior [76]. In contrast to these conceptualizations of guidance, which Miller [77] frames as recommendation-driven, some guidance is conceptualized as a different decision-support paradigm, where the uncertainty is mitigated by a system *evaluation* of the user's analytical path. In the following, we summarize our findings for the five guidance roles.

Analysis. Guidance in its *analysis* role is conceptualized as a derivation of knowledge-assisted visualization [75], where explicit knowledge is externalized by users and used to power the guidance process. Without the externalization of user knowledge, successive data transformations can only lead to lower information richness than the original dataset. This means that guidance, in its analytical role, needs user input and domain knowledge to provide something "more" than what could be achieved without it. In our conceptualization of guidance, this means that *insight* uncertainties can be overcome only by introducing information not present in the dataset (which are, from the system side, an external uncertainty). Otherwise, a problem could be automated, and there would be no need for a VA solution. Silva et al. [56] discuss foundations for eye tracking support in VA systems. They identify themes for integrating this technology for guidance as "modeling higher level intents" and "adaptive support", suggesting that *analysis* guidance can also address *hypothesis* uncertainties.

Ottley [76] conceptualizes guidance using Monadjemi et al.'s agent-based framework [78]. There, users and guidance are considered free-acting agents interacting within a visualization environment. The affordances of this environment are key to predicting user behavior and providing adequate analysis guidance. The uncertainties addressed in this strategy are mostly *interaction* and *knowledge* uncertainties. However, the source of prediction in this paradigm remains at the low scope of guidance (experience-driven).

Miller [77] offers a different perspective on guidance. The author contrasts recommendation-driven to what he proposes as hypothesis-driven decision support, the former being system-initiative guidance while the latter is system-reactive, addressing uncertainty by proposing an evaluation of user hypotheses and decisions. Hypothesis-driven support acts as a second opinion that supports iterative refinement of solutions proposed by the user. This inversion of the initiative — the guidance only providing feedback to user decisions — is conceived as a way to reduce the uncertainty in user-driven choices, particularly in *knowledge* uncertainty events such as *decision-making bias* and *incompleteness of knowledge*. In this paradigm, low to medium scope guidance is discussed, but the high scope is discouraged as this would fall back into classic explainable AI, from which it departs.

Accessibility. Two articles from ACM *Interactions* stress the need for accessible visualization [79,80]. Haptic technologies and sonification [48] can augment visual analysis tasks with guidance beyond the visual spectrum, not only for the visually or cognitively impaired. Elmqvist [79] proposes that the use of sound should go beyond screen-reading (text-to-speech) and involve other sonification strategies to enhance disabled users' experiences. They highlight the need for solutions that do not require acquiring expensive special equipment. Marriott et al. [80] argue that blind users need ways to reason spatially about data, a type of communication not afforded by text or audio presentation. Elmqvist also proposes that addressing disabilities should go beyond blindness. An example of this has been developed by While et al. [81], named *GerontoVis*. This system recognizes older adults as an important group in need of guidance for impairments for which haptic technologies and sonification are not deemed suitable. Guidance here is aimed particularly at balancing visualization literacy. In our understanding, these works suggest translating data to media other than visual to address *perception* and *interaction* uncertainties.

Collaboration. Concepts of guidance for collaboration have mostly focused on user-to-user, low scope guidance. In this direction, Bovo et al. [82] have proposed a cone of vision as a model that can effectively cue in collaborative settings to direct users' attention. This model addresses an important and evident uncertainty in VA—namely, *where should I look at?* (*knowledge* uncertainty). This deictic function is key to bridging knowledge gaps between experts and novices (knowledge transfer) [82]. Kraus et al. [83] make a similar point for immersive analytics in remote collaboration scenarios, where participants share a common virtual background; thus, the guidance addresses several uncertainty events in the *insight* component.

Design and Informativeness. We report no recent literature that tackles uncertainties regarding *design* and *informativeness* guidance at the conceptual level.

In conclusion, recent literature conceptualizes guidance predominantly in its roles of *analysis*, which mostly address *knowledge* and *hypothesis* uncertainties. *Analysis* guidance conceptualizes the whole range of guidance scopes (as orienting, directing, and prescribing guidance). There is, however, a potential for guidance in its *accessibility* role for addressing *perception* and *interaction* uncertainties. *Collaboration*, *Design* and *informativeness* roles, as well as *data* uncertainties, have not been explored in these works.

5.2. Characterizing and designing guidance

Analysis guidance design models and frameworks are well-studied [44]. Its theoretical foundations can also be used as generalizable design models for all other guidance roles. On the other hand, *informativeness guidance* is a trending topic in AI, i.e., AI explainability [84], but not within the context of VA. Interestingly, *design guidance* models and frameworks have also been a trending area of investigation recently [85–88]. This section discusses how the proposed models and frameworks address uncertainty in VA and the proposed design components.

Designing for uncertainty. Ottley et al. [89] emphasize integrating a mixed-initiative strategy to designing effective guidance. Their proposed framework focuses on designing a mechanism to infer the user intent, enabling the design of an effective mixed-initiative strategy. They propose modeling user behavior observations with a hidden Markov model. The generalizability of the method is its main challenge, especially in different analysis patterns. However, if accurate, inferences from users' behavior can optimize when to address *visualization* uncertainties in VA. It can also optimize how to address these uncertainties with guidance for different user backgrounds. Ha et al. [90] compare Ottley et al.'s [89] model to seven other modeling techniques. Their study reveals issues in the reproducibility of models. It also highlights the challenge of generalizing models to different patterns of analysis. Ha et al. [90] find that accounting for bias is crucial to effectively implementing user intent prediction models.

Our survey yielded one framework that addresses uncertainties connected to collaborative analysis [91]. However, Alsaiari et al. [91] focus on the physical aspect of collaborative analysis. They propose a framework to optimize cross-device VA. The *accessibility guidance* framework also addresses physical aspects of the uncertainty. These uncertainties are related to *perception* uncertainty, i.e., *perceptual* uncertainty events, with frameworks to design accessibility guidance for users with various disabilities. However, the literature focuses on visual impairment disability [92–94]. Unlike simple screen-readers or methods integral to the VA system, they orient the user and guide their analysis by providing contextual and insightful information.

On the other hand, South and Borkin [95] propose a design framework that addresses *interaction* uncertainties, i.e., *thinking* and *usage* uncertainties events, in photosensitive users. They propose a method to mitigate risks for photosensitive users during navigation, filtering, and selection. Conversely, research on guidance design models for users with intellectual and developmental disabilities (IDD) is scarce [96,97].

Design guidance models and framework addresses uncertainties in visualization. They mainly focus on uncertainties in visual *mapping* [86,88]. These models are also calibrated to address user-related uncertainties, such as *incomplete knowledge*. For example, Wang et al. [88] propose to direct the design of visualization to assist the user who lacks expertise in the design of visualization and to save them time. Their framework proposes using a chart knowledge-based library to address *mapping* uncertainties. This strategy can optimize recommendations for different data. However, it is only effective for statistical charts.

On the other hand, Qian et al. [87] focus on user-context. They propose to eliminate data dependency in the recommendations. Their framework proposes designing user-specific guidance by observing implicit and explicit user feedback while addressing *visualization* uncertainties.

Analysis guidance frameworks address uncertainties in the VA cycle's user *interaction*, *knowledge*, and *perception* components. They propose general steps and guidelines and discuss design decisions and risks. The uncertainties are addressed by analyzing the analysis goals and knowledge gaps [98]. However, the generality of the frameworks can also present new uncertainties to the design space. Gómez et al. [99] propose a more specific strategy to address clinical application uncertainties. Their framework specifically targets domain experts to tackle uncertainties in the user *insight* component. Specifically, the framework addresses the uncertainties in *thinking* and *interacting* with complex data. On the other hand, Lohfink et al. [100] address *knowledge* uncertainties by framing their work as a *knowledge-assisted system*.

The literature presents different focal points. We reviewed agent-based [78], task-driven [39], and co-adaptive [101] frameworks. A co-adaptive [101] design framework emphasizes a user-specific uncertainty analysis. Its success is dependent on accurate models to externalize uncertainties in real time. Additionally, Monadjemi et al.'s [78] agent-based strategy considers the system's behavior as an agent in a mixed-initiative process. This strategy boosts the design space; thus, it adds a new layer of complexity to design decisions.

Conversely, Pérez-Messina et al. [39] propose a methodology for *analysis guidance* design that generalizes uncertainty through abstract tasks. Thus, uncertainty is framed as a pre-diagnosed problem. The result, which encompasses all scopes of guidance, follows from a structured analysis of uncertainty associated with each user search task.

The anatomy of design models. Design guidance frameworks present partial components to address specific problems, such as mechanisms to observe feedback for a user-specific recommendation [87] or a pipeline to design data-agnostic visualization recommendations [88]. Additionally, Ahmad et al.'s [85] pipeline focuses on boosting the performance and cost-efficiency of visualization recommenders. Conversely, Lei et al. [86] propose *GeoLinter* as a framework that guides the user in addressing errors in mapping choropleth maps. Although they focus on one visualization type, Lei et al. [86] present a practical and complete design guidance framework. Their framework builds on three guideline components to classify recommendations, cartographic symbology, and map projects, thus addressing *visualization* uncertainties, i.e., *mapping* uncertainty events.

The limitations in addressing different chart types are also present in frameworks to design *accessibility guidance*. Components to provide an overview or detail on request are an integral part of a VA system for visually impaired users delivered with screen-readers or touch-based assistance. However, the guidance aspect of the system is achieved with the context and insight-awareness elements. This strategy can be leveraged to address *interaction* or *perception* uncertainties. A context-awareness component in the accessibility frameworks is a common aspect that orients visually-impaired users during the analysis [92,94]. However, for practicality, these frameworks must present more details on designing strategies to detect and convey context during VA. Context detection can be supported with element detection models [93]. This detection model can also be a helpful addition to the accessibility design framework that supports users with photosensitivities [95].

On the other hand, although they do not propose a framework, Lundgard et al. [102] discuss helpful sociotechnical design guidelines that can be incorporated into accessibility guidance frameworks. Unlike frameworks for the visually impaired, guidelines to design IDD *accessibility guidance* emphasize values and characteristics of the design, mainly empathy [97]. Wu [96] does not present a model to design *accessibility guidance*. However, she proposes visualization guidelines that help integrate them into frameworks to design IDD *accessibility guidance*. Besides *perception* and *interaction* uncertainties, Wu [96]'s proposed guidelines can support designers in addressing *visualization* uncertainty for an inclusive guidance design that considers the needs of visually impaired users.

Pérez-Messina et al. [42] propose a helpful typology that can support thinking about a guidance design framework. The four high-level questions, why, how, what, and when, offer a blueprint for decision trees that can develop guidelines for design frameworks. It can also offer a basis for analyzing design requirements and defining the design space. By identifying the flow of uncertainty to the user, the framework allows the designer to address *interaction* uncertainties by offering guidance at the optimal time—when needed and helpful only.

Analysis guidance offers an opportunity to adapt to different guidance categories. Ceneda et al.'s [37] framework is a stepping stone for much work on *analysis guidance* in VA. It presents a comprehensive design framework. The framework maintains the broadness of the steps to allow for the model's generalizability. However, the *general steps* presented support guidance designers in the process in a practical way. It also discusses *possible risks* to consider. Ceneda et al.'s [37] framework, seen in Fig. 8, proposes four iterative steps supported by 12 questions and five requirements. Thus, the designer's reasoning impacts the framework's applicability. However, more concrete evaluation methods are needed to assess the guidance design and design frameworks.

Moreover, externalizing analytical uncertainties and properties of users' attitudes, such as confidence and trust [103], is a prerequisite for the practical application of the design framework. This prerequisite is also highlighted in the work of Sperrle et al. [40]. Their proposed framework introduces four linear elements with a partial iterative loop. The first two elements, guidance design space and specifications, inform the guidance engine's iterative design and adaptation to the VA workspace. They emphasize a context-aware and strategy-centered strategy supported by a guidance library to implement the strategies. Complementarily, Wang et al. [17] propose a workflow to externalize user intent. Their strategy could improve the guidance design frameworks, especially user-centered design models. Jianu et al. [104] propose detecting thinking and perceptual uncertainties with the eye-tracking technology to provide timely guidance. Their

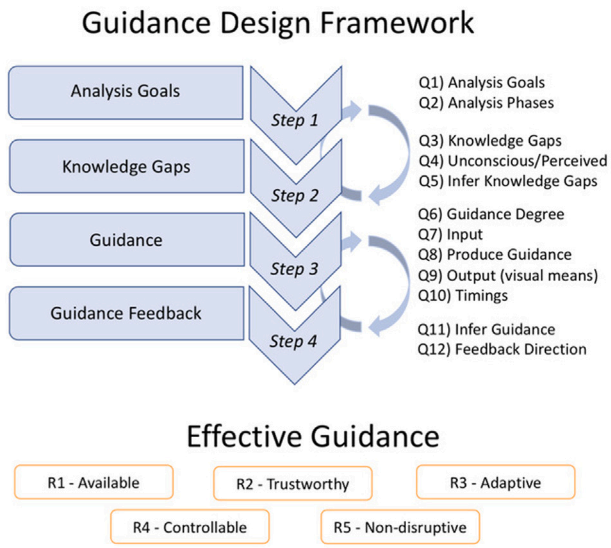

Fig. 8. A framework for guidance designers [37].

design framework emphasizes that the system should allow the user to maintain agency by finding the right balance between automation and guidance. The timeliness of guidance is also emphasized in the work of Pérez-Messina et al. [105], which address the issue of data size and complexity. Their work proposes a framework that couples guidance with progressiveness to prevent analysis from stalling.

Sperrle et al. [101] present a co-adaptive framework emphasizing user context. Their framework looks at guidance in the context of the overall VA process. The workflow is resource-intensive, which can hinder its applicability. These challenges are also present in the agent-based framework of Monadjemi et al. [78]. However, their proposed framework is simplified at a higher level of abstraction. It does not offer clear guidelines and steps for designing guidance. A co-adaptive agent-based strategy is concisely summed in the conceptual model proposed by Holter and El-Assady [106].

On the other hand, similar to Ceneda et al. [37]'s framework, Pérez-Messina et al.'s [39] task-driven methodology allows domain-based generalizability by characterizing user and guidance tasks. Conversely, Gómez et al. [99] incorporate the analysis guidance design recommendations within a more specific framework to design VA in clinical applications. The framework adopts a narrow scope; thus, it is challenging to generalize to other domains. Nonetheless, it offers an interesting strategy to incorporating guidance design decisions within the VA design decisions. It presents guidance as VA-specific and offers an opportunity to boost its effectiveness. Conversely, Lohfink et al.'s [100] work is narrow from the visualization perspective. They discuss design strategies for two chart types: a line graph and a spiral plot.

In conclusion, various frameworks for the design of guidance systems emphasize the importance of a user-context design, for example, by inferring user intent or optimizing guidance for user expertise. User context is particularly crucial in designing *accessibility guidance* that addresses the needs of diverse users with various disabilities. Moreover, proposing guidelines can be helpful in effectively following models to drive design decisions.

6. Guidance methods and techniques

This section examines how distinct guidance techniques have been leveraged to address uncertainty in diverse VA scenarios. We also illustrate how the proposed methods enhance decision-making by providing guidance to the user. Moreover, we highlight which guidance methods and encoding can work better than others to address specific uncertainty events. We include a summary of the main results of the taxonomy in Fig. 9. In the supplementary material, a tabular overview provides a more detailed view of the survey results. The subsections are structured to correspond to the taxonomy discussed in Section 4. Each subsection reviews the literature thematically on: (1) the uncertainty components and events addressed by the guidance role, (2) the guidance scopes useful for addressing uncertainties, and (3) the features of guidance and how they are implemented. We organize the first and second themes by the most prevalent in the literature. The third theme cross-discusses the six features of a guidance for comprehensibility and concludes with how guidance is implemented.

6.1. Analysis

In this section, we discuss 30 papers that present techniques for *analysis guidance*. Some proposed guidance strategies mend future knowledge gaps by addressing uncertainties in the *hypothesis*, *insight-perception*, and *insight-knowledge* components of the VA cycle. Other strategies provide feedback to the user on their *insight-interactions*, i.e., confirmatory and predictive strategies. Although research on confirmatory and predictive strategies in VA is abundant, only a few prior works present solutions that act as *analysis guidance* to the user.

Uncertainties. Most of the work on *analysis guidance* seems to address user *thinking* and *perceptual* uncertainty events. Chen et al. [107] attempt to also address *memory* and *incomplete knowledge* uncertainties by guiding users in a notebook environment. Their work focuses on revealing structures in the process and exploration provenance. Additionally, *incomplete knowledge* uncertainty was addressed in the work of Han and Schulz [38]. Contrary to Chen et al. their method addressed temporal uncertainties.

Leveraging a reinforced learning-based system, Shi et al. [108] address *usage* uncertainty among users with low visual analytics expertise. Similarly, Jiang et al. [109] develop a guidance mechanism that can address the lack of expertise among some users. Their approach aims to address the complexity of exploring the data and the *knowledge* uncertainty that comes with it.

Prediction models can be employed to provide *analysis guidance*. This strategy relies on predictions primarily to address *thinking* uncertainty events [110–113]. Gadhave et al. [110] predict patterns in user intent, guiding the user by addressing *thinking* uncertainties. This strategy could also benefit *collaboration guidance* by addressing user *interaction* uncertainties resulting from various expertise levels. On the other hand, Monadjemi et al. [114] propose that predicting user intent from their low-level interactions can help address exploration biases; thus, it addresses *decision-making bias* uncertainty (*knowledge* component).

Besides *thinking* uncertainties, feedback in the *analysis guidance* can also address *usage* uncertainty events (*interaction* component). This technique helps the user by providing a better understanding of their interaction with the system [115,116], and the approach continuously monitors user actions during the analytical process. For example, Li and Zhu's strategy [115] supports the user interaction in 3D analytics by providing constant feedback or feed-forward on their interactions. In comparison, Paden et al. [57] help users by providing feedback on their analysis not their interactions. An interesting guiding mechanism that infuses both *analysis* and *informativeness guidance* is proposed by Han et al. [117]. Their strategy addresses *thinking*, *perceptual*, and *memory* uncertainty events in the *insight* component. On the other hand, the informativeness aspect addresses uncertainties in the *knowledge* as well as *hypothesis* components, i.e., *incomplete knowledge* and *parameter*, respectively. Valdivia and Baca [118] finally propose a guidance mechanism that addresses interaction uncertainties while fostering user trust by adding a layer of explainability to guidance, i.e., explainable guidance [119].

GUIDANCE ROLES	GUIDANCE SCOPES								UNCERTAINTY COMPONENTS			
	Low	Inter	High	L+I	L+H	I+H	All	None	Data	Hyp	Vis	Ins
Analysis (30)	10	9	3	0	3	1	1	3	0	0	0	30
Collaboration (11)	3	4	1	0	1	2	0	0	0	0	0	11
Design (11)	3	0	5	1	0	2	0	0	0	0	11	1
Accessibility (9)	1	3	2	1	0	1	0	1	0	0	0	9
Informativeness (8)	0	6	1	0	0	0	1	0	0	6	0	7

Fig. 9. A table depicting our main findings, following our proposed taxonomy w.r.t. guidance roles, scopes (low, intermediate, and high), and uncertainty components (data, hypothesis, visualization, and insight), with the purpose of showing which categories are still in need of further development. Although not very common, a guidance tool can address multiple uncertainty components.

Scope. In analysis guidance, guidance-enhanced VA designers prefer to present *low-scope* guidance when they target domain experts to avoid a conflict with users' expertise and knowledge. This trend has been confirmed in the evaluation of Pérez-Messina et al.'s color-scheme guidance [62], seen in Fig. 10. They support the unexploded ordnance detection system with orienting guidance (*low scope*) and prescribing guidance (*high scope*). The user study showed that the expert domain users only used the orienting guidance and did not use the prescribing guidance. However, the orienting guidance does not seem sufficient to some users, especially in the presence of *data* uncertainty [11,120]. *Analysis guidance* can also be used to orient the user with *low-scope* experience-based predictions [111–113]. For example, Wang et al.'s strategy [112] constructs *analysis guidance* by assessing the user's experience in the VA, i.e., the user's exploratory patterns. The low-scope is also preferred when providing the user with feedback on their interaction, i.e., feedback on whether the user's interaction intention agrees with the system status after the interaction [115].

However, an *intermediate scope* is also common with *analysis guidance*. Analysis guidance often directs users by displaying ranked data-driven forecasts [110]. This scope aims to address uncertainties in different contexts. For example, Leite et al. [121] add directing guidance (*intermediate scope*) to their orienting guidance (*low scope*) to limit arbitrariness in the user's analytical decisions. On the other hand, Han et al. [117] present an *intermediate-scope* guidance, presenting the user with several trajectories to drive their analysis. In this case, the user has the option to control how much guidance they receive. In strategies targeting the general public, the *intermediate-scope* guidance seems more helpful [107,122,123]. Yen et al. [124] break this trend by proposing a *high-scope* and *low-scope* guidance to a domain-agnostic solution.

On the other hand, mechanisms addressing a visualization problem seem to prefer using a *high-scope* guidance [63,125]. This scope is less common with analysis guidance. When designed, it is often added to other scope options. For example, for users with low visualization expertise, Shi et al. [108] present both *intermediate-scope* guidance in a suggestion panel and *high-scope* guidance with a step-by-step sequence of abstractions. Providing *high-scope* guidance seems more helpful when it provides feedback on their analysis, as this task requires higher accuracy [57]. Few methods attempts to focus on designing multiple scopes. In our surveyed analysis guidance, only Valdivia and Baca's guidance mechanism [118] supports user analysis with three different scopes, *low*, *intermediate*, and *high*, based on their needs and the context.

Features. *Analysis guidance* can provide feedback on the *system status*, *model's results*, or *thinking biases* (**Why?**). In the papers surveyed, the guidance approaches provide feedback by tracking *user's interaction* as an input to an *explicitly-programmed algorithm* (**What?**). The reviewed methods target *all users* of the system without considering specific user contexts (**To whom?**), and they usually present the guidance *intrusively* on the visualization (**Where?**). The guidance can be presented to the user continuously or upon gap detection (**When?**).

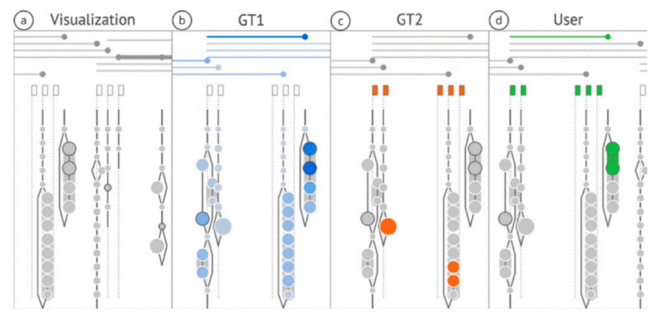

Fig. 10. Example of an *analysis guidance*; Pérez-Messina et al.'s [62] color scheme to guide the user in *low scope* (blue), *high scope* (orange), and *no guidance* (green).

For example, Li and Zhu [115] use animation to present a *continuous* visual feedback on users' interactions during a 3D VA session. Their strategy leverages the narration structure to maintain the user's trust in the system. Their strategy uses light, color, and shape (cubes and bubbles) (**How?**) to boost users' confidence in the usage of the system and to enhance the sense-making process. Similarly, Narechania et al. [116] use coloring as an intrusive strategy to orient the user about their interaction. However, they also present a quantification of the analytic behavior using three other non-intrusive guidance tools, such as tabular views and distribution plots, to allow the user to understand their analytic behavior better. Their guidance qualifies on which attributes the user focuses on.

Other strategies [57,117,126] aim to *promote insight discovery* and *mitigate bias* by providing feedback to the user on their interaction. Paden et al.'s BiasBuzz [57], for example, provides *haptic* guidance of user *thinking biases*. This feedback is presented when a bias is detected, i.e., *on-gap*. Han and Schulz [126] also leverage vibrations as a channel to provide user guidance. However, their studies show that the vibrotactile cues are not better guidance forms than the visual cues (**How?**). It can be more effective to use both channels in a complementary fashion.

Analysis guidance can also support users with predictions. This guidance can be an ad-hoc to support specific domain users or they can be domain agnostic [110] (**To whom?**). They use prediction models (**What?**) to enhance the sense-making process (**Why?**) by suggesting ranked options in a separate box (**Where?**) on-demand (**When**). These suggestions are usually presented to the user with color highlighting (**How?**).

For example, Gadhave et al.'s strategy [110] presents ranked predictions to guide the user in their analytical process. They input interaction provenance and user annotations into their intelligent algorithm. Although they do not describe a complete guidance mechanism, Gotz et al. [111] and Wang et al. [112,113] present a partial structure of prediction techniques, counterfactual operators, that can help design a guidance tool. Their proposed guidance can also be implemented for *informativeness guidance*. It aims to enhance users' understanding and improve decision-making. Additionally, Wang et al. [113] present the *Co-op* library that proposes guidelines for visually designing the guidance from the counterfactual computations. On the other hand, Monadjemi et al. [114] present a practical Bayesian inference strategy to predict user intent. Their method can help design *analysis guidance* based on user interaction. However, the paper stops short of proposing how these inferences can be visually integrated into the VA to guide the user in their analysis.

Other surveyed *analysis guidance* present a diversity in goals (**Why?**), strategies (**What?**; **How?**), and settings (**When?**; **Where?**). The surveyed strategies target users with different expertise levels **(To whom?**). Several papers use Ceneda et al.'s [37] framework to design their *analysis guidance* strategies [118,120,127,128].

For example, Piccolotto et al. [120] propose four different guidance mechanisms to enhance the sense-making process. The mechanisms guide the user in selecting exploration parameters with an intelligent algorithm that computes relations, correlations, and covariances. They present the guidance in several charts, such as tabular views, parallel coordinates plots, and line plots. This guidance is displayed non-intrusively in a separate box. Leite et al. [121] also integrate multiple components into their proposed guidance mechanism. They use a combination of chart views to direct the user and color highlights to orient them and preserve their mental map. Also, Musleh et al. [11] aim to preserve users' mental maps by guiding them through the uncertainties in radiation doses in brain CT scans.

Musleh et al. [11] continue the trend of integrating a multitude of intrusive and non-intrusive mechanisms to guide domain experts. Their strategy considers a matrix of guidance detail-orientation and intrusiveness, presenting six combinations of guidance features that can be delivered on demand. Filipov et al. [63] also provide guidance on demand to support the exploration of a temporal network using coloring as a guidance mechanism.

Unlike the general trend, Li et al. [122] address uncertainties for a general user population that lacks analysis expertise (**To whom?**). They employ a long short-term memory (LSTM) model that uses sequences of view abstractions and interactions as input to recommend interactions to the user. Harris et al.'s [123] strategy also offers guidance through view abstractions. Their method infers insights from the charts and employs a ranking algorithm to output insightful visual recommendations. On the other hand, Yen et al.'s [124] strategy supports a general user population by presenting guidance as glyphs flashing on the screen to draw users' attention to visual evidence of patterns. They also recommend visualizing other data features to the user in another view box. Their strategy enhances sense-making. Several papers [62,63,108,127,128] present strategies to guide users in analyzing temporal data to promote insight discovery in time-series data. Shi et al. [108] target users with low VA expertise. To improve users' understanding and facilitate the exploration, their strategy presents an analysis abstraction sequence with verbal insights.

The analysis guidance can also be presented when a knowledge gap is detected, i.e., on-gap. Identifying a gap can be a challenging task. However, Han and Schulz [38] propose to use a multiple-criteria decision analysis model to detect the need for guidance. Their strategy is domain-agnostic and uses visualization charts to guide the user. Ceneda et al. [98] propose facial recognition as another helpful mechanism to detect a need for guidance. Studies show that co-adaptive methods can help optimize guidance to address the uncertainties effectively [53,129]. Rodrigues et al. [129] propose using eye-tracking in optimizing recommendations to facilitate pattern discovery. On the other hand, Sperrle et al. [53] propose a mechanism, seen in Fig. 11, that observes direct and indirect user feedback to decide when to provide guidance, i.e., on-gap. They support their verbalized guidance with an explanation to boost users' trust. User trust is further enhanced with the verbalization form of the guidance. Srinivasan and Setlur [130] also leverage what they call *conversational visual analysis* to provide trusted guidance. Their natural language-based algorithm uses metadata as input. Similarly, Witschard et al. [125] propose using multiple embeddings to compute text similarity. Their guidance is presented as glyphs that direct the user in setting the thresholds for each embedding.

Multiple contexts drive the design of *analysis guidance*. For example, Srinivasan and Setlur's guidance is driven by the so-called *context state object*. This context-aware model is constructed with three components: active charts and mark selections, most recent utterance, and user interaction logs (attributes, values, intents). The latter item is used to calculate an interaction score. Although the context-aware approach is common in guided VA, the components of the analyzed context may differ. For example, Han and Schulz's [38] framework analyzes who the users are, their goals and tasks, their resources and their environment. In their work, guidance implementation is a three-step process which builds on the context to further identify decision points and assess need for guidance.

6.2. *Accessibility*

We reviewed nine papers discussing *accessibility guidance* strategies that support users with disabilities through the VA cycle. These mechanisms are part of a broader toolkit known as assistive technologies, a common term used to describe *accessibility guidance*.

Uncertainties. *Accessibility guidance* primarily addresses *thinking* uncertainty in the *interaction* component of the VA cycle. In the reviewed papers, this uncertainty stems from users' visual impairments, which limit their ability to perceive and, thereafter, think about and interact with visualizations. Guidance mitigates this with chart information at increasing levels of granularity and communicates it to the user through alternative sensory systems. For instance, *AutoVizuA11y* [131] surfaces low-level metadata as well as high-level summaries accessible through screen readers.

Guidance can also address other uncertainties in the *insight* component. For example, *TactualPlots* [132] uses auditory feedback to address *usage* uncertainty that arises from interacting with tactile plots, while *AutoVizuA11y* [131] provides keyboard shortcuts for navigating the chart as well as retrieving different levels of information. In our papers, the uncertainty of *incomplete knowledge* is addressed with screen-readers that are integral for users with total visual impairment and, therefore, outside the scope of guidance. However, guidance can address incomplete knowledge for users with other grades or forms of visual impairments, e.g., low vision, focus impairment, and color blindness.

While these technologies also address limitations in visual perception, we did not classify them as *perceptual* uncertainties due to Gillmann et al.'s [8] uncertainty taxonomy, which defines perceptual uncertainties as cognitive limitations. Uncertainty events have not been defined for VA users with visual impairments or other forms of disabilities.

Scope. The reviewed papers present varying scopes of guidance. Unlike the trend with *analysis guidance*, an intermediate scope that directs the user with multiple inferences is more common with *accessibility guidance*. For example, Alam et al. [64] provide *intermediate-scope* guidance in the form of chart descriptions of varying granularity as seen in Fig. 12(a), e.g., metadata vs. descriptive statistics. On the contrary high-scope guidance, presents an assertive guidance with one inferred summary. For example, Obeid and Hoque [65] provide *high-scope* guidance that gives users a single summary of the visualization with descriptive statistics to direct the user to a specific analytical path.

Only one paper by Chundury et al. [132] describes only a *low-scope* guidance in the form of auditory feedback for finding insights. Couple of papers provide more than one scope of *accessibility guidance*. For example, as illustrated in Fig. 12(c), *AutoVizuA11y* [131] can provide

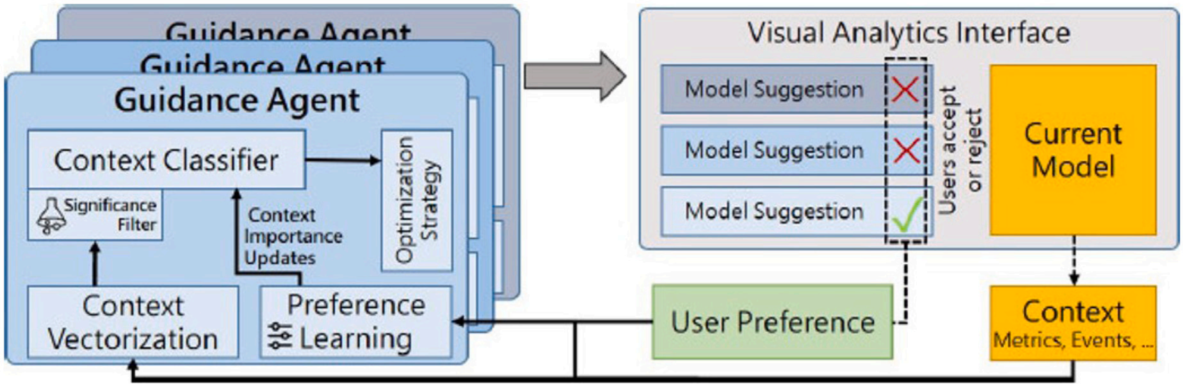

Fig. 11. Example of an *analysis guidance*; Sperrle et al.'s [53] adaptive model to provide guidance; it highlights how indirect (orange) and direct (green) feedback is leveraged to construct a context-aware guidance (blue).

low-scope guidance, such as navigating chart elements of a bar graph. But it also provides *intermediate-scope* guidance, such as generating data descriptions of varying granularity or calculating statistical insights using keyboard shortcuts. Note that the scope of guidance depends on the grade/level of visual impairment. Take Hoque et al. [58] for example, which presents a strategy that provides natural-sound data sonification as a way to interpret the data as seen in Fig. 12(b). For users with low to partial visual impairment, this can be considered *intermediate-scope* guidance that provides multiple analytical paths, e.g., visual and audio. For users with total visual impairment, data sonification is presented as a *high-scope* guidance that provides a single analytical path, if not integral to the system.

Features. In the papers reviewed, all systems were intended for *users with visual impairments, specifically blind or low vision* (**To whom**?); six papers involved their target users in the design and/or evaluation [58, 64,131–134]. The guidance mechanisms in these systems aim (**Why?**) to enhance understanding of the dataset, e.g., [64], promote insight discovery, e.g., [132], and facilitate usability and navigation of the chart, e.g., [131]. As mentioned in the scope section, some systems fulfill multiple goals by providing knowledge at different levels of granularity and insight [58,64,131].

Guidance given in the form of *verbal/text* (**How?**) can be generated and ranked using AI-based algorithms (**What?**), e.g., natural language generation [64,65], large language models (LLM) [131,133], or rule-based [134–136]. In contrast, *audio* guidance strategies (**How?**) are generated only with explicitly programmed algorithms (**What?**).

Most *accessibility guidance* is *on-demand* (**When?**), except for *SeeChart* [64] that provides chart summaries on-demand but updates it *continuously* while the chart is being manipulated. Spatially, guidance in the form of text can appear in the *margins* of the system (**Where?**), such as beside or below the chart [64,65,134,136]. It can also appear in the *screen-reader view* [131] or in *auditory space* [58,132]. The timing of guidance is identified as a critical design consideration [44]. However, some papers do not explicitly describe the timing of their proposed guidance [65,135]. Moreover, Al-Kady et al. [135] do not specify the spatial setting of their proposed guidance.

Similar to some *analysis guidance* tools [130], accessibility guidance is also driven by detecting the state of the chart and marking. However, the modeling of the guidance seems to be more constrained and less dynamic. For example, after detecting the context, Alam et al. [64]'s *SeeChart* implements a template-based natural language general approach. The scope of the template is constrained to the evaluation conducted by the researchers for a particular work. This limitation is also present in the audio-based guidance in Susurrus [58], as seen in Fig. 12(b). Data is mapped to natural sound meaningful to the specific research, which may not be generalizable.

6.3. Collaboration

Collaboration guidance helps the user by augmenting and integrating knowledge from other users into the process. The guidance is implemented as an auxiliary to a VA system. In this section, we discuss 11 papers presenting collaborative strategies to guide users in VA. The proposed guidance role takes several forms, addressing multiple uncertainty types in the VA-cycle components.

Uncertainties. The *collaboration guidance* strategies address different uncertainty events within the insight component (Fig. 2). All the papers propose strategies to mitigate uncertainty events produced by the *knowledge* component. The user's *incomplete knowledge* (i.e., the uncertainty) is a target concern of all the papers that presented *collaboration guidance* strategies. On top of that, few papers addressed user *ignorance*. This trend is prevalent in systems that aim to mitigate the gap between data scientists and domain experts [59].

For example, Langer et al. [59] address the *ignorance* of data scientists in analyzing complex industrial data, see Fig. 13(a). They leverage *collaboration guidance* to address this uncertainty with provenance for domain experts. Similarly, Liu et al. [137] augment insight generation from multiple users with diverse domain expertise. Also, the so-called Casual Collaborative VA by Ens et al. [138] leverages multiple tangible and immersive modalities and diverse user expertise to guide a user to make a knowledgeable decision. Contrary to both, Li et al. [68] address *ignorance* uncertainty through an asynchronous guidance strategy. Their strategy merges VA abstracts and insights of multiple users to detect knowledge conflicts. In doing so, they also target the *perceptual* and *thinking* uncertainties. Similarly, Liu et al. [137] help users improve their cognitive ability to understand and think about volume data by leveraging knowledge from multiple users in multiple analysis modalities.

The uncertainty events in the *perception* and *interaction* components have also been addressed in other *collaboration guidance* strategies. Mathisen et al. [67] address three challenges, two related to uncertainties in the collaborative context. Their strategy records details of an analytical session to address the diversity in expertise and interest levels on one hand and the non-linear collaborative analytics on the other. Thus, their strategy addresses *memory* uncertainty. Similarly, Park et al. [139] and Coelho et al. [66] propose strategies that guide the user through *memory* uncertainty. The latter also aims to address *decision-making bias*, an important uncertainty event that should be emphasized more in the *collaboration guidance* strategies. Park et al. [139] also address the *perceptual* uncertainty in the *perception* component. This uncertainty is addressed by Garrido et al. [140] by leveraging the capabilities of Unity3D and virtual reality. Virtual reality is also leveraged in the strategies of Ens et al. [138] and Bovo et al. [141] to mitigate users' *interaction* uncertainty, i.e., *usage* uncertainty.

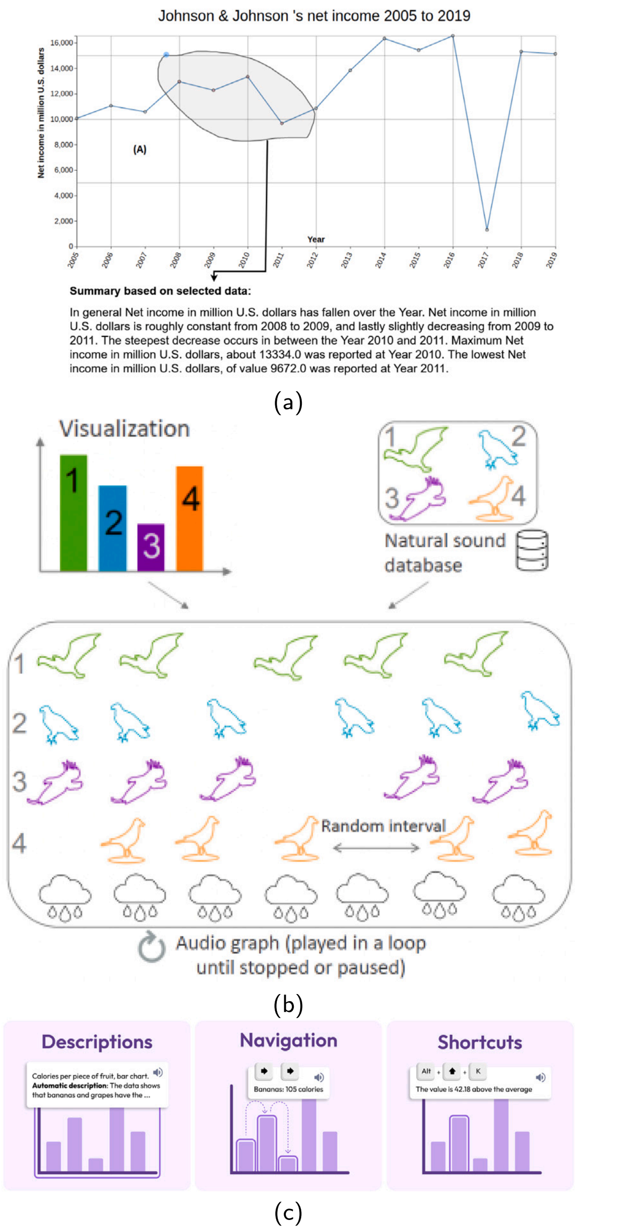

Fig. 12. Examples of *accessibility guidance*; (a) *SeeChart* generates natural language summaries of D3 charts, Figure courtesy of Alam et al. York University from their work [64]; (b) *Susurrus* sonifies data (bottom) by mapping natural sounds (top right) to chart elements (top left) enabling users to perceive multiple data points in parallel [58]; (c) *AutoVizuA11y* provides multiple scope guidance via keyboard shortcuts by presenting intermediate-scope guidance (data descriptions) or low-scope guidance (navigation elements and statistical insights) [131].

Scope. Like *accessibility guidance*, an *intermediate scope* is more common when designing collaboration guidance. The synchronous collaboration tools, e.g., Reski et al.'s [142] hybrid asymmetric system, guide users' analysis with real-time options of insights to pursue. This *intermediate-scope* guidance is also afforded in Mathisen et al.'s [67], *InsideInsights* seen in Fig. 13(b), data-driven narratives and Li et al.'s [68] guidance method. These strategies present multiple options to the user to resolve conflicts that arise from uncertainties in the *perception* component. However, these two guidance strategies also allow a *high-scope* guidance that directs the user's analysis into one path by presenting a complete

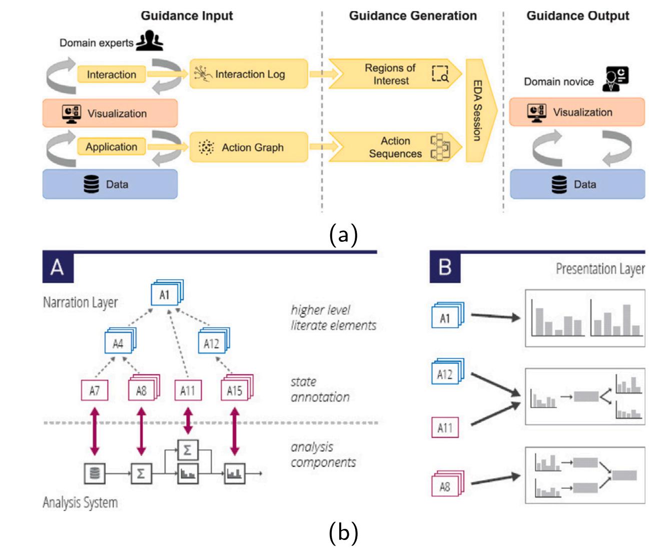

Fig. 13. Examples of *collaboration guidance*; (a) Overview of Langer et al.'s [59] guidance design;(b) Mathisen et al.'s [67] *InsideInsights* guidance generate analytical narratives with intelligent algorithms.

resolution path to conflicts in insight arising from *memory* or *thinking* uncertainties.

Collaborative guidance can address *knowledge* uncertainties by providing a *low-scope* guidance to raise user awareness of their decision-making bias [66] and insufficient knowledge [137,138]. An interesting disagreement arises in the best guidance scope to address *perceptual* uncertainties. While Liu et al. [137] direct the analysis by augmenting multi-user knowledge into one ideal path based on their assigned tasks. Conversely, Park et al. [139] propose a *low scope* of *collaboration guidance* by presenting a trail view of how users perceive different insights in similar VA tasks.

Features. *Collaboration guidance* strategies are multi-modal. Techniques that propose leveraging synchronous immersive analytics with *physical systems* (**How?**), such as augmented reality (AR), virtual reality (VR), or cross-virtuality (XR) [140–143], use real-time data as an *input* to their guidance techniques. The guidance output is also in the AR/VR/XR mechanisms and verbal communication (**What?**). Additionally, Garrido et al. [140] and Seraji et al. [143] present guidance in using color highlighting (**How?**). This guidance form is also used by Liu et al. [137] who use multiple physical machines and an explicitly programmed algorithm that inputs real-time data to *output* real-time insights and abstractions as guidance (**What?**). On the other hand, Ens et al. [138] propose leveraging tangible widgets [138] to support asynchronous analytics that uses *insight provenance* as an *input* to provide users with an analysis narrative as guidance (**What?**). In synchronous analytics, the guidance is *continuous* (**When?**). Contrary to the asynchronous strategies, where guidance is provided *on-demand* (**When?**). The guidance in the strategies that leverage physical systems is presented in the VA pipeline and processes (**Where?**).

On the other hand, other techniques trace insight and abstraction provenance as input to generate guidance with explicitly programmed algorithms [59,66,68,139] or intelligent algorithms [67] to generate the guidance. These algorithms generate guidance as blockchains [66], insight graphs [68], abstracts graphs [139], or analysis narratives and annotations [67] (**What?**). The guidance is presented in different forms, such as glyphs [66], node-link diagrams [68,139], or verbal text [67] (**How?**). While Coelho et al.'s [66] and Li et al.'s [68] strategies present non-intrusive guidance in the margins, Mathisen et al. [67] and Park et al.'s [139] strategies provide the guidance intrusively on the visualization (**Where?**). Li et al.'s [68] insight graph is provided *on-demand*, similar to Park et al.'s [139] story facets. However, the algorithm of the guidance attempts to resolve conflicts *on gap* detection. This strategy is in contrast with Mathisen et al. [67] and Coelho et al.'s [66] strategies that present the guidance continuously during the analytical process (**When?**).

Finally, the *collaboration guidance* methods aim to promote insight discovery, enhance user understanding, and improve decision-making by sharing knowledge and creating mutual awareness between domain users of different expertise levels and backgrounds (**Why?** and **To whom?**). Some guidance in physical systems is calibrated for system experts as well [138,142]. Naturally, *collaboration guidance* in physical systems involves analytical communication between users [138]. Interestingly, other strategies also guide the user in communicating with external stakeholders [66,139]. Currently, this lies outside the VA cycle. However, we discuss this interesting gap in Section 8.3.

Opposite to the common context detection, *collaboration guidance*, guidance is driven by contextual mismatch. However, as most other guidance roles, observing user interactions and chart states is the main source for contextual detection. Collaboration guidance, unlike analysis guidance for example, is not called-up through an automated process. The user declares the need for guidance.

6.4. Design

Design guidance supports users in effective visualization design by addressing *visualization* uncertainty. In this section, we discuss 11 papers describing guidance strategies that support users in designing and encoding visualization to support an effective VA.

Uncertainties. In the reviewed papers, uncertainties primarily stem from the limits of the user's knowledge concerning visualization design and implementation. These limitations hinder the user from mapping data to visual variables to support analytical tasks. Guidance can help address a user's *visualization-mapping* uncertainty by ranking visualizations using some measure of visualization expressiveness and effectiveness for the given dataset [60,70,144,145] or generating intent-based visualizations to address uncertainties with task abstraction [145–147]. These strategies increase the time-efficiency of visualization construction by fully automating the design of recommendations [60,70,145–149] or by providing users with "next steps" for the visualization design process [150]. *Design guidance* also addresses *visualization-mapping* uncertainty by drawing attention to erroneous design decisions that may have been missed by the chart author [69,151]. One paper by Zhu et al. [147] touches upon *insight* uncertainty in addition to *visualization* uncertainty, describing visualization recommendation as a way of exploring dataset possibilities and capturing overlooked insights.

Scope. The majority of reviewed papers describe a single scope of *design guidance*. Seven applications describe *high-scope* guidance that recommends and often ranks fully-designed visualizations to the user [60,70,145–149]. For example, Chen et al. [70] recommend fully-designed visualizations based on the appropriateness of chart idioms and color aesthetics for a given dataset. Though full designs are given to the user, some applications allow the user to use portions of the recommended visualizations, e.g., [146] or adjust their visual design, e.g., [149].

Three papers present *low-scope* guidance enhancing the original, underlying visualization without altering it. Both *VisualLint* [69] and *EmphasisChecker* [151] guide the user in avoiding visualization design pitfalls by adding annotations overlaying erroneous chart elements. *AdaptiveMaps* [144] adds checkmarks next to visualization idioms that suit the input dataset but does not bar the user from exploring other idioms.

One application describes mixed scopes of guidance. *Mystique* [150] starts with *low-scope* guidance that suggests data mapping steps to the author without altering the visualization but ends with *intermediate-scope* guidance by inferring visual encodings for the user.

Features. In the reviewed papers, *design guidance* tends to have one of the following goals (**Why?**) and users (**To whom?**): (1) lower design and/or programming skill barriers for *visualization novices*, or (2) ease the discovery of insights for *data workers*. For the first goal, applications support visualization novices at the encoding level, e.g., glyphs [149], local level, e.g., individual chart [60], or global level e.g., dashboard compositions [146] as seen in Fig. 14(a). Applications can also meet the first goal by helping novices recognize visualization pitfalls. For example, VisualLint [69] guides chart authors with low visual literacy by rendering sketchy annotations on top of erroneous chart elements, as seen in Fig. 14(b). On the other hand, Dowsing [147] is an example of the second goal; this application generates task-based visualizations to help analysts explore the dataset and find insights.

Design guidance tends to present *on-demand* at the start of the design process (**When?**), as a *main panel* of a dashboard (**Where?**) displaying a *list of ranked visualization recommendations* (**How?**). This ranking is determined by an explicitly programmed or machine learning (neural network-based) algorithm (**What?**), and there is a balanced split between these two strategies in the reviewed papers. For example, Chen et al. [70] describe a neural network-based visualization recommender that displays ranked visualizations in a central dashboard panel. While Pandey et al. [146] describe an explicitly-programmed algorithm to score recommendations based on user-specified analytical intent, data attributes, and views of interest.

There are certainly exceptions to the norm. Systems with a *low scope* of *design guidance* provide support *on-gap* (**When?**). For example, *VisualLint* [69] and *EmphasisChecker* [151] both provide guidance *only* when erroneous design choices are detected. Spatially, these two guidance mechanisms also appear *"in situ"* (**Where?**) as sketchy annotations, overlaying the original chart for a more direct mapping to the source of error. Similarly, *Mystique* [150] provides guidance as visual cues overlaying the constructed chart. Some systems place the recommended visualizations in the margins of a dashboard (**Where?**). For instance, *GlyphCreator* [149] and Dowsing [147] generate recommended charts in the margins, which are later added to a canvas by the user to organize or explore their ideas. Lastly, some mechanisms do not provide a ranked list of design options. These mechanisms show only one design possibility per input [69,146,148,150,151] or multiple, unranked design possibilities [144,149] (**How?**).

Design guidance is driven by an AI-in-the-loop workflow. For example, *GeoVis* [70] and *GlyphCreator* [149] use a deep learning model to translate raw data into guidance. *GeoVis* generates a kernel density map from an input datasheet, wich is encoded with a deep learning method to generate visual chart recommendations. On the other hand, *GlyphCreator* is fueled by the observed user interaction. The system introduces the input image and data to a trained CNN model to recommend alternative examples of a circular glyph design.

6.5. Informativeness

Informativeness guidance intersects with work on explainability in VA. The system primarily helps users in the presence of uncertainty by providing information to support their analysis. However, explainability strategies are not always designed *to guide the user* in VA. For example, AI explainability strategies are often additional visualization representation that allows the user *to guide the system*.

In this section, we discuss eight papers that present *informativeness* strategies that can be implemented as an auxiliary to a VA system. The proposed strategies guide users' analysis by raising their awareness through interpretations or transparency. Scalability is an important challenge in developing *informativeness* strategies because additional information and visual cues can cognitively overload users.

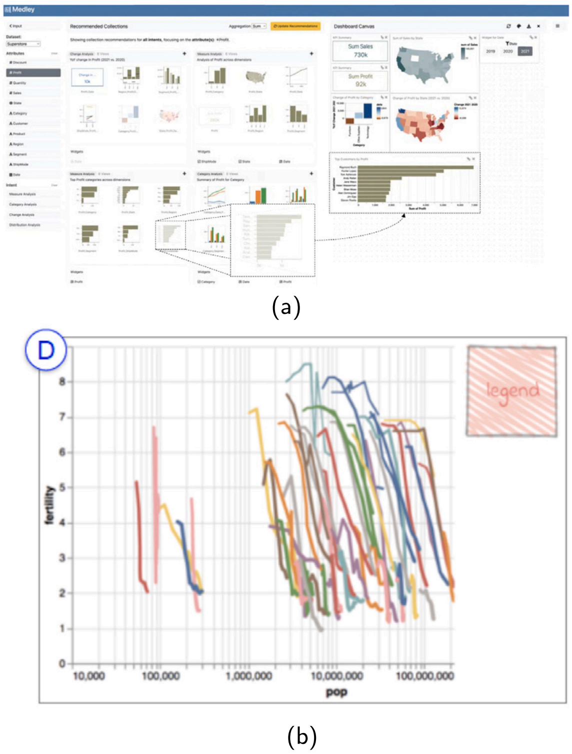

Fig. 14. Examples of *design guidance*; (a) *Medley* suggests dashboard compositions based on user-specified analytical intent [146]; (b) *VisualLint* uses sketchy annotations to surface chart construction errors in situ [69].

Uncertainties. Unlike other reviewed guidance roles, reviewed informativeness guidance strategies proportionally and simultaneously address uncertainties in multiple components: *model* and *insight*. *Informativeness* guidance are often integrate in VA processes supported by AI and ML models. For example, the guidance addresses the uncertainties by explaining dimensionality reduction (DR) models represented in scatter plots [152]. They also guide the user through the *thinking* uncertainty by providing different explanations. Tian et al.'s [152] explanatory technique, for instance, presents six different explanations for scatter plots that a user can explore. This technique is demonstrated in case studies but not evaluated for usability and efficacy.

Thijssen et al. [153] extend the work by exploring different explanations to address these uncertainties. They further conduct a user study to test the efficacy of explanations in guiding users. Their evaluation shows that *informativeness guidance* can be helpful in the analysis of tabular data. However, they highlight that it cannot effectively address *dataset* uncertainties, namely, missing data. Some strategies leverages natural language processing (NLP) to construct guidance. For example, Srinivasan et al.'s [154] NLP model generates guidance to inform users and guide them through *thinking* uncertainties. However, they highlight gaps in methods to evaluate the effectiveness of such guidance strategies properly. Their work also proposes leveraging inference methods and narrative forms to address these uncertainties more effectively.

Some methods address uncertainties by assessing whether to show or hide information instead of revealing new information. For example, Behrisch et al.'s [71] strategy aims to guide users in analyzing relational data such as network graphs and matrices. Their method addresses *model parameters* uncertainty in the *hypothesis* component. Distinctly, Belyakov et al. [73] guide users in analyzing cartographic images, seen in Fig. 15(b). Their method attempts to address *usage* and *thinking* uncertainties stemming from the *interaction* component in the VA cycle.

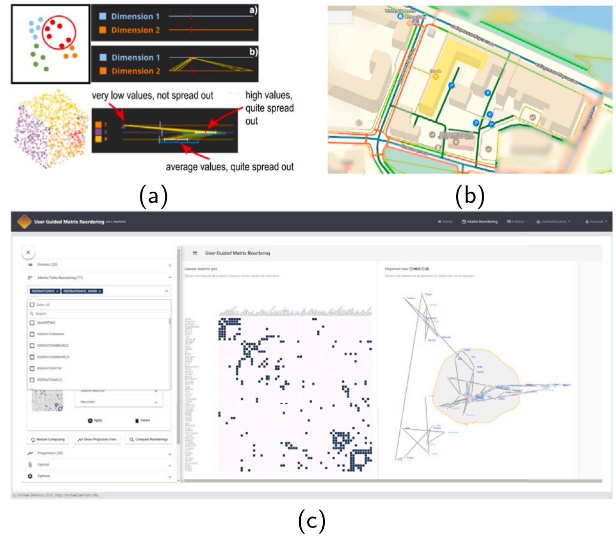

Fig. 15. Examples of *informativeness guidance*; (a) PCP and range line plot proposed by Thijssen et al. [153] to present the explanation to users; (b); Belyakov et al.'s [73] strategy processes information with intelligent algorithms to show/hide information to guide the analytical process; (c) *GUIRO* guides the user in analyzing relational data; figure courtesy of Behrisch et al. Utrecht University from their work [71].

Scope. Predominantly, most *informativeness guidance* methods do not merely provide more transparency to underlying information. Instead, they provide explanations (*intermediate scope*) using elaborate mathematical and statistical equations without further elaborating on how this explanation might impact the analysis (*high scope*). Only one reviewed *informativeness* approach incorporates multiple scopes. Behrisch et al.'s [71] work presents a *low scope*, clarifying the underlying parameters. It also presents an *intermediate scope* in unlocking the black box of the model and a *high scope* in depicting the results of different reordering algorithms with quality metrics and index comparison (explication). Contrarily, in managing the visibility of information, Belyakov et al.'s [73] strategy implies the impact of one specific analysis direction on the analysis process, thus presenting a *high-scope* guidance.

Features. All *informativeness* methods presents the guidance on to *domain experts* (**To whom?**) on-demand (**When?**) to *promote insight discovery* (**Why?**). Except for Behrisch et al.'s *Guiro* [71] that presents guidance on the left margin, *informativeness* techniques present the guidance intrusively on the visualization (**Where?**).

Techniques that address the understandability of DR plots present the guidance as an attribute-based explanation generated by an explicitly programmed algorithm that uses the metadata as an input (**What?**). For instance, Tian et al.'s [152] strategy allows the user to manipulate the guidance using a matrix view that controls the color-highlighting on the view. Alternatively, Thijssen et al. [153] incorporate the brushing and coloring technique through range line plots connected with a parallel coordinates plot, seen in Fig. 15(a) (**How?**). On the other hand, on-hoovering, Marcílio, and Eler [155] present the information in two tool-tips of line and dot plots and a side heatmap (**How?**). Corbugay et al. [156] integrate the guidance into the scatter plot view with contour maps. They focus specifically on interpreting non-linear DR projections, such as t-SNE. Also, Bibal et al. [157] integrate their explanation of the decision-tree errors (**What?**) into the scatter plot; however, they use direct coloring of the dots (**How?**).

Other strategies use intelligent algorithms to learn and select which information to show [73,154]. For example, Belyakov et al. [73] propose an algorithm that processes the map context data to show/hide information on the map (**What?**)—the guidance updates based upon the user's request. Belyakov et al. [73] evaluated their strategy with 23 analysts to determine its usability and efficacy. They determined that the strategy was most effective in a time-constrained analysis setting. Their strategy also aims to improve decision-making [73].

On the other hand, *Guiro* [71], seen in Fig. 15(c), provides *informativeness* in a mixed-initiative framework. The guidance improves the model's transparency to enhance the user's understanding of the data topology (**Why?**). The method allows the user to manipulate modeling algorithms through the control in the left margin while illustrating 16 reordering quality metrics and index comparison (**What?**). The tabular view (**How?**) intends to allow interpretability by users with various levels of expertise.

The need for *informativeness guidance* is detected through the continuous tracking of user interaction. For example, *IXVC* [157] detects the need for guidance by monitoring user knowledge gap. On the other hand, *GUIRO* [71], for example, relies on a manual user feedback to construct the guidance.

7. Evaluating guidance

Evaluations and evaluation methodologies (such as user studies) are the main ways designers assess the effectiveness of information displays to support specific perceptual tasks [158]. In this, user studies (either qualitative or quantitative) certainly play an important role in evaluating the effectiveness of the guidance strategies themselves (i.e., to assess whether they were able to address specific knowledge gaps). They also highlight factors and weaknesses that could be addressed or partially solved with guidance-enhanced solutions. Standard evaluation practices in VA primarily focus on assessing visualization effectiveness or task performance. Contrarily, evaluating guidance specifically requires considering how well the system addresses user knowledge gaps and supports decision-making throughout the analysis process. Besides measuring task outcomes, guidance evaluation investigates how it influences user behavior, trust, and analytical reasoning. While many evaluations still follow traditional user study designs, guidance evaluation demands additional criteria and tailored methodologies to capture these unique aspects. In this case, the results obtained could serve as additional input for designers and inform the development of future information visualizations and VA tools.

7.1. Evaluation approaches

We first analyze and describe evaluation strategies used to assess the effectiveness of guidance. To the best of our knowledge, the heuristic method by Ceneda et al. [159] is the only evaluation methodology that is specific for guidance-enhanced strategies. It describes a set of eight quality criteria that the guidance should uphold to be effective and a set of heuristics and questions to evaluate them in practical scenarios. For the rest, most strategies simply resolve to use traditional qualitative (e.g., [98]) and quantitative methods (e.g., [160]) that are typically used to assess VA methods (also, with no guidance) [158]. The *accessibility* strategy of Amorin and Pugliesi [161] show the effectiveness of using dynamic flow maps as guidance means to support perceptual tasks such as path and route identification for people with visual impairment. Still, concerning accessible visualization research, Kim et al. [162] present two techniques (namely, structured navigation and conversational interaction) to help and guide visually impaired users to navigate and explore a visualization display. Considering *analytical* strategies, Ceneda et al. [160] describe a guidance-infused strategy to support the analysis of cyclical patterns in time-series data, which is evaluated qualitatively employing questionnaires and user input. Still, Pérez-Messina et al. [62] employ a mixture of quantitative and qualitative methods to assess a guidance methodology to support the selection of aerial images. The *analytical* strategy by Ha et al. [163] describes an AI-based guidance strategy that aims to support data exploration. The strategy is evaluated qualitatively and quantitatively, considering various factors to investigate user behavior, trust, and guidance usage, shedding light on the design of human-AI collaboration strategies.

In *collaborative* environments, Block et al. [164] investigate how different types of provenance information influence analysts in a collaborative analysis task. Provenance can be considered a form of guidance in this context. It provides a structured way for analysts to understand and build upon prior work by offering insights into what has already been covered (data coverage) or the sequence of actions taken (interaction history). Other forms of visual guidance are also present in prior work. Kang et al. [165] investigate collaborative learning dynamics in an immersive astronomy simulation, focusing on joint attention as an indicator of collaboration. Liu et al. [166] compare three collaborative visualization techniques (zooming, interactive lenses, and overview+detail) on large displays for map-based tasks. Interestingly, in confirmation scenarios of *analysis guidance*, we also witness non-visual guidance: Alroe et al. [167] use haptic force feedback for user guidance in visualizations. Finally, in prediction strategies, Ha et al. [168] (see Fig. 16(a)) evaluate a mixed-initiative system designed to improve interactions with complex datasets and dense visualizations. The system has been designed to guide users' focus on potentially interesting data points, adjusting the visualization to highlight relevant information in dense visualizations. The paper of Wang et al. [169] explores how counterfactual, hypothetical scenarios can improve users' understanding of causal relationships in data visualizations. Broadly speaking, this is also a form of guidance, as their counterfactual visualization design aligns with principles of guided visual analytics, e.g., to lead users toward better understanding and decision-making.

7.2. Design and user studies

We now continue describing evaluation strategies whose results could be used as a base for enhancing existing or new VA strategies with guidance. As usual, we start describing *accessibility* guidance. The literature on accessibility consists mainly of strategies that investigate how persons with different types of intellectual or developmental disabilities interact, use, and visualize data (e.g., [170–173]). Most accessibility issues and problems are typically subjective and hard to identify before the analysis [174]. Thus, one of the main outcomes of accessibility research is that we need more personalized solutions that could adapt (the level of support, i.e., the scope) to the different abilities and severity of the disability. Wu et al. [96], for instance, suggest a set of guidelines — as the use of personalization and physicalizations — to improve the interaction with data. Engel et al. [175] present two studies that examine the perceived content of scatterplots in detail. The results, which align with extant explainable interfaces research for effective guidance [159] (see Fig. 16(b)), form the basis for creating chart descriptions for people with blindness or visual impairments. These descriptions reflect the perceived content of the chart. Elavsky et al. [176] describe a set of heuristics for evaluating the accessibility of visual interactive data displays. While the purpose of such heuristics is mainly evaluations, they could also serve as a base to derive the necessary guidance in accessible visualizations, e.g., if a problem is detected. For the *analysis* guidance, Sperrle et al. [177] investigates the efficacy of guidance strategies. Their study highlights the need for a co-adaptive guidance design that responds to the user context.

Within the frame of *collaboration*, we see several mixed-method studies that relate to immersive mixed reality environments [178–180]. These works either investigate co-located AR collaboration using different display devices [178], evaluate immersion and collaboration impacts on visual analytics [179], or explore team behaviors in shared spaces [180]. Bao et al. [181] investigate what public health analysts value in the *design* of visualization recommendation systems, highlighting the importance of domain context and user intent. Conversely, Zehrung et al. [182] explore how users trust human-made vs. algorithmic visualization recommendations. Their crowd-sourced

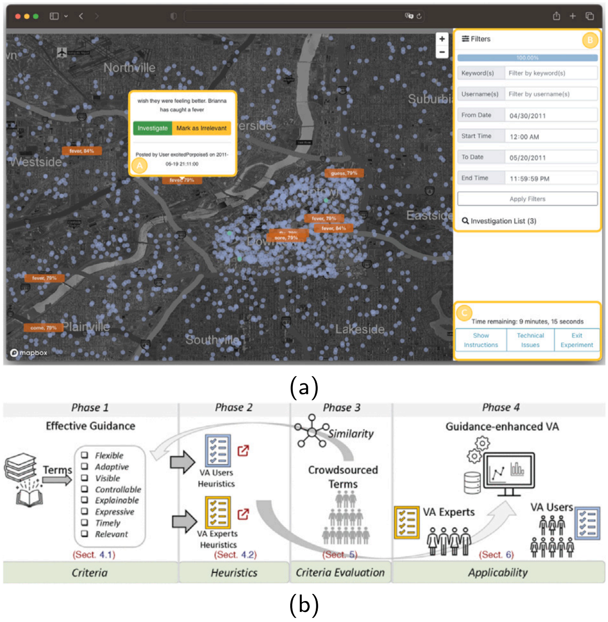

Fig. 16. (a) The interface of Ha et al.'s [168] mixed-initiative system designed to improve interactions with complex datasets and dense visualizations; (b) Methodological strategy that guides the evaluation design proposed by Ceneda et al. [159].

Explore new guidance roles	• Onboarding • Narrative • Persuasion	• Confirmation • Prediction
Improve uncertainty taxonomy	• Consider ***communication*** uncertainty • Investigate impairment-related uncertainty events • Redefine current uncertainty events	
Address guidance gaps	• Target accessibility-associated impairments e.g., IDD and Situational • Implement context-aware multiple scopes • Implement uncertainties beyond ***insight***, i.e., ***data*** & ***hypothesis***	

Fig. 17. Our main recommendations: explore new guidance roles, improve uncertainty taxonomy, and address guidance gaps.

study indicates that although human recommendations are often preferred, recommendation relevance is often prioritized over its source. Finally, Seipp et al. [6] specifically target uncertainty, identifying effective visual variables (e.g., opacity, texture) for its communication and for helping users make *informed*, uncertainty-aware adjustments to improve analysis.

8. Discussion

This section outlines areas of sparsely researched guidance strategies addressing uncertainties highlighted in the taxonomy section and why they are valuable to the community. We also discuss three gaps identified in our survey: onboarding, narrative, and persuasion guidance. Finally, we present opportunities and challenges to addressing uncertainties with guidance, also highlighted in Fig. 17.

8.1. Gaps in reviewed guidance

Addressing disabilities. *Accessibility guidance* can support systems to be more accessible to a broader user pool. In our survey, we did not find application papers describing guidance strategies for **disabilities beyond vision**, such as attention-deficit/hyperactivity disorder (ADHD), IDD, physical disabilities, or situational disabilities. In such a context, guidance strategies can be instrumental, as accessibility issues are typically subjective, thus requiring subjective guidance solutions. The results of our survey are reflected by Wimer et al. [183], who note that accessibility research in visualization and VA is focused mainly on vision impairment. For a broader research agenda, the literature needs **a taxonomy of disabilities** that can potentially influence user analysis.

Moreover, visual impairment can include users with focus impairment, low-vision impairment, and color blindness. These visual impairments may require different strategies to address their analysis uncertainties. Understanding the needs and requirements to address uncertainties under conditions of other disabilities can be challenging as it **demands interdisciplinary research**.

The chart types studied in the literature are also **limited to standard charts**, such as line, pie, bar, and scatter plots. It is unclear whether or how guidance can make bespoke and high-dimensional visualizations, commonly found in VA systems, more accessible. Often, *accessibility guidance* work proposes summaries of insights to assist their target users with visual impairments. However, this type of guidance can be equally helpful for sighted users. Thus, it is questionable whether these contributions should be positioned as strategies specifically supporting users with visual impairments. There is a lack of **diverse solutions** when addressing impairment-related uncertainties because of a limitation in classifying these uncertainties.

Guidance combination. Certain guidance tools can take several roles. In this paper, we classified the work based on the primary role of guidance. However, investigating how a **combination of roles** addresses uncertainties can be intriguing. For example, a guidance strategy can guide the user to re-design the visualization and analyze the data simultaneously. Thus, investigating the secondary (or even further on) supporting roles demands a more extensive analysis. Such an investigation could lead to a more comprehensive guidance solution to alleviate the cognitive load in multiple ways during the analysis process.

Moreover, specific guidance methods and encoding may work better than others to address specific types of uncertainties. In our analysis, we noticed a heavy focus on addressing uncertainty events in the *insight* component of the VA cycle. However, guidance strategies can expand their targets to address other **uncertainties beyond *insight* component**. For example, collaboration guidance discussed in Section 6.3 mainly addresses uncertainties in the *insight* component. Yet, it can potentially address uncertainty events that originate in the *hypothesis* component by guiding the user in setting the parameters of a model, for instance, by augmenting and integrating knowledge from other users. Interestingly, none of the reviewed papers addressed uncertainties emerging from the data component. This gap could be due to the lack of incentive to build a visualization in the presence of data uncertainty, such as data incompleteness. Within this frame, data uncertainty can be perceived as an impediment to the visualization credibility.

In our work, we initially considered proposing two additional guidance roles *prediction* and *confirmation*. Prediction guidance can support users by mending a future knowledge gap by addressing uncertainties in **hypothesis**, **(insight-)interaction** or **(insight-)knowledge** components of the VA cycle, such as using predictive models [110]. On the other hand, confirmation relates to guidance that facilitates the analysis by validating user actions or hypotheses [167]. These two roles can be seen as sub-branches of the *analysis* guidance. Thus, we decided to integrate these strategies under the umbrella of *analysis guidance* to avoid an overly fragmented conceptualization. However, we recommend exploring these additional roles as separate strategies to guide users in VA in the future. They may present interesting and more robust solutions to address uncertainties emerging in the *insight* and *hypothesis* components of the VA cycle. Yet, a concrete conceptualization separating these guidance strategies is needed to establish practical design guidelines.

In general, **revisiting the conceptualization of guidance** in VA is crucial to allow for more concrete design models and applications. We propose that the conceptualization of guidance should consider the role of the guidance in the VA cycle as a whole—going even beyond the analysis role. This characterization should also allow an inclusive understanding of guidance encompassing assistive tools in all components of the VA cycle.

Guidance scope. Our analysis in Section 6 reveals that design decisions in guided-VA ignore **context-aware choices** for guidance scope. Only a few papers consider multiple scopes. Studies reveal that a *high scope* could be ineffective to users with advanced domain expertise [62]. Thus, instead of addressing the uncertainty, it risks producing more uncertainties and damaging user trust. In such cases, *low-scope* and *intermediate-scope* guidance seem more appropriate for addressing the uncertainties of expert users, while *high-scope* guidance better suits the needs of novice users. Furthermore, **switching between guidance scopes** and the **timing of guidance** remains a cumbersome research problem [44]. These research questions are crucial to address uncertainties in VA—yet, they remain largely unanswered.

Interestingly, we found a high proportion of *high-scope* design (7/11 papers) relative to other guidance roles. This finding suggests that visual mapping is viewed by visualization designers as more challenging to make executive decisions about, particularly for a novice (e.g., data worker). Design is viewed as an end product or artifact resulting from the analysis session, and its process is not necessarily a priority in the VA cycle. Assuming there is a "best" visualization for the analytical task, it is thus more effective to design *high-scope* guidance that advises users on the entire visualization design while maintaining their agency. This strategy can **unload cognitive burden** and produce a more efficient VA process.

However, relying continuously on *high-scope* guidance could risk the integrity of the process, as it can propagate bias in the analysis. For example, in a *high-scope collaboration guidance*, the system asserts one option to augment knowledge that favors toward a dominant knowledge, which may contain certain biases. The strategies in *collaboration guidance* (Section 6.3) show that a user can benefit more from guidance when **multiple scopes** are present. They can rely on *high-scope* guidance when they are entirely uncertain [138] but appreciate an *intermediate scope* when they have **enough expertise to assess** multiple suggested analytical paths [67]. On the other hand, a *low-scope* guidance seems to be accepted in most cases, especially when it is not intrusive [11,66].

8.2. Onboarding as guidance

Onboarding, as defined by Stoiber et al. [74], is a way to support the usability of VA. Collins et al. [45] propose designing training systems (onboarding) as guidance tools. Guiding users through VA has been identified as one of the valuable objectives of a guidance system. However, Stoiber et al. [74] draw a distinction between onboarding and guidance in VA. The gap between these two perspectives is related to the analysis stage and the guidance goal.

In VA, onboarding often takes place before the analysis even starts. Thus, it cannot be seen as a guidance tool [74]. For example, Dhanoa et al. [184] distinguish onboarding from guidance by connecting the former to usability knowledge gaps and the latter to sense-making knowledge gaps. However, suppose the scope of investigation regards the entire process from data collection to decision-making: the onboarding system can be considered internal to the VA process. This consideration allows it to be viewed as a guidance tool in the VA cycle. Moreover, onboarding strategies can also be presented during the interactive session, not to support the user's analysis and sense-making but to support the tool's usability. The purpose of *analysis guidance* is to support user insight, but the *onboarding guidance* supports usability and the user's understanding of the system [74].

More recently, work on onboarding began to converge in theory with guidance. For example, Stoiber et al. [185] present onboarding as a guiding tool. In that sense, *onboarding guidance* can address uncertainties produced by the user's *incomplete knowledge* or *ignorance* in interacting with a VA system (*knowledge* uncertainty component). Additionally, it can address *usage* uncertainty events in the *interaction* component, as seen in Fig. 18.

8.3. Guidance through communication uncertainty: Narrative and Persuasion

Through our analysis in Section 6.3, we identified communication as an additional source of uncertainty in the VA cycle. Only a few reviewed papers describe mechanisms intended to improve VA by improving the analyst's ability to impart VA insights in the decision-making process [66,139].

Communication uncertainty can arise when authoring visualizations and text to convey specific takeaways or messages about the data (e.g., [151]) to stakeholders during the VA cycle. This uncertainty is also evident in collaborative VA, which leverages social interaction for data exploration and analysis. For example, Coelho et al. [66], Mathisen et al. [67], and Park et al. [139] use provenance tracking to help analysts communicate the context and outcome of their visual exploration process to collaborators and viewers. The latter two also integrate presentation (slideshow) views, suggesting the importance of visually communicating insights during collaborative sense-making.

These uncertainties affecting VA communication, context, and messaging can potentially be addressed by *narrative guidance* [186] that helps users tailor the communication of insights to specific stakeholders, particularly to achieve rhetorical and persuasive goals [187]. Indeed, some of the aforementioned papers already draw inspiration from data-driven storytelling to design guidance for interpreting analysis results, bridging the explorative and communicative aspects of data analysis [67,139].

Moreover, we infer another possible role from the theme of trust that emerges in guidance: *persuasion guidance*. This guidance role relates to affective computing and persuasive systems design [188,189]. Oinas-Kukkonen and Harjumaa define persuasive systems as "systems designed to reinforce change or shape attitudes or behaviors or both without using coercion or deception" [190, p. 200]. As such, *persuasion guidance* can be deployed to address user knowledge uncertainties. It can be designed to change how the user conducts the analysis, given that a VA system is designed to be used for an extended period.

In consideration of possible social-ethical concerns [191], emphasizing that persuasive systems should not use *coercion or deception* is crucial. Moreover, to address uncertainties in knowledge, i.e., domain analysis, the guidance design should consider state-of-the-art knowledge. Otherwise, *persuasion guidance* can be a tool that propagates bias in the domain. Although these issues are challenging, *persuasion guidance* has the potential to effectively address uncertainties, presenting a forward-thinking strategy in guided VA design.

8.4. Limitations

We noted a crucial limitation in identifying the uncertainties addressed by guidance. These uncertainties were not explicitly discussed in the reviewed literature, and we had to explicitly infer and derive the uncertainty addressed by the reviewed papers. The most significant challenge in doing this was working with existing taxonomies to connect existing tools to specific uncertainty categories described in literature taxonomies. Revising the taxonomy of uncertainties can help address uncertainties more efficiently and effectively.

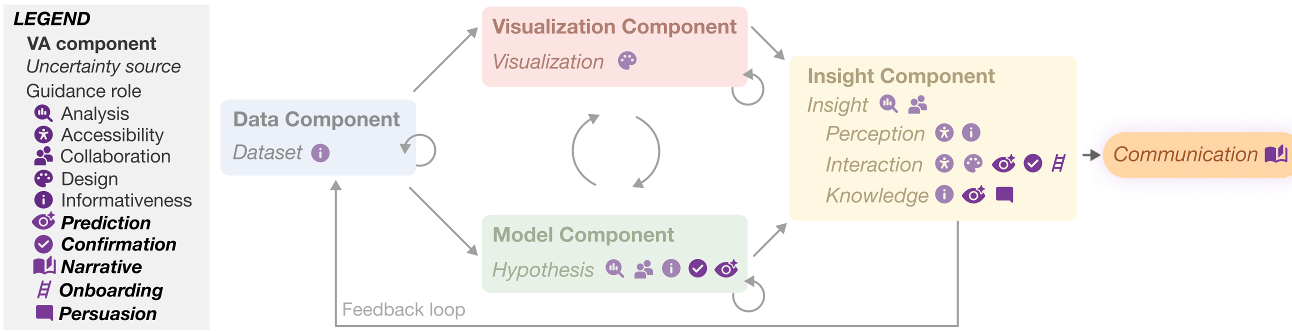

Fig. 18. We add potentially interesting guidance **roles** to explore to those in Fig. 1: onboarding, persuasion, and narrative guidance. In addition, we consider a new possible source of uncertainty: communication, i.e. uncertainty that arises when data is communicated to stakeholders.

In this STAR, we relied on Gillmann et al.'s [8] taxonomy that combines several taxonomies discussed in the literature. However, the description of the uncertainty events in this taxonomy is **complex to break apart**. For example, *perceptual* and *thinking* uncertainty events refer to the cognitive inability of the user to understand and think about visualizations, respectively. Distinguishing the user's understanding from thinking can be challenging; thus, it hinders the conclusive distinction between the two events. In design guidance, the techniques aim to address *perceptual* uncertainties in visualization to design visualizations. However, in the taxonomy, this event refers exclusively to users' cognition inability to read the visualization. This taxonomy can be improved by: (1) considering new uncertainty components, i.e., communication uncertainty; (2) investigating impairment-related uncertainty events; and (3) redefining current uncertainty events. Moreover, Gillmann et al.'s [8] taxonomy does not consider uncertainty accumulation and propagation through the analytical process. In such scenarios, guidance can also help unravel how uncertainties trickle down the pipeline.

Our understanding of uncertainties develops as our understanding of the human use of VA tools improves. Contemporary VA tools and processes can invite new uncertainty events not identified previously. With current practices, the user is given more agency in altering the VA system, for example, having a say in the visualization design, whether at the start or during the analysis. Uncertainties in communicating insights to stakeholders outside the system and its users are also increasingly influential in today's VA and decision-making processes. To address this gap, it is also helpful to **expand the traditional VA cycle model**. The model should include *communication* as an extra component given the contemporary understanding of how decisions are taken—including decisions through proxies, as seen in Fig. 18. For example, a patient can be seen as a user in the cycle, making decisions on their therapy plans through medical doctors as proxy users. Section 8.3 explains how guidance can address uncertainties in the *communication* component using *narrative guidance*.

Moreover, as discussed in Section 8.1, *accessibility guidance* techniques can address the knowledge gap produced by uncertainties triggered by several disabilities, such as visual impairment and IDD. However, taxonomies of uncertainties in VA, i.e., taxonomy in Fig. 2, need to consider events in the *insight* component generated by the physical, not only cognitive, disabilities. For example, the taxonomy refers to *usage* and *thinking* uncertainty in the *interaction* component. Neither of them sufficiently reflects the uncertainty faced by a user with either a visual disability or IDD. As discussed in Section 8.1, identifying uncertainties emerging from disabilities can allow **more inclusive VA** tools.

Furthermore, although our hybrid deductive-inductive approach to construct our taxonomy was conducted with rigor and extensive discussions among the co-authoring experts in visualization, visual analytics, and guidance, the inductive stage remains susceptible to bias. As highlighted in Section 3, two authors independently classified the papers into the conceptualized roles to minimize discrepancies in understanding the roles. Additional co-authors further reviewed these classifications and reclassified papers where necessary. This process did not show any significant misinterpretation of any of the five roles in our taxonomy. Moreover, the definition of the roles were defined in an iterative process. Given the breadth of the reviewed literature, we reached a theoretical saturation, where the inductive approach is comprehensive.

Finally, our taxonomy enables generalizability and robustness in the design of guidance to address uncertainties in the VA workflow. However, because guided VA is currently a vibrant and rich field of research, many guidance approaches may seem like a niche ad-hoc tool. Thus, the taxonomy might not be sufficient in its own to address this challenge. Coupling this taxonomy with templating frameworks, such as the recent Visual Analytics Context Protocol (VACP) [192], may provide a vehicle for a more comprehensive solution. Such solutions can also address the bias in conceptualizing guidance, particularly, knowledge, anchoring, and label biases. These biases can contribute to challenges and disagreements in identifying and classifying guidance in VA.

9. Conclusion and future research agenda

This paper presents a survey of guidance tools addressing uncertainties in VA. Our survey highlights several gaps in uncertainty taxonomies and guidance methods. Our work also highlights how guidance can effectively address uncertainties to overcome the challenges of quantifying and visualizing uncertainties. Guidance can address uncertainties in the analytical process more subtly without damaging users' trust. However, these tools can be improved when explicitly studied for their effectiveness in addressing uncertainties.

Our survey has revealed the need to extend the VA cycle. Also, a more comprehensive taxonomy of uncertainties is needed for future work to support more targeted guidance strategies. Moreover, guidance research must consider the appropriate design features based on the role of the guidance intervention. Future work can focus on expanding our understanding of uncertainties in VA and the application of guidance. Future research must also explore new sources of uncertainty in VA, i.e., communication uncertainty, re-conceptualize existing strategies as guidance, i.e., onboarding, and improve the richness of work that targets less-researched guidance roles, i.e., accessibility guidance. Finally, our work discusses six features of guidance. However, this survey does not go deep to taxonomize each feature. This endeavor is an open opportunity for future surveys as it is expected to enable researchers to improve choices in guidance design.

Reviewed papers key

Guidance roles:

Analysis (53); Accessibility (29); Collaboration (21); Design (16); Informativeness (9).

Uncertainty components:*
Insight (58); Visualization (11); Hypothesis (6);
Data (0)

Uncertainty scopes:*
Low (17); Intermediate (23); High (12).
Intermediate and High (6);
Low and High (4);
Low and Intermediate (2);
All scopes (2);
* *For papers reviewed in Section 6*

CRediT authorship contribution statement

Maath Musleh: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Davide Ceneda:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Ke Er Amy Zhang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Formal analysis, Data curation, Conceptualization. **Laura Garrison:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Conceptualization. **Ignacio Pérez-Messina:** Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. **Silvia Miksch:** Writing – review & editing, Conceptualization. **Renata G. Raidou:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.cag.2026.104739.

Data availability

Data will be made available on request.

References

[1] Cui W. Visual analytics: A comprehensive overview. Access 2019;7:81555–73. http://dx.doi.org/10.1109/ACCESS.2019.2923736.
[2] Thomas JJ, Cook KA. Illuminating the path: The research and development agenda for visual analytics. National Visualization and Analytics Center, U.S. Department of Homeland Security; 2005.
[3] Wong PC, Thomas J. Visual analytics. Cga 2004;24(5):20–1. http://dx.doi.org/10.1109/MCG.2004.39.
[4] Jusufi I, Musleh M, Chatzimparmpas A. The trust paradox in visualization: From building confidence to calibrating trust. In: EuroVis 2026 - short papers. The Eurographics Association; 2026, http://dx.doi.org/10.2312/evs.20261020.
[5] Raidou RG. Uncertainty visualization: Recent developments and future challenges in prostate cancer radiotherapy planning. In: euroVis workshop on reproducibility, verification, and validation in visualization. 2018, p. 13–7. http://dx.doi.org/10.2312/eurorv3.20181143.
[6] Seipp K, Gutiérrez F, Ochoa X, Verbert K. Towards a visual guide for communicating uncertainty in visual analytics. Jcl 2019;50:1–18. http://dx.doi.org/10.1016/j.jvlc.2018.11.004, .
[7] Keim DA, Mansmann F, Schneidewind J, Thomas J, Ziegler H. Visual data mining: Theory, techniques and tools for visual analytics. Springer Berlin Heidelberg; 2008, p. 76–90. http://dx.doi.org/10.1007/978-3-540-71080-6_6.
[8] Gillmann C, Maack RGC, Raith F, Pérez JF, Scheuermann G. A taxonomy of uncertainty events in visual analytics. Cga 2023;43(5):62–71. http://dx.doi.org/10.1109/MCG.2023.3299297.
[9] Maack RGC, Scheuermann G, Hagen H, Peñaloza JTH, Gillmann C. Uncertainty-aware visual analytics: Scope, opportunities, and challenges. Vc 2023;39(12):6345–66. http://dx.doi.org/10.1007/s00371-022-02733-6.
[10] Feng Y, Wang X, Pan B, Wong KK, Ren Y, Liu S, Yan Z, Ma Y, Qu H, Chen W. XNLI: Explaining and diagnosing NLI-based visual data analysis. TVCG 2024;30(7):3813–27. http://dx.doi.org/10.1109/TVCG.2023.3240003.
[11] Musleh M, Muren LP, Toussaint L, Vestergaard A, Gröller E, Raidou RG. Uncertainty guidance in proton therapy planning visualization. Cag 2023;111:166–79. http://dx.doi.org/10.1016/j.cag.2023.02.002, .
[12] Hawkins JM, editor. The Oxford encyclopedic English dictionary. New York: Oxford University Press; 1991.
[13] Ceneda D, Gschwandtner T, May T, Miksch S, Schulz HJ, Streit M, Tominski C. Characterizing guidance in visual analytics. TVCG 2017;23(1):111–20. http://dx.doi.org/10.1109/TVCG.2016.2598468.
[14] Bae J, Falkman G, Helldin T, Riveiro M. Data science in practice. Springer; 2019, p. 133–55. http://dx.doi.org/10.1007/978-3-319-97556-6_8.
[15] Ceneda D, Gschwandtner T, May T, Miksch S, Streit M, Tominski C. Guidance or no guidance? A decision tree can help. In: EuroVis workshop on visual analytics. 2018, p. 19–23. http://dx.doi.org/10.2312/eurova.20181107.
[16] Govender K. Age of agency. Productivity Press; 2023, p. 65–73. http://dx.doi.org/10.4324/9781032684895-7.
[17] Wang Y, Qi Y, Zhang XL, Chen S. Graph-neural-network-based user intent understanding for visual analytics. In: IEEE Pacific visualization symposium. 2024, p. 11–21. http://dx.doi.org/10.1109/PacificVis60374.2024.00011, .
[18] MacEachren AM. Visual analytics and uncertainty: Its not about the data. In: EuroVis workshop on visual analytics. 2015, p. 55–9. http://dx.doi.org/10.2312/eurova.20151104.
[19] Sacha D, Senaratne H, Kwon BC, Ellis G, Keim DA. The role of uncertainty, awareness, and trust in visual analytics. TVCG 2016;22(1):240–9. http://dx.doi.org/10.1109/TVCG.2015.2467591.
[20] Gillmann C, Saur D, Wischgoll T, Scheuermann G. Uncertainty-aware visualization in medical imaging - A survey. Cgf 2021;40(3):665–89. http://dx.doi.org/10.1111/cgf.14333.
[21] Potter K, Rosen P, Johnson CR. From quantification to visualization: A taxonomy of uncertainty visualization approaches. In: Uncertainty quantification in scientific computing. 2012, p. 226–49. http://dx.doi.org/10.1007/978-3-642-32677-6_15.
[22] Botha C, Preim B, Kaufman A, Takahashi S, Ynnerman A. Scientific visualization. Springer; 2014, p. 265–82. http://dx.doi.org/10.1007/978-1-4471-6497-5_23.
[23] Johnson CR, Sanderson AR. A next step: Visualizing errors and uncertainty. Cga 2003;23(5):6–10. http://dx.doi.org/10.1109/MCG.2003.1231171.
[24] Griethe H, Schumann H. The visualization of uncertain data: Methods and problems. In: Proceedings of the simulation und visualisierung. 2006, p. 143–56.
[25] Tannert C, Elvers HD, Jandrig B. The ethics of uncertainty: In the light of possible dangers, research becomes a moral duty. EMBO Rep 2007;8(10):892–6. http://dx.doi.org/10.1038/sj.embor.7401072.
[26] Bonneau GP, Hege HC, Johnson CR, Oliveira MM, Potter K, Rheingans P, Schultz T. Scientific visualization. Springer; 2014, p. 3–27. http://dx.doi.org/10.1007/978-1-4471-6497-5_1.
[27] Brodlie K, Osorio RA, Lopes A. Expanding the frontiers of visual analytics and visualization. Springer; 2012, p. 81–109. http://dx.doi.org/10.1007/978-1-4471-2804-5_6.
[28] Pang AT, Wittenbrink CM, Lodha SK. Approaches to uncertainty visualization. Vc 1997;13(8):370–90. http://dx.doi.org/10.1007/s003710050111.
[29] Ristovski G, Preusser T, Hahn HK, Linsen L. Uncertainty in medical visualization: Towards a taxonomy. Cag 2014;39:60–73. http://dx.doi.org/10.1016/j.cag.2013.10.015.
[30] Böröndy Á, Furmanová K, Raidou RG. Understanding the impact of statistical and machine learning choices on predictive models for radiotherapy. In: Eurographics workshop on visual computing for biology and medicine. 2022, p. 65–9. http://dx.doi.org/10.2312/vcbm.20221188.
[31] Pandey AV, Rall K, Satterthwaite ML, Nov O, Bertini E. How deceptive are deceptive visualizations? An empirical analysis of common distortion techniques. In: Proc. CHI conf. on human factors in computing systems. 2015, p. 1469–78. http://dx.doi.org/10.1145/2702123.2702608.
[32] Padilla LM, Ruginski IT, Creem-Regehr SH. Effects of ensemble and summary displays on interpretations of geospatial uncertainty data. Crpi 2012;2:40. http://dx.doi.org/10.1186/s41235-017-0076-1.
[33] Munzner T. A nested model for visualization design and validation. TVCG 2009;15(6):921–8. http://dx.doi.org/10.1109/TVCG.2009.111.
[34] Gillmann C, Smit NN, Gröller E, Preim B, Vilanova A, Wischgoll T. Ten open challenges in medical visualization. Cga 2021;41(5):7–15. http://dx.doi.org/10.1109/MCG.2021.3094858.
[35] Silver MS. Decisional guidance for computer-based decision support. Mis 1991;15(1):105–22. http://dx.doi.org/10.2307/249441.

[36] Silver MS. Handbook on decision support systems 2: Variations. Springer Berlin Heidelberg; 2008, p. 261–91. http://dx.doi.org/10.1007/978-3-540-48716-6_13.

[37] Ceneda D, Andrienko N, Andrienko G, Gschwandtner T, Miksch S, Piccolotto N, Schreck T, Streit M, Suschnigg J, Tominski C. Guide me in analysis: A framework for guidance designers. Cgf 2020;39(6):269–88. http://dx.doi.org/10.1111/cgf.14017, .

[38] Han W, Schulz HJ. Providing visual analytics guidance through decision support. InfoVis 2023;22(2):140–65. http://dx.doi.org/10.1177/14738716221147289, .

[39] Pérez-Messina I, Ceneda D, Miksch S. A methodology for task-driven guidance design. In: EuroVis workshop on visual analytics. 2023, p. 37–42. http://dx.doi.org/10.2312/eurova.20231094, .

[40] Sperrle F, Ceneda D, El-Assady M. Lotse: A practical framework for guidance in visual analytics. TVCG 2023;29(1):1124–34. http://dx.doi.org/10.1109/TVCG.2022.3209393, .

[41] Yanez F, Conati C, Ottley A, Nobre C. The state of the art in user-adaptive visualizations. Cgf 2025;44(1):e15271. http://dx.doi.org/10.1111/cgf.15271.

[42] Pérez-Messina I, Ceneda D, El-Assady M, Miksch S, Sperrle F. A typology of guidance tasks in mixed-initiative visual analytics environments. Cgf 2022;41(3):465–76. http://dx.doi.org/10.1111/cgf.14555, .

[43] Lee DJL, Dev H, Hu H, Elmeleegy H, Parameswaran A. Avoiding drill-down fallacies with VisPilot: Assisted exploration of data subsets. In: Proceedings of the international conference on intelligent user interfaces. 2019, p. 186–96. http://dx.doi.org/10.1145/3301275.3302307.

[44] Ceneda D, Gschwandtner T, Miksch S. A review of guidance approaches in visual data analysis: A multifocal perspective. Cgf 2019;38(3):861–79. http://dx.doi.org/10.1111/cgf.13730.

[45] Collins C, Andrienko N, Schreck T, Yang J, Choo J, Engelke U, Jena A, Dwyer T. Guidance in the human–machine analytics process. VisInfo 2018;2(3):166–80. http://dx.doi.org/10.1016/j.visinf.2018.09.003.

[46] Böck AJ, Größßbacher S, Vrablicz J, Stoiber C, Rind A, Suschnigg J, Schreck T, Aigner W, Wagner M. KAVAI: A systematic review of the building blocks for knowledge-assisted visual analytics in industrial manufacturing. Asci 2025;15(18):10172. http://dx.doi.org/10.3390/app151810172.

[47] Domova V, Vrotsou K. A model for types and levels of automation in visual analytics: A survey, a taxonomy, and examples. TVCG 2023;29(8):3550–68. http://dx.doi.org/10.1109/TVCG.2022.3163765.

[48] Enge K, Elmquist E, Caiola V, Rönnberg N, Rind A, Iber M, Lenzi S, Lan F, Höldrich R, Aigner W. Open your ears and take a look: A state-of-the-art report on the integration of sonification and visualization. Cgf 2024;43(3). http://dx.doi.org/10.1111/cgf.15114, e15114.

[49] Zhu S, Sun G, Jiang Q, Zha M, Liang R. A survey on automatic infographics and visualization recommendations. VisInfo 2020;4(3):24–40. http://dx.doi.org/10.1016/j.visinf.2020.07.002.

[50] Soni P, de Runz C, Bouali F, Venturini G. A survey on automatic dashboard recommendation systems. VisInfo 2024;8(1):67–79. http://dx.doi.org/10.1016/j.visinf.2024.01.002.

[51] Lock O, Bednarz T, Leao SZ, Pettit C. A review and reframing of participatory urban dashboards. Ccs 2020;20:100294. http://dx.doi.org/10.1016/j.ccs.2019.100294.

[52] Morana S, Schacht S, Scherp A, Maedche A. A review of the nature and effects of guidance design features. Dcs 2017;97:31–42. http://dx.doi.org/10.1016/j.dss.2017.03.003.

[53] Sperrle F, Schäfer H, Keim D, El-Assady M. Learning contextualized user preferences for co-adaptive guidance in mixed-initiative topic model refinement. Cgf 2021;40(3):215–26. http://dx.doi.org/10.1111/cgf.14301, .

[54] Horvitz E. Principles of mixed-initiative user interfaces. In: Proceedings of the SIGCHI conference on human factors in computing systems. 1999, p. 159–66. http://dx.doi.org/10.1145/302979.303030.

[55] Brisse R, Boche S, Majorczyk JF. KRAKEN: A knowledge-based recommender system for analysts, to kick exploration up a notch. In: Innovative security solutions for information technology and communications, vol. 13195, 2022, p. 1–17. http://dx.doi.org/10.1007/978-3-031-17510-7_1.

[56] Silva N, Blascheck T, Jianu R, Rodrigues N, Weiskopf D, Raubal M, Schreck T. Eye tracking support for visual analytics systems: Foundations, current applications, and research challenges. In: Proc. ACM symposium on eye tracking research & applications. 2019, http://dx.doi.org/10.1145/3314111.3319919, Article 11, 1–10, .

[57] Paden JR, Narechania A, Endert A. BiasBuzz: Combining visual guidance with haptic feedback to increase awareness of analytic behavior during visual data analysis. In: Extended abstracts of the CHI conference on human factors in computing systems. 2024, http://dx.doi.org/10.1145/3613905.3651064, Article 59, 1–7, .

[58] Hoque MN, Ehtesham-Ul-Haque M, Elmqvist N, Billah SM. Accessible data representation with natural sound. In: Proc. CHI conf. on human factors in computing systems. 2023, http://dx.doi.org/10.1145/3544548.3581087, Article 826, 1–19, .

[59] Langer T, Meyes R, Meisen T. Guided exploration of industrial sensor data. Cgf 2024;43(1):e15003. http://dx.doi.org/10.1111/cgf.15003, .

[60] Fadloun S, Meshoul S, Choutri K. CircleVis: A visualization tool for circular labeling arrangements and overlap removal. Asci 2022;12(22):11390. http://dx.doi.org/10.3390/app122211390, .

[61] Schelling X, Robertson S. A development framework for decision support systems in high-performance sport. Ijcss 2020;19(1):1–23. http://dx.doi.org/10.2478/ijcss-2020-0001.

[62] Pérez-Messina I, Ceneda D, Miksch S. Guided visual analytics for image selection in time and space. TVCG 2024;30(1):66–75. http://dx.doi.org/10.1109/TVCG.2023.3326572, .

[63] Filipov V, Ceneda D, Archambault D, Arleo A. TimeLighting: Guided exploration of 2D temporal network projections. Tvcg 2025;31(3):1932–44. http://dx.doi.org/10.1109/TVCG.2024.3514858, .

[64] Alam MZI, Islam S, Hoque E. SeeChart: Enabling accessible visualizations through interactive natural language interface for people with visual impairments. In: Proceedings of the international conference on intelligent user interfaces. 2023, p. 46–64. http://dx.doi.org/10.1145/3581641.3584099, .

[65] Obeid J, Hoque E. Chart-to-text: Generating natural language descriptions for charts by adapting the transformer model. In: Proceedings of the international conference on natural language generation. 2020, p. 138–47. http://dx.doi.org/10.18653/v1/2020.inlg-1.20, .

[66] Coelho D, Trailor R, Sill D, Engle S, Joshi A, Mankovskii S, Velez-Rojas M, Greenspan S, Mueller K. Collaborative visual analytics using blockchain. In: Cooperative design, visualization, and engineering, vol. 12341, 2020, p. 209–19. http://dx.doi.org/10.1007/978-3-030-60816-3_24, .

[67] Mathisen A, Horak T, Klokmose CN, Grønbæk K, Elmqvist N. InsideInsights: Integrating data-driven reporting in collaborative visual analytics. Cgf 2019;38(3):649–61. http://dx.doi.org/10.1111/cgf.13717, .

[68] Li JK, Xu S, (Chris) Ye Y, Ma KL. Resolving conflicting insights in asynchronous collaborative visual analysis. Cgf 2020;39(3):497–509. http://dx.doi.org/10.1111/cgf.13997, .

[69] Hopkins AK, Correll M, Satyanarayan A. VisuaLint: Sketchy in situ annotations of chart construction errors. Cgf 2020;39(3):219–28. http://dx.doi.org/10.1111/cgf.13975, .

[70] Chen H, Jiang S, Yu X, Yin H, Wang X, Hu Y, Wang C, Li C. GeoVis: A data-driven geographic visualization recommendation system via latent space encoding. Jvis 2024;27(4):603–22. http://dx.doi.org/10.1007/s12650-024-00986-y, .

[71] Behrisch M, Schreck T, Pfister H. GUIRO: User-guided matrix reordering. TVCG 2020;26(1):184–94. http://dx.doi.org/10.1109/TVCG.2019.2934300, .

[72] Baumberger C. Explicating objectual understanding: Taking degrees seriously. J Gen Philos Sci 2019;50(3):367–88. http://dx.doi.org/10.1007/s10838-019-09474-6.

[73] Belyakov S, Bozhenyuk A, Rozenberg I. Guidance in the visual analytics of cartographic images in the decision-making process. In: Advances in soft computing. 2020, p. 351–69. http://dx.doi.org/10.1007/978-3-030-60884-2_26, .

[74] Stoiber C, Ceneda D, Wagner M, Schetinger V, Gschwandtner T, Streit M, Miksch S, Aigner W. Perspectives of visualization onboarding and guidance in VA. VisInfo 2022;6(1):68–83. http://dx.doi.org/10.1016/j.visinf.2022.02.005.

[75] Miksch S, Leitte H, Chen M. Foundations of data visualization. Springer, Cham; 2020, p. 61–85. http://dx.doi.org/10.1007/978-3-030-34444-3_4, .

[76] Ottley A. The dance of logic and unpredictability: Examining the predictability of user behavior on visual analytics tasks. In: Proceedings of the international joint conference on computer vision, imaging and computer graphics theory and applications. 2024, p. 11–20. http://dx.doi.org/10.5220/0012671100003660, .

[77] Miller T. Explainable AI is dead, long live explainable AI! Hypothesis-driven decision support using evaluative AI. In: Proc. ACM conference on fairness, accountability, and transparency. 2023, p. 333—-342. http://dx.doi.org/10.1145/3593013.3594001, .

[78] Monadjemi S, Guo M, Gotz D, Garnett R, Ottley A. Human–computer collaboration for visual analytics: An agent-based framework. Cgf 2023;42(3):199–210. http://dx.doi.org/10.1111/cgf.14823, .

[79] Elmqvist N. Visualization for the blind. Interactions 2023;30(1):52–6. http://dx.doi.org/10.1145/3571737, .

[80] Marriott K, Lee B, Butler M, Cutrell E, Ellis K, Goncu C, Hearst M, McCoy K, Szafir DA. Inclusive data visualization for people with disabilities: A call to action. Interactions 2021;28(3):47–51. http://dx.doi.org/10.1145/3457875, .

[81] While Z, Crouser RJ, Sarvghad A. GerontoVis: Data visualization at the confluence of aging. CGF 2024;43(3):e15101. http://dx.doi.org/10.1111/cgf.15101, .

[82] Bovo R, Giunchi D, Alebri M, Steed A, Costanza E, Heinis T. Cone of vision as a behavioural cue for VR collaboration. Hci 2022;6(CSCW2). http://dx.doi.org/10.1145/3555615, Article 502, 27 pages, .

[83] Kraus M, Klein K, Fuchs J, Keim DA, Schreiber F, Sedlmair M. The value of immersive visualization. Cga 2021;41(4):125–32. http://dx.doi.org/10.1109/MCG.2021.3075258, .

[84] Vilone G, Longo L. Notions of explainability and evaluation approaches for explainable artificial intelligence. Inf Fusion 2021;76:89–106. http://dx.doi.org/10.1016/j.inffus.2021.05.009.
[85] Ahmad GS, Agarwal S, Mitra S, Rossi R, Doshi M, Porwal V, Paila SMK. ScaleViz: Scaling visualization recommendation models on large data. In: Advances in knowledge discovery and data mining, vol. 14649, 2024, p. 93–104. http://dx.doi.org/10.1007/978-981-97-2262-4_8, .
[86] Lei F, Fan A, MacEachren AM, Maciejewski R. GeoLinter: A linting framework for choropleth maps. TVCG 2024;30(2):1592–607. http://dx.doi.org/10.1109/TVCG.2023.3322372, .
[87] Qian X, Rossi RA, Du F, Kim S, Koh E, Malik S, Lee TY, Ahmed NK. Personalized visualization recommendation. TWEB 2022;16(3). http://dx.doi.org/10.1145/3538703, Article 11, 1–47, .
[88] Wang J, Li X, Li C, Peng D, Wang AZ, Gu Y, Lai X, Zhang H, Xu X, Dong X, Lin Z, Zhou J, Liu X, Chen W. AVA: An automated and AI-driven intelligent visual analytics framework. VisInfo 2024;8(2):106–14. http://dx.doi.org/10.1016/j.visinf.2024.06.002, .
[89] Ottley A, Garnett R, Wan R. Follow the clicks: Learning and anticipating mouse interactions during exploratory data analysis. Cgf 2019;38(3):41–52. http://dx.doi.org/10.1111/cgf.13670, .
[90] Ha S, Monadjemi S, Garnett R, Ottley A. A unified comparison of user modeling techniques for predicting data interaction and detecting exploration bias. TVCG 2023;29(1):483–92. http://dx.doi.org/10.1109/TVCG.2022.3209476, .
[91] Alsaiari A, Johnson A, Nishimoto A. PolyVis: Cross-device framework for collaborative visual data analysis. In: International conference on systems, man and cybernetics. 2019, p. 2870–6. http://dx.doi.org/10.1109/SMC.2019.8914209, .
[92] Kim NW, Joyner SC, Riegelhuth A, Kim YS. Accessible visualization: Design space, opportunities, and challenges. Cgf 2021;40(3):173–88. http://dx.doi.org/10.1111/cgf.14298, .
[93] Mishra P, Shrawankar U. Human vs. Machine eye for chart interpretation. In: IEEE region 10 symposium. 2022, p. 1–6. http://dx.doi.org/10.1109/TENSYMP54529.2022.9864560, .
[94] Zong J, Lee C, Lundgard A, Jang J, Hajas D, Satyanarayan A. Rich screen reader experiences for accessible data visualization. CGF 2022;41(3):15–27. http://dx.doi.org/10.1111/cgf.14519, .
[95] South L, Borkin MA. Photosensitive accessibility for interactive data visualizations. TVCG 2023;29(1):374–84. http://dx.doi.org/10.1109/TVCG.2022.3209359, .
[96] Wu K. Towards a universal cognitive tool: designing accessible visualization for people with intellectual and developmental disabilities. SIGACCESS 2021;(131). http://dx.doi.org/10.1145/3507912.3507913, Article 1, 1–6, .
[97] Wu K, Szafir DA. Empowering people with intellectual and developmental disabilities through cognitively accessible visualizations. In: IEEE workshop on visualization for social good. 2023, p. 1–5. http://dx.doi.org/10.1109/VIS4Good60218.2023.00007, .
[98] Ceneda D, Arleo A, Gschwandtner T, Miksch S. Show me your face: Towards an automated method to provide timely guidance in visual analytics. TVCG 2022;28(12):4570–81. http://dx.doi.org/10.1109/TVCG.2021.3094870, .
[99] Gómez DA, Charpak N, Montealegre A, Hernández JT. VALS: Supporting visual data analysis in longitudinal clinical studies. Access 2023;11:28820–30. http://dx.doi.org/10.1109/ACCESS.2023.3259972, .
[100] Lohfink AP, Anton SDD, Leitte H, Garth C. Knowledge rocks: Adding knowledge assistance to visualization systems. TVCG 2022;28(1):1117–27. http://dx.doi.org/10.1109/TVCG.2021.3114687, .
[101] Sperrle F, Jeitler A, Bernard J, Keim D, El-Assady M. Co-adaptive visual data analysis and guidance processes. CAG 2021;100:93–105. http://dx.doi.org/10.1016/j.cag.2021.06.016, .
[102] Lundgard A, Lee C, Satyanarayan A. Sociotechnical considerations for accessible visualization design. In: IEEE visualization and visual analytics. 2019, p. 16–20. http://dx.doi.org/10.1109/VISUAL.2019.8933762, .
[103] Musleh M, Ceneda D, Ehlers H, Raidou RG. ConAn: Measuring and evaluating user confidence in visual data analysis under uncertainty. Cgf 2024;44(1):e15272. http://dx.doi.org/10.1111/cgf.15272.
[104] Jianu R, Silva N, Rodrigues N, Blascheck T, Schreck T, Weiskopf D. Gaze-aware visualisation: Design considerations and research agenda. Cgf 2025;44(6):e70097. http://dx.doi.org/10.1111/cgf.70097, .
[105] Pérez-Messina I, Angelini M, Ceneda D, Tominski C, Miksch S. Coupling guidance and progressiveness in visual analytics. Cgf 2025;44(3):e70115. http://dx.doi.org/10.1111/cgf.70115, .
[106] Holter S, El-Assady M. Deconstructing human-AI collaboration: Agency, interaction, and adaptation. Cgf 2024;43(3):e15107. http://dx.doi.org/10.1111/cgf.15107, .
[107] Chen C, Hoffswell J, Guo S, Rossi R, Chan YY, Du F, Koh E, Liu Z. WhatsNext: Guidance-enriched exploratory data analysis with interactive, low-code notebooks. In: IEEE symposium on visual languages and human-centric computing. 2023, p. 209–14. http://dx.doi.org/10.1109/VL-HCC57772.2023.00033, .
[108] Shi Y, Chen B, Chen Y, Jin Z, Xu K, Jiao X, Gao T, Cao N. Supporting guided exploratory visual analysis on time series data with reinforcement learning. TVCG 2024;30(1):1172–82. http://dx.doi.org/10.1109/TVCG.2023.3327200, .
[109] Jiang Q, Sun G, Li T, Tang J, Xia W, Zhu S, Liang R. Qutaber: Task-based exploratory data analysis with enriched context awareness. Jvis 2024;27:503–20. http://dx.doi.org/10.1007/s12650-024-00975-1, .
[110] Gadhave K, Görtler J, Cutler Z, Nobre C, Deussen O, Meyer M, Phillips JM, Lex A. Predicting intent behind selections in scatterplot visualizations. InfoVis 2021;20(4):207–28. http://dx.doi.org/10.1177/14738716211038604, .
[111] Gotz D, Wang W, Chen AT, Borland D. Visualization model validation via inline replication. InfoVis 2019;18(4):405–25. http://dx.doi.org/10.1177/1473871618821747, .
[112] Wang AZ, Borland D, Gotz D. Beyond correlation: Incorporating counterfactual guidance to better support exploratory visual analysis. TVCG 2025;31(1):776–86. http://dx.doi.org/10.1109/TVCG.2024.3456369, .
[113] Wang AZ, Borland D, Gotz D. A framework to improve causal inferences from visualizations using counterfactual operators. InfoVis 2024;24(1):24–41. http://dx.doi.org/10.1177/14738716241265120, .
[114] Monadjemi S, Garnett R, Ottley A. Competing models: Inferring exploration patterns and information relevance via Bayesian model selection. TVCG 2021;27(2):412–21. http://dx.doi.org/10.1109/TVCG.2020.3030430, .
[115] Li T, Zhu Y. Functional narrative animation as visual feedback for interactions in 3D visualization. Cav 2022;33(3–4):e2086. http://dx.doi.org/10.1002/cav.2086, .
[116] Narechania A, Coscia A, Wall E, Endert A. Lumos: Increasing awareness of analytic behavior during visual data analysis. TVCG 2022;28(1):1009–18. http://dx.doi.org/10.1109/TVCG.2021.3114827, .
[117] Han Q, Thom D, John M, Koch S, Ertl T, Heimerl F. Visual quality guidance for document exploration with focus+context techniques. In: IEEE Pacific visualization symposium. 2019, p. 158–73. http://dx.doi.org/10.1109/PacificVis.2019.00026, .
[118] Palomino Valdivia Fd, Huillcen Baca HA. Guidance for interactive visual analysis in multivariate time series preprocessing. Sensors 2025;25:5617. http://dx.doi.org/10.3390/s25185617, .
[119] Musleh M, Raidou RG, Ceneda D. TrustME: A context-aware explainability model to promote user trust in guidance. Tvcg 2025;31(10):8040–56. http://dx.doi.org/10.1109/TVCG.2025.3562929.
[120] Piccolotto N, Bögl M, Gschwandtner T, Muehlmann C, Nordhausen K, Filzmoser P, Miksch S. TBSSvis: Visual analytics for temporal blind source separation. VisInfo 2022;6(4):51–66. http://dx.doi.org/10.1016/j.visinf.2022.10.002, .
[121] Leite RA, Arleo A, Sorger J, Gschwandtner T, Miksch S. Hermes: Guidance-enriched visual analytics for economic network exploration. VisInfo 2020;4(4):11–22. http://dx.doi.org/10.1016/j.visinf.2020.09.006, .
[122] Li Y, Qi Y, Shi Y, Chen Q, Cao N, Chen S. Diverse interaction recommendation for public users exploring multi-view visualization using deep learning. TVCG 2023;29(1):95–105. http://dx.doi.org/10.1109/TVCG.2022.3209461, .
[123] Harris C, Rossi RA, Malik S, Hoffswell J, Du F, Lee TY, Koh E, Zhao H. Visual insight recommendation: From ranking insight visualizations to insight types. In: IEEE international conference on big data (bigData). 2023, p. 1716–25. http://dx.doi.org/10.1109/BigData59044.2023.10386099, .
[124] Yen CH, Yen YC, Fu WT. An intelligent assistant for mediation analysis in visual analytics. In: Proceedings of the international conference on intelligent user interfaces. 2019, p. 432—-436. http://dx.doi.org/10.1145/3301275.3302325, .
[125] Witschard D, Jusufi I, Kucher K, Kerren A. Visually guided network reconstruction using multiple embeddings. In: IEEE Pacific visualization symposium. Pacificvis, 2023, p. 212–6. http://dx.doi.org/10.1109/PacificVis56936.2023.00031, .
[126] Han W, Schulz HJ. Exploring vibrotactile cues for interactive guidance in data visualization. In: Proceedings of the international symposium on visual information communication and interaction. 2020, http://dx.doi.org/10.1145/3430036.3430042, Article 14, 1–10, .
[127] Palomino Valdivia Fd, Huillcen Baca HA, Cuadros Valdivia AM. Guided visual analysis of multivariate time series. In: Advances in information and communication. 2022, p. 247–62. http://dx.doi.org/10.1007/978-3-030-98012-2_19, .
[128] Palomino Valdivia Fd, Huillcen Baca HA, Soria Solis I, Aquino Cruz M, Cuadros Valdivia AM. Guided interactive visualization for detecting cyclical patterns in time series. In: Advances in information and communication, vol. 651, 2023, p. 391–402. http://dx.doi.org/10.1007/978-3-031-28076-4_29, .
[129] Rodrigues N, Shao L, Yan JJ, Schreck T, Weiskopf D. Eye gaze on scatterplot: Concept and first results of recommendations for exploration of SPLOMs using implicit data selection. In: Proc. ACM symposium on eye tracking research & applications. 2022, http://dx.doi.org/10.1145/3517031.3531165, Article 59, 1–7, .

[130] Srinivasan A, Setlur V. Snowy: Recommending utterances for conversational visual analysis. In: The annual ACM symposium on user interface software and technology. 2021, p. 864–80. http://dx.doi.org/10.1145/3472749.3474792.

[131] Duarte D, Costa R, Bizarro P, Duarte C. AutoVizuA11y: A tool to automate screen reader accessibility in charts. Cgf 2024;43(3):e15099. http://dx.doi.org/10.1111/cgf.15099.

[132] Chundury P, Reyazuddin Y, Jordan JB, Lazar J, Elmqvist N. TactualPlot: Spatializing data as sound using sensory substitution for touchscreen accessibility. TVCG 2024;30(1):836–46. http://dx.doi.org/10.1109/TVCG.2023.3326937.

[133] Gorniak J, Kim Y, Wei D, Kim NW. VizAbility: Enhancing chart accessibility with LLM-based conversational interaction. In: The annual ACM symposium on user interface software and technology. 2024, http://dx.doi.org/10.1145/3654777.3676414, Article 89, 1–19.

[134] Mishra P, Kumar S, Chaube MK, Shrawankar U. ChartVi: Charts summarizer for visually impaired. Jcl 2022;69:101107. http://dx.doi.org/10.1016/j.cola.2022.101107.

[135] Al-Kady Y, Abdel-Wahab N, Hassanein F, Al-Alfy R, El-Malatawy L, Ammar R, Al-Shetairy M, Amin S. Chartlytics: Chart image classification and data extraction. In: International conference on intelligent computing and information systems. 2023, p. 515–22. http://dx.doi.org/10.1109/ICICIS58388.2023.10391160.

[136] McNutt A, McCracken MK, Eliza IJ, Hajas D, Wagoner J, Lanza N, Wilburn J, Creeem-Reger S, Lex A. Accessible text descriptions for UpSet plots. Cgf 2025;44(3):e70102. http://dx.doi.org/10.1111/cgf.70102.

[137] Liu R, Wen X, Jiang M, Yang G, Zhang C, Chen X. Multiuser collaborative illustration and visualization for volumetric scientific data. Spe 2021;51(5):1080–96. http://dx.doi.org/10.1002/spe.2935.

[138] Ens B, Goodwin S, Prouzeau A, Anderson F, Wang FY, Gratzl S, Lucarelli Z, Moyle B, Smiley J, Dwyer T. Uplift: A tangible and immersive tabletop system for casual collaborative visual analytics. TVCG 2021;27(2):1193–203. http://dx.doi.org/10.1109/TVCG.2020.3030334.

[139] Park D, Suhail M, Zheng M, Dunne C, Ragan E, Elmqvist N. StoryFacets: A design study on storytelling with visualizations for collaborative data analysis. InfoVis 2022;21(1):3–16. http://dx.doi.org/10.1177/14738716211032653.

[140] Garrido D, Jacob J, Silva DC. Building a prototype for easy to use collaborative immersive analytics. In: Computational science – ICCS, vol. 12742, 2021, p. 628–41. http://dx.doi.org/10.1007/978-3-030-77961-0_50.

[141] Bovo R, Giunchi D, Sidenmark L, Newn J, Gellersen H, Costanza E, Heinis T. Speech-augmented cone-of-vision for exploratory data analysis. In: Proc. CHI conf. on human factors in computing systems. 2023, http://dx.doi.org/10.1145/3544548.3581283, Article 162, 1–18.

[142] Reski N, Alissandrakis A, Tyrkkö J, Kerren A. "Oh, that's where you are!" – Towards a hybrid asymmetric collaborative immersive analytics system. In: Proceedings of the 11th nordic conference on human-computer interaction: shaping experiences, shaping society. 2020, http://dx.doi.org/10.1145/3419249.3420102, Article 5, 1–12.

[143] Seraji MR, Stuerzlinger W. XVCollab: An immersive analytics tool for asymmetric collaboration across the virtuality spectrum. In: IEEE international symposium on mixed and augmented reality adjunct. 2022, p. 146–54. http://dx.doi.org/10.1109/ISMAR-Adjunct57072.2022.00035.

[144] Degbelo A, Sarfraz S, Kray C. Data scale as cartography: A semi-automatic approach for thematic web map creation. Cgis 2020;47(2):153–70. http://dx.doi.org/10.1080/15230406.2019.1677176.

[145] Sharaf MA, Helal H, Zaki N, Alketbi W, Alkaabi L, Alshamsi S, Alhefeiti F. Automated recommendation of aggregate visualizations for crowdfunding data. Algorithms 2024;17(6):244. http://dx.doi.org/10.3390/a17060244.

[146] Pandey A, Srinivasan A, Setlur V. MEDLEY: Intent-based recommendations to support dashboard composition. TVCG 2023;29(1):1135–45. http://dx.doi.org/10.1109/TVCG.2022.3209421.

[147] Zhu J, Wu M, Zhou Y, Cao N, Zhu H, Zhu M. Dowsing: A task-driven approach for multiple-view visualizations dynamic recommendation. Jvis 2024;27(4):695–712. http://dx.doi.org/10.1007/s12650-024-00989-9.

[148] Song Y, Zhao X, Wong RCW. Marrying dialogue systems with data visualization: Interactive data visualization generation from natural language conversations. In: Proceedings of of the SIGKDD conference on knowledge discovery & data mining. 2024, p. 2733–44. http://dx.doi.org/10.1145/3637528.3671935.

[149] Ying L, Tang T, Luo Y, Shen L, Xie X, Yu L, Wu Y. GlyphCreator: Towards example-based automatic generation of circular glyphs. TVCG 2022;28(1):400–10. http://dx.doi.org/10.1109/TVCG.2021.3114877.

[150] Chen C, Lee B, Wang Y, Chang Y, Liu Z. Mystique: Deconstructing SVG charts for layout reuse. TVCG 2024;30(1):447–57. http://dx.doi.org/10.1109/TVCG.2023.3327354.

[151] Kim DH, Choi S, Kim J, Setlur V, Agrawala M. EMPHASISCHECKER: A tool for guiding chart and caption emphasis. TVCG 2024;30(1):120–30. http://dx.doi.org/10.1109/TVCG.2023.3327150.

[152] Tian Z, Zhai X, van Driel D, van Steenpaal G, Espadoto M, Telea A. Using multiple attribute-based explanations of multidimensional projections to explore high-dimensional data. CAG 2021;98:93–104. http://dx.doi.org/10.1016/j.cag.2021.04.034.

[153] Thijssen J, Tian Z, Telea A. Interactive tools for explaining multidimensional projections for high-dimensional tabular data. CAG 2024;122:103987. http://dx.doi.org/10.1016/j.cag.2024.103987.

[154] Srinivasan A, Drucker SM, Endert A, Stasko J. Augmenting visualizations with interactive data facts to facilitate interpretation and communication. TVCG 2019;25(1):672–81. http://dx.doi.org/10.1109/TVCG.2018.2865145.

[155] Marcílio-Jr WE, Eler DM. Explaining dimensionality reduction results using Shapley values. Eswa 2021;178:115020. http://dx.doi.org/10.1016/j.eswa.2021.115020.

[156] Corbugy S, Marion R, Frénay B. Gradient-based explanation for non-linear non-parametric dimensionality reduction. Dmkd 2024. http://dx.doi.org/10.1007/s10618-024-01055-6.

[157] Bibal A, Clarinval A, Dumas B, Frénay B. IXVC: An interactive pipeline for explaining visual clusters in dimensionality reduction visualizations with decision trees. Array 2021;11:100080. http://dx.doi.org/10.1016/j.array.2021.100080.

[158] Mackinlay J. Automating the design of graphical presentations of relational information. TOG 1986;5(2):110–41. http://dx.doi.org/10.1145/22949.22950.

[159] Ceneda D, Collins C, El-Assady M, Miksch S, Tominski C, Arleo A. A heuristic approach for dual expert/end-user evaluation of guidance in visual analytics. TVCG 2024;30(1):997–1007. http://dx.doi.org/10.1109/TVCG.2023.3327152.

[160] Ceneda D, Gschwandtner T, Miksch S, Tominski C. Guided visual exploration of cyclical patterns in time-series. In: Proceedings of the IEEE symposium on visualization in data science. 2018, p. 1–8.

[161] Amorim FR, Pugliesi EA. Static and dynamic flow maps: Comparing the usability between impaired color vision and normal color vision. Bcg 2021;27(4):e2021029. http://dx.doi.org/10.1590/s1982-21702021000400029.

[162] Kim NW, Ataguba G, Joyner SC, Zhao C, Im H. Beyond alternative text and tables: Comparative analysis of visualization tools and accessibility methods. Cgf 2023;42(3):323–35. http://dx.doi.org/10.1111/cgf.14833.

[163] Ha S, Monadjemi S, Ottley A. Guided by AI: Navigating trust, bias, and data exploration in AI-guided visual analytics. Cgf 2024;43(3):e15108. http://dx.doi.org/10.1111/cgf.15108.

[164] Block JE, Esmaeili S, Ragan ED, Goodall JR, Richardson GD. The influence of visual provenance representations on strategies in a collaborative hand-off data analysis scenario. TVCG 2023;29(1):1113–23. http://dx.doi.org/10.1109/TVCG.2022.3209495.

[165] Kang J, Zhou Y, Rajarathinam RJ, Tan Y, Shaffer DW. Unveiling joint attention dynamics: Examining multimodal engagement in an immersive collaborative astronomy simulation. Compedu 2024;213(C). http://dx.doi.org/10.1016/j.compedu.2024.105002.

[166] Liu Y, Zhang Z, Pan Y, Li Y, Liang HN, Craig P, Yu L. A study of zooming, interactive lenses and overview+detail techniques in collaborative map-based tasks. In: IEEE Pacific visualization symposium. 2023, p. 11–20. http://dx.doi.org/10.1109/PacificVis56936.2023.00009.

[167] Alrøe SF, Hoggan E, Schulz HJ. Highways and tunnels: Force feedback guidance for visualisations. In: EuroVis. 2024, p. 1–5. http://dx.doi.org/10.2312/evs.20241060.

[168] Ha S, Kern A, Bancilhon M, Ottley A. Expectation versus reality: The failed evaluation of a mixed-initiative visualization system. In: IEEE workshop celebrating the scientific value of failure. 2020, p. 1–5. http://dx.doi.org/10.1109/FailFest51498.2020.00005.

[169] Wang AZ, Borland D, Gotz D. An empirical study of counterfactual visualization to support visual causal inference. InfoVis 2024;23(2):197–214. http://dx.doi.org/10.1177/14738716241229437.

[170] Alcaraz-Martínez R, Ribera M, Adeva-Fillol A, Pascual-Almenara A. Enhancing statistical chart accessibility for people with low vision: Insights from a user test. Uais 2024. http://dx.doi.org/10.1007/s10209-024-01111-4.

[171] Cherukuru NW, Bailey DA, Fourment T, Hatheway B, Holland MM, Rehme M. Beyond visuals: Examining the experiences of geoscience professionals with vision disabilities in accessing data visualizations. In: IEEE visualization and visual analytics. 2022, p. 160–4. http://dx.doi.org/10.1109/VIS54862.2022.00041.

[172] Chundury P, Patnaik B, Reyazuddin Y, Tang C, Lazar J, Elmqvist N. Towards understanding sensory substitution for accessible visualization: An interview study. TVCG 2022;28(1):1084–94. http://dx.doi.org/10.1109/TVCG.2021.3114829.

[173] Wu K, Petersen E, Ahmad T, Burlinson D, Tanis S, Szafir DA. Understanding data accessibility for people with intellectual and developmental disabilities. In: Proc. CHI conf. on human factors in computing systems. 2021, http://dx.doi.org/10.1145/3411764.3445743, Article 606, 1–16.

[174] Angerbauer K, Rodrigues N, Cutura R, Öney S, Pathmanathan N, Morariu C, Weiskopf D, Sedlmair M. Accessibility for color vision deficiencies: Challenges and findings of a large scale study on paper figures. In: Proc. CHI conf. on human factors in computing systems. 2022, http://dx.doi.org/10.1145/3491102.3502133, Article 134, 1–23, .

[175] Engel C, Schmalfuß-Schwarz J. ExcelViZ: Automated generation of high-level, adaptable scatterplot descriptions based on a user study. In: Universal access in human-computer interaction, vol. 14698, 2024, p. 393–412. http://dx.doi.org/10.1007/978-3-031-60884-1_27, .

[176] Elavsky F, Bennett C, Moritz D. How accessible is my visualization? Evaluating visualization accessibility with chartability. Cgf 2022;41(3):57–70. http://dx.doi.org/10.1111/cgf.14522, .

[177] Sperrle F, El-Assady M, Arleo A, Ceneda D. A wizard of Oz study of guidance strategies and dynamics. Tvcg 2025;31(9):4968–82. http://dx.doi.org/10.1109/TVCG.2024.3418782, .

[178] Friedl-Knirsch J, Stach C, Pointecker F, Anthes C, Roth D. A study on collaborative visual data analysis in augmented reality with asymmetric display types. TVCG 2024;30(5):2633–43. http://dx.doi.org/10.1109/TVCG.2024.3372103, .

[179] Garrido D, Jacob J, Silva DC. Performance impact of immersion and collaboration in visual data analysis. In: IEEE international symposium on mixed and augmented reality. 2023, p. 780–9. http://dx.doi.org/10.1109/ISMAR59233.2023.00093, .

[180] Lee B, Hu X, Cordeil M, Prouzeau A, Jenny B, Dwyer T. Shared surfaces and spaces: Collaborative data visualisation in a co-located immersive environment. TVCG 2021;27(2):1171–81. http://dx.doi.org/10.1109/TVCG.2020.3030450, .

[181] Bao CS, Li S, Flores SG, Correll M, Battle L. Recommendations for visualization recommendations: Exploring preferences and priorities in public health. In: Proc. CHI conf. on human factors in computing systems. 2022, http://dx.doi.org/10.1145/3491102.3501891, Article 411, 1–17, .

[182] Zehrung R, Singhal A, Correll M, Battle L. Vis ex machina: An analysis of trust in human versus algorithmically generated visualization recommendations. In: Proc. CHI conf. on human factors in computing systems. 2021, http://dx.doi.org/10.1145/3411764.3445195, Article 602, 1–12, .

[183] Wimer BL, South L, Wu K, Szafir DA, Borkin MA, Metoyer RA. Beyond vision impairments: Redefining the scope of accessible data representations. Tvcg 2024;30(12):7619–36. http://dx.doi.org/10.1109/TVCG.2024.3356566.

[184] Dhanoa V, Walchshofer C, Hinterreiter A, Stitz H, Groeller E, Streit M. A process model for dashboard onboarding. Cgf 2022;41(3):501–13. http://dx.doi.org/10.1111/cgf.14558.

[185] Stoiber C, Moitzi D, Stitz H, Grassinger F, Prakash ASG, Girardi D, Streit M, Aigner W. VisAhoi: Towards a library to generate and integrate visualization onboarding using high-level visualization grammars. VisInfo 2024;8(3):1–17. http://dx.doi.org/10.1016/j.visinf.2024.06.001.

[186] Segel E, Heer J. Narrative visualization: Telling stories with data. Tvcg 2010;16(6):1139–48. http://dx.doi.org/10.1109/TVCG.2010.179.

[187] Hullman J, Diakopoulos N. Visualization rhetoric: Framing effects in narrative visualization. Tvcg 2011;17(12):2231–40. http://dx.doi.org/10.1109/TVCG.2011.255.

[188] Oinas-Kukkonen H, Harjumaa M. Persuasive systems design: Key issues, process model, and system features. Cais 2009;24:485–501. http://dx.doi.org/10.17705/1CAIS.02428.

[189] Tao J, Tan T. Affective computing: A review. In: Affective computing and intelligent interaction, vol. 3784, 2005, p. 981–95. http://dx.doi.org/10.1007/11573548_125.

[190] Oinas-Kukkonen H, Harjumaa M. Towards deeper understanding of persuasion in software and information systems. In: First international conference on advances in computer-human interaction. 2008, p. 200–5. http://dx.doi.org/10.1109/ACHI.2008.31.

[191] Subagdja B. Agent-based modeling for developing pervasive persuasive systems. In: International conference on advanced computer science and information systems. 2015, p. 23–8. http://dx.doi.org/10.1109/ICACSIS.2015.7415198.

[192] Stähle T, Gyarmati PF, Spinner T, Sevastjanova R, Moritz D, El-Assady M. VACP: Visual analytics context protocol. 2026, URL https://arxiv.org/abs/2603.29322, arXiv:2603.29322.