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# Exploring annotation taxonomy in grouped bar charts: A qualitative classroom study

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**Abstract**

Annotations are an essential part of data analysis and communication in visualizations, which focus a readers attention on critical visual elements (e.g. an arrow that emphasizes a downward trend in a bar chart). Annotations enhance comprehension, mental organization, memorability, user engagement, and interaction and are crucial for data externalization and exploration, collaborative data analysis, and narrative storytelling in visualizations. However, we have identified a general lack of understanding of how people annotate visualizations to support effective communication. In this study, we evaluate how visualization students annotate grouped bar charts when answering high-level questions about the data. The resulting annotations were qualitatively coded to generate a taxonomy of how they leverage different visual elements to communicate critical information. We found that the annotations used significantly varied by the task they were supporting and that whereas several annotation types supported many tasks, others were usable only in special cases. We also found that some tasks were so challenging that ensembles of annotations were necessary to support the tasks sufficiently. The resulting taxonomy of approaches provides a foundation for understanding the usage of annotations in broader contexts to help visualizations achieve their desired message.

**Keywords**

Human-centered computing, visualization, empirical study, bar chart, annotation, taxonomy

## Introduction

Annotations, which are supplementary graphical or textual elements added to visualizations,[1] play a pivotal role in data visualizations. They not only enhance comprehension by providing additional context and emphasizing specific data elements,[1] but also significantly improve memorability, recall,[2–4] and user interaction.[5–8] Furthermore, annotations facilitate tasks such as data externalization and exploration,[9–17] thereby supporting interactive visual analysis[9,18] and collaborative data analysis,[12,19–26] as well as enriching narrative storytelling.[27–34]

Despite the recognized benefits of annotations in data visualization, a comprehensive categorization of their types and practical uses remains elusive, as does understanding how they interact with the analytic tasks[35] people perform when exploring data. This gap highlights the need for a structured design space for annotations, calling for an in-depth exploration of the diverse annotation techniques. Such an exploration is vital to grasp how different annotations are applied

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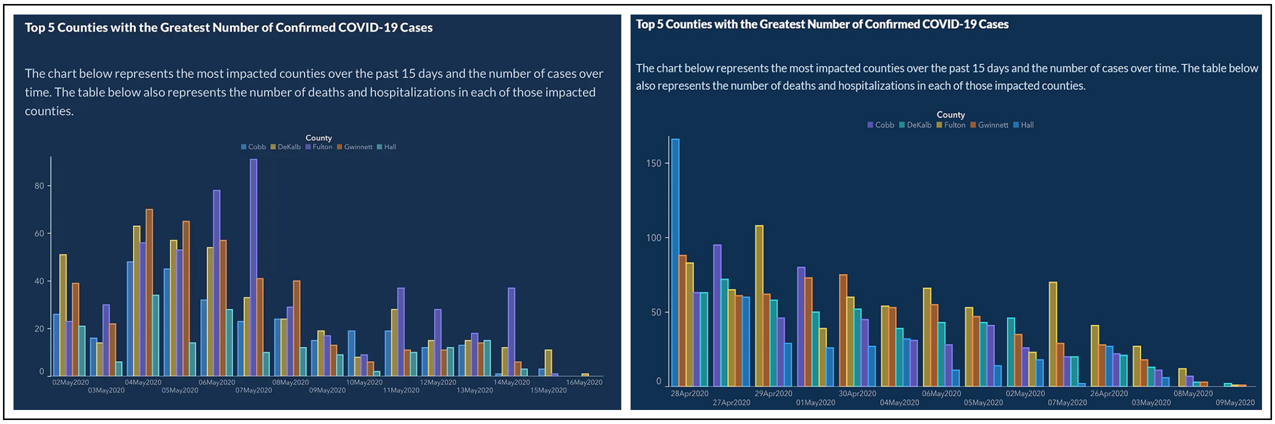


**Figure 1.** The viral visualization (left) and the corrected version (right) were created by the Georgia Department of Public Health (GDPH).[36] The viral visualization was generally criticized for its unorthodox highest-to-lowest ordering of bars, whereas the corrected one uses chronological arrangement.

and the specific analytic tasks they facilitate. This deeper understanding will significantly enrich the practice of data visualization, guiding us to our central research question: What are the specific encodings used in annotations, and how do these support various analytic tasks in data visualizations?

As a motivating example, in 2020, a Georgia Department of Public Health (GDPH) visualization became a viral sensation for its misleading nature (see Figure 1).[36] The grouped bar chart was seen as deceptive for its unorthodox ordering of bars, ordered from highest to lowest instead of chronologically. Clear labeling of the graphic can help to overcome such issues,[37] and from a technical perspective, the GDPH graphic did have the dates labeled. However, the graphic failed to draw the viewer's attention to the unorthodox ordering. Although some may have considered the visualization irredeemable, better use of annotations could have overcome or at least mitigated such an issue. This incident underscores the importance of understanding the application of annotations in visualization, prompting our exploration into how diverse annotation techniques can be strategically employed to enhance clarity and comprehension.

We conducted a study to better understand the available techniques for annotating a visualization, particularly bar charts, which are known for their widespread use and straightforward structure. This structure facilitates easy interpretation and annotation, making bar charts ideal for exploring how annotations support visual analytic tasks.[3,37,38] The study focused on the forms of annotations used by undergraduate and graduate visualization students when prompted with high-level questions about the data, aiming to better understand the options available for annotating the visualization and the analysis tasks they support. Our study provided students with three grouped bar chart visualizations, each with four high-level questions. We asked students to individually enumerate which of five low-level tasks (retrieve the value, filter, compute a derived value, find extremum, and sort) were required to answer those questions and annotate the bar charts to make the questions as easy as possible to answer. The goal of this activity was ideation, that is, we wanted students to creatively explore the space of possible annotation types so that we could later extract the breadth of options available. Figure 2 illustrates several examples of the annotations used by participants.

We coded and summarized the resulting annotated visualizations and identified that five primary annotation types were used: enclosure, connectors, text, marks, and color. Within this context, we found that most annotation types could be utilized for certain low-level tasks, specifically the retrieve value and filter tasks. For the other tasks, specifically computing a derived value, finding extremum, and sorting, we observed more targeted use of a subset of annotation types. Further investigation also revealed that ensembles of annotations, that is, multiple annotation types used in conjunction, were used for difficult-to-annotate tasks. For example, enclosure, connector, and text were frequently used together to annotate computing-derived value tasks.

These results help frame the design space of annotations within the low-level tasks they support. Practitioners can use the resulting information as a reference guide for different annotation types to help visualizations achieve their desired message.

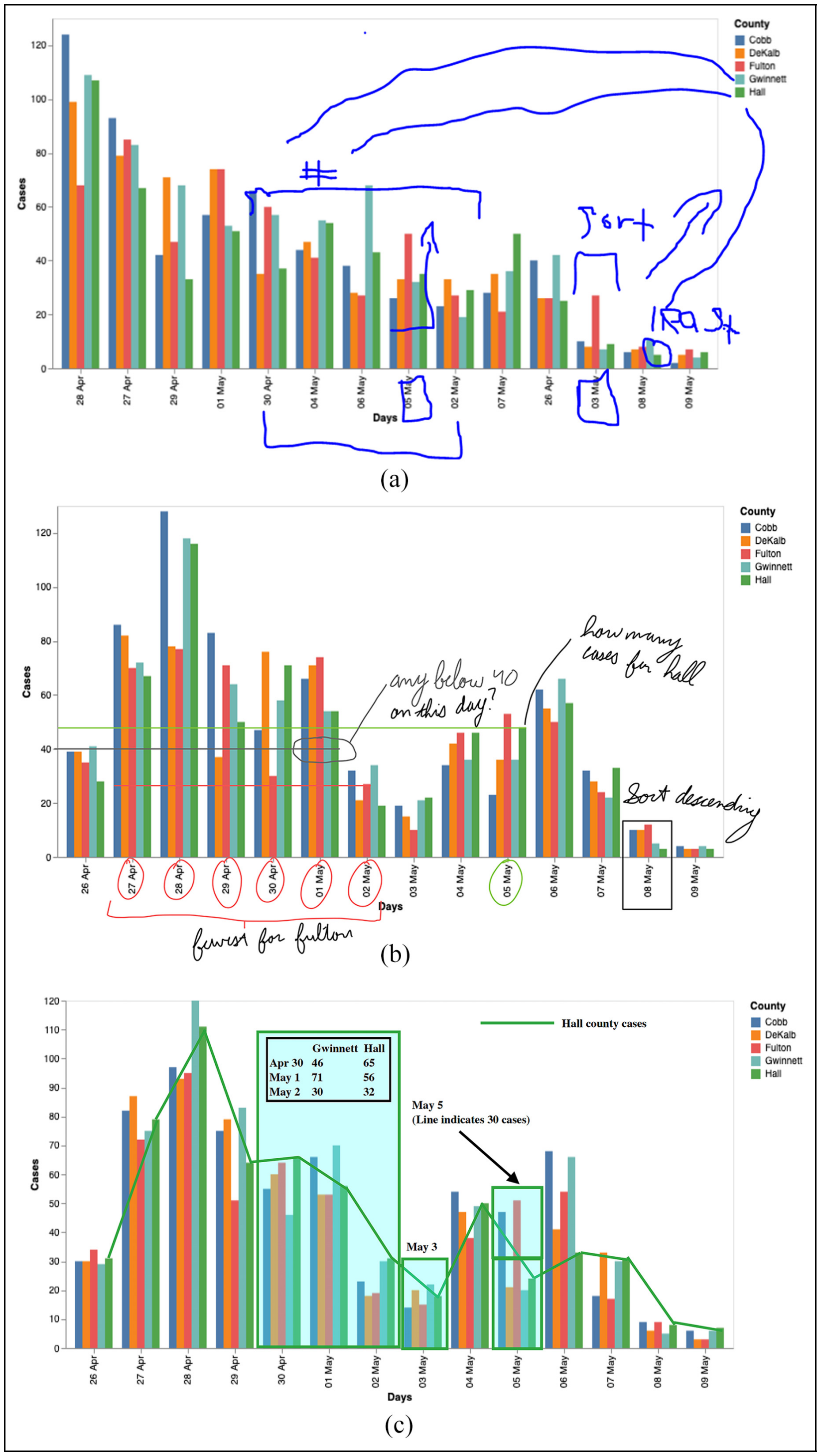


**Figure 2.** Three examples of annotated bar chart submissions. In the assignment, students were asked to annotate the bar charts to support answering several high-level questions about the data. Despite being asked similar questions, we observed a variety of annotations coming from the students, which we later coded and summarized into five types (enclosure, connector, text, mark, and color) that each support one or more low-level analytic tasks (retrieve value, filter, compute a derived value, find extremum, and sort). (a) One student used rectangles for filtering, text on bars for retrieving values and pointing out the extrema, and a legend for filtering important dates. (b) A second student annotated the chart with ellipses, rectangles, and lines for filtering, and text for filtering and as an identifier. (c) A final student used rectangular shapes and highlights for filtering, texts as an identifier, a trend line for finding extrema, and a legend for filtering.

## Background

We provide an overview of annotations in data visualization, covering their definitions, existing design spaces, and diverse roles in different visual contexts in this section.

### *What is an annotation?*

Annotations in visualization are elements that are integrated into a pre-existing visualization. These elements can be textual, such as tooltips, summary statistics, explanatory phrases or sentences, etc.,[5] or graphical, including shapes, such as arrows, rectangles, circles, brackets, etc.[39] When these annotations are associated with data points, they become additional characteristics of those elements, enriching the overall context of the visual representation. Annotations are designed to enhance, contextualize, or clarify the data within the visualization, aligning with the perspective that they transform into new attributes or provide additional context within the existing visualization framework.[1,40]

### *Design spaces of annotations*

A design space of annotations in visualizations refers to the framework that categorizes and defines various annotation types and their applications, providing a structured approach to understanding how annotations can be used to enhance data visualizations. Ren et al. proposed a design space categorizing annotations into forms (text, shapes, highlights, and images) and targets (data items, coordinate space, chart elements, and prior annotations), focusing on how they enhance visual narratives.[43] Hullman et al.[31] differentiated annotations into additive (adding external information) and observational (directly related to displayed data), whereas Kong and Agrawala[39] viewed them as external and internal visual cues, further detailing them as graphical overlays such as reference structures and highlights. While these design spaces categorized annotations based on different criteria in different contexts, none of these considered looking into how these annotations support the low-level tasks that people perform during visual data analysis.

### *Applications and utilities of annotations*

*Annotations in Data Externalization and Exploration* Annotations are a key component in articulating an analyst's reasoning within visualizations, crucial for underscoring significant data points.[10] Studies focusing on user-generated annotation graphs have shown that annotations are central to interpreting data, facilitating meta-analysis, and externalizing data.[18] During exploratory data analysis, the act of annotating, utilizing elements like text and arrows, is a fundamental step. The importance of this practice is illustrated in the application of annotations in VisInReport, a visual analysis tool for creating insight reports from discourse transcripts, where annotations are vital for delineating events across various perspectives. The necessity of annotations for including all relevant data aspects in reports has been emphasized by participants in these studies.[11] Additionally, annotations have been identified as a valuable tool in the analysis of intricate datasets in visualizations, enhancing clarity in a range of contexts, as highlighted in research involving various visualization methodologies and tools.[42–45]

*Annotations in Collaborative Data Analysis* Annotations are crucial in collaborative data analysis, as they are used in visualizations to enhance communication, synthesis, and decision-making across various contexts. Annotations showcase their versatility and effectiveness in various collaborative settings,[26,46–48] enhancing group performance and aiding in problem-solving, both within organizations and in co-located environments.[12,49] The integration of annotations in visual analytics and collaborative environments enhances team interactions and data interpretation,[25,50–52] particularly in asynchronous collaboration, where they play a crucial role in improving efficiency and highlighting significant patterns.[20,53] Furthermore, annotations foster community engagement in visual data analysis.[54,55]

*Annotations in Narrative Visualizations* Annotations play a critical role in enhancing the narrative quality of data visualizations by offering context and interpretive guidance, enriching the storytelling aspect of visual representations, and maintaining narrative coherence.[29,34] Moreover, annotations improve viewer comprehension and engagement, especially in domains like online journalism and professional narratives.[27,56] This effectiveness extends across various storytelling mediums, including data comics and data videos, where annotations articulate trends, add context, and are integrated into practical applications like DataToon, which utilize diverse annotation types to enhance storytelling.[59,60,61–63] Automated annotation techniques continue to evolve, demonstrating trends in annotation integration for effective data visualization,[31,41,62] whereas interactive visualization tools leverage annotations to enhance engagement and information delivery, showcasing their flexibility in various narrative structures.[32,63–65] Also, specialized storytelling tools, such as Timeline Storyteller and NewsViews, emphasize the vital role of annotations in crafting engaging and accessible narratives within complex data visualizations.[66,67]

Annotations also find utility in enhancing user interaction and engagement,[5–8] contributing to provenance visualizations,[68–73] aiding uncertainty visualizations,[74–76] and supporting visual debugging,[7,77–79] demonstrating their broad applicability across various visualization domains.

## Methodology and study

Our study aimed to understand how people annotate bar charts when prompted with specific questions about the data. To do this, we utilized and analyzed a course assignment in a mixed undergraduate and graduate data visualization course. In particular, we conducted a study where we evaluated annotation patterns on grouped bar charts based on the GDPH visualization (see Figure 1).

### Study procedure

For our study, the assignment was presented to students in conjunction with a lecture on potentially deceptive practices in visualization. We began with a brief in-class discussion (10–15 min) about the GDPH visualization. We then verbally reviewed the written assignment instructions and answered any questions. Students had 7 days to complete the assignment individually, which was done outside of class. They had the freedom to choose whatever tools they felt they needed to complete the study.

### Participants

The participants are the students from *Interactive Data Visualization* course that one of the authors taught at *The University of South Florida* in Spring 2022. The course was a cross-listed elective for senior-level undergraduate and master's- and Ph.D.-level graduate students, with a total of 39 students (21 undergraduate and 18 graduate). The assignment was given approximately halfway through the semester. Up to that point, the class had covered the foundations of visualization (e.g. data abstraction, visual encoding, perception, etc.). No lecture had a specific focus on bar charts or annotations.

### Assignment

Each assignment had three bar charts, each with four high-level questions (12 questions in total). For each question in the assignment, subjects were asked to (1) identify low-level analysis tasks and (2) annotate the visualization to make answering that question easier. A sample assignment is available in the Supplemental Materials.

*Datasets and Visualizations* We wanted each student to have different data but similar trends within the data. Therefore, the datasets we used were generated using a random number for each county from the GDPH visualization from April 26 to May 9. We ensured that each random number fell within a specific range, for example, for Fulton on May 4, the range was set to a minimum of 33 and a maximum of 56.

We used Vega-Lite[80] to create the grouped bar charts from the generated data. As with the GDPH visualization, we had five bars, one per county, of different colors for each day from April 26 to May 9. Like the GDPH visualization, we had two variants of the x-axis: one non-chronological (like the viral GDPH visualization) and one chronological (like the corrected GDPH visualization). We generated 150 bar charts, half chronological and half non-chronological. We built 40 unique assignments of three bar charts each. Half of them had two bar charts with chronological dates and one with non-chronological dates, whereas the other half had two bar charts with non-chronological dates and one with chronological dates. The purpose of using both chronological and non-chronological bar charts was to investigate how students apply annotations differently when dealing with time-ordered versus unordered data, helping us understand how the structure of data affects their annotation choices.

*High-Level Questions Students were asked to annotate the visualization based on questions about the data in the charts. There were four types of questions*:

- finding a specific value (e.g. how many COVID cases are there in Hall County on May 5?);
- filtering some values from others (e.g. which counties have fewer than 40 cases of COVID on May 1?);
- aggregating (e.g. how many total COVID cases does Dekalb County have from May 1 to May 4?); and
- sorting (e.g. sort the counties in descending order based on the number of COVID cases on May 8).

*Subject Tasks* Each high-level question required subjects to perform two tasks.

1. *Low-Level Analysis Task Identification.* We developed the high-level questions so that the students could answer them by performing one or more low-level analysis tasks. We used Amar et al. 's low-level analysis task taxonomy, which enumerated 10 tasks people frequently use to understand data in visualizations.[35] From that set, we selected five that fit into our study,

including *retrieve a value (RV)*, *filter*, *compute a derived value (CDV)*, *find extremum (FE)*, and *sort*. Students were asked to enumerate which of these low-level analysis tasks were used to answer each of the high-level questions. Among the 12 total questions per assignment, RV and filter appear most commonly in our questions. RV and filter were associated with most of the questions. For other tasks, there were at least three CDV tasks, two FE tasks, and two sort tasks.

2. *Annotating the Visualization.* We instructed the students to annotate the charts in a way that made the questions as easy as possible to determine without necessarily writing the answer on the visualization. Students were allowed to annotate by hand or on the computer using whatever tools they preferred. The only instruction was that they were not to collaborate with any classmates.

## Evaluation

### Data collected

A total of 38 students completed the study assignment. Once we received all the submissions, we anonymized them, assigned each a random number, and performed quality checks. Our evaluation included 20 submissions and excluded 18 (13 had no annotations, and 5 had minimal, unrelated annotations). One student annotated only two of the three charts, but their work was included in the evaluation. Of the evaluated submissions, nine had one chronological and two non-chronological grouped bar charts, while 11 had the opposite arrangement, resulting in 31 chronological and 29 non-chronological charts. The average number of annotations per student was approximately 45, with considerable variation among submissions. For example, some students, such as in worksheet 13, used significantly more annotations, whereas others, such as in worksheet 37, used fewer. Despite this variability, no distinct patterns emerged regarding the frequency of annotations per student. All anonymized submissions are included in our Supplemental Materials.

### Data coding

*Individual Annotations* To evaluate and summarize the submitted assignments, two co-authors went through all the annotated charts and hand-coded them using an open-coding approach in several iterations. In the first iteration, they separately identified a set of annotation types based on the shapes, colors, and texts used by the participants in their submissions. We were able to link the low-level analysis tasks performed by the participants and the associated annotations by carefully examining the submissions. Next, all authors discussed their findings and agreed on an initial taxonomy of annotation types. In the second and subsequent iterations, the two coding co-authors independently revisited each submitted assignment, recategorizing the annotations, and the group revised the taxonomy. The process continued until a complete consensus was reached on the taxonomy and coding of individual assignments.

*Ensemble Annotations* While coding the individual annotations, we began to notice that the participants frequently used multiple annotation types together for a single low-level analysis task when either the task was too challenging for an individual annotation or when the visualization was too cluttered to fit an annotation. Therefore, after coding the individual annotations, we engaged in several additional coding iterations to better understand these annotation ensembles. We followed a similar procedure, where two coding co-authors individually identified ensembles. Then, all authors discussed the findings and agreed upon a taxonomy in an iterative process that was repeated until a consensus was reached.

*Summary* The taxonomy is summarized as follows:

1. *Individual Taxonomy.* We identified 14 annotation types, which were grouped into five top-level annotation types: *Enclosure, Connector, Text, Mark*, and *Color*. The resulting two-level individual taxonomy is shown in Figure 3.
2. *Ensemble Taxonomy.* We identified three classes of ensemble annotation: 2-annotation, 3-annotation, and 4-annotation ensembles, as shown in Figures 5 and 6.

For the tables, each instance is a unique use of annotation/task combination within a single bar chart.

## Taxonomies

### Individual annotations

The two-level taxonomy, along with the frequency of usage of annotations, can be found in Figure 3.

*Enclosure* Enclosure annotations featuring enclosed or semi-enclosed borders include shapes such as *ellipses, brackets, half-boxes*, and *rectangles*. These types of annotations had been utilized in a wide array of situations. For example, in Figure 2(a), the rectangle was used for filtering the number of cases in Fulton county on May 1. Similarly, in Figure 2(b), ellipses were used for the filtering, half-boxes are used to support the filtering, and a rectangle is used for a sorting

| Task Type | Enclosure | | | | Connector | | Text | | | Mark | Color | | | | Other |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Ellipse | Bracket | Half Box | Rectangle | Arrow | Line | Descprition | Values | Legend | Identifier | Highlights | Category | Questions | Values | |
| **Retrieve Value** | 15 | 4 | 0 | 14 | 18 | 52 | 19 | 11 | 4 | 1 | 0 | 33 | 14 | 2 | 0 |
| **Filter** | 20 | 18 | 10 | 31 | 34 | 47 | 35 | 4 | 11 | 27 | 7 | 30 | 55 | 2 | 0 |
| **Compute Derived Value** | 1 | 6 | 0 | 8 | 0 | 9 | 11 | 8 | 4 | 1 | 0 | 15 | 3 | 1 | 5 |
| **Find Extremum** | 11 | 0 | 0 | 5 | 11 | 15 | 21 | 7 | 3 | 3 | 0 | 14 | 9 | 0 | 0 |
| **Sort** | 0 | 0 | 0 | 1 | 6 | 9 | 14 | 1 | 3 | 1 | 0 | 6 | 3 | 0 | 0 |
| Total | 47 | 28 | 10 | 59 | 69 | 132 | 100 | 31 | 25 | 33 | 7 | 98 | 84 | 5 | 5 |

**Figure 3.** Summary of the two-level taxonomy of individual annotations. The taxonomy includes 14 annotation types, grouped into five high-level categories at the top, with the low-level visual analytic tasks listed on the left. Box colors indicate the frequencies of the annotation type used for an analytic tasks: 1-9 10-19 20+.

task. Brackets were used to mark the range indicating the bar/axes in Figure 2(b) from April 27 to May 2. Enclosure was generally used for RV and filter tasks and CDV and FE tasks to a lesser extent. Overall, ellipse and rectangle annotations were used most frequently.

*Connector* A connector annotation is characterized by its use of lines, such as solid, dotted, or directional, and falls into categories, such as *arrow* (directional) and *line* (undirected). Line annotations were used, for example, to mark the height of a bar relative to the axis (see Figure 4(a)) or to represent the trend in the height of bars (see Figure 2(c)). Similarly, arrow annotations were used for pointing text to a particular bar or group of bars (see Figures 2(c) and 4(a)) or to point the enclosure annotation to a bar, axis-value, or legend, or vice-versa. Students used connector annotations for RV, filter, and, to a lesser extent, FE tasks. Connectors were used for some sort tasks. Notably, connectors did not appear alone most of the time but were combined with other annotations (i.e. into ensembles) for a given task.

*Text* Text annotations employ words, phrases, and sentences to clarify or respond to questions about the data and include specific types such as *descriptions*, *values*, and *legends*. A *description* annotation is defined in our taxonomy as text that describes a process, information, computation, or derivation that supports a particular task annotation, for example, in Figure 2(a), where the text "Hall has the highest cases on May 5." *Value* is another annotation that is a specific text-based annotation used to highlight the exact data of the bar, for example, in Figure 2(b) and (c), where a number is used to represent the bar length. *Legend* is the final text-based annotation, which was used for any labels on legends, for example, the text enclosed in the colored boxes in Figure 2(a) or annotating the trend in a number of cases in Hall County in Figure 2(c). From Figure 3, description-based text annotations were broadly applied for all five tasks. Text enumerating values was used frequently for RV tasks. Finally, legend text was frequently used for filter tasks. Overall, text annotations seemed to be used for elaborating on what other annotations were highlighting and as a last resort when no other annotations were suitable.

*Mark* Marks, as annotations, utilize symbols or shapes to provide answers about the data, specifically serving the purpose of *identifying* distinct objects or categories, such as a specific county or date. For example, in Figure 4(b), different marks (i.e. *i*, *ii*, *iii*, etc.) were used to denote the question numbers. In the same submission, circular and T-shaped marks were used to denote different dates. Further, marks were always accompanied by color to differentiate the marks captured by the color category. From Figure 3, mark-based annotations were primarily used for filter tasks.

*Color* Color annotations utilize various color properties, primarily hue, to convey information about data. These are categorized into second-level hierarchies like *highlights, category, questions*, and *values*, each serving a specific function in data interpretation. The *highlight*-based annotations use different colors to highlight an area, bars, or group of bars (see Figure 2(c)) that helps annotate a given task. Color for *values* annotations is an annotation type that aligns with text for value annotations (similar to a color map). The *category*-based color annotations highlight different categories (e.g. counties, dates/months, etc.) and are typically used in

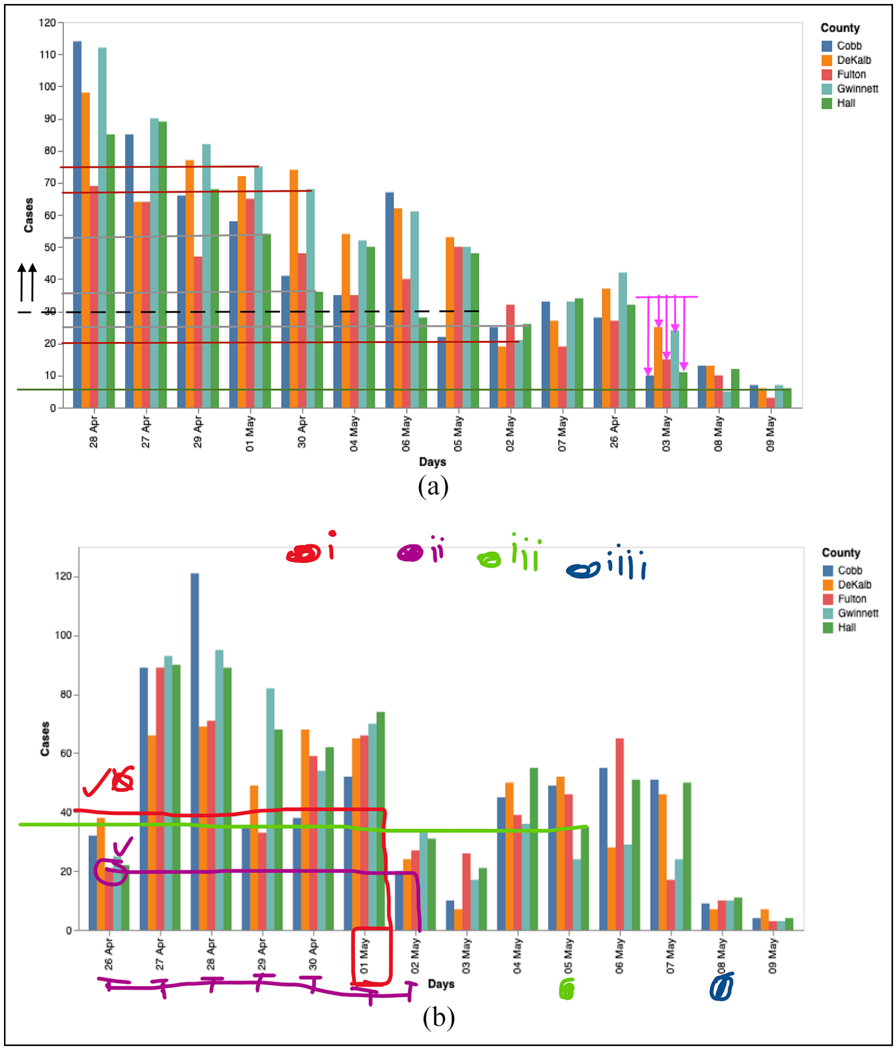


**Figure 4.** (a) An example of student annotations of the chart, including rectangles, lines, and arrows used for filtering and arrows used for sorting, and (b) another example including lines, circles, T-shaped, and circular marks.

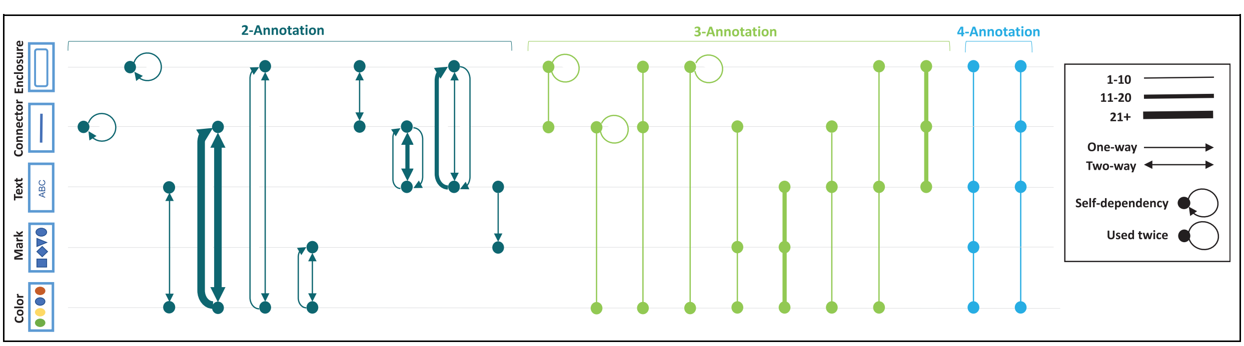


**Figure 5.** This visualization shows the configuration and frequency of the annotation ensembles we identified. Each row denotes an individual ensemble category, and each column denotes a particular annotation ensemble, grouped into 2-, 3-, and 4-annotation ensembles denoted with distinctive colors. The points indicate which individual ensemble was used, while the lines and arrows indicate their relationship. Lines show relations and loops denote multiple usages of an annotation type. Arrows denote the direction of dependency, and loops with arrows denote self-dependency. The width of the lines denotes the frequency with which the ensembles were observed.

| Ensemble Type | Ensembles | Count of Each | | | | | Total |
|---|---|---|---|---|---|---|---|
| | | RV | Filter | CDV | FE | Sort | |
| 2–Annotation Ensembles | connector–color | 19 | 18 | 3 | 7 | | 47 |
| | connector–connector | | 2 | | | | 2 |
| | connector–text | 6 | 11 | | 2 | 2 | 21 |
| | enclosure–color | 1 | 4 | 2 | 4 | | 11 |
| | enclosure–connector | | 2 | | | | 2 |
| | enclosure–enclosure | | 1 | | | | 1 |
| | enclosure–other | | | 1 | | | 1 |
| | enclosure–text | | 7 | 6 | 1 | 3 | 17 |
| | mark–color | | 5 | | | | 5 |
| | text–color | | | 1 | | | 1 |
| | text–mark | | 2 | | | | 2 |
| 3–Annotation Ensembles | connector–color–other | | | 2 | | | 2 |
| | connector–connector–color | | 5 | | | 2 | 7 |
| | connector–mark–color | | | 1 | | | 1 |
| | connector–text–color | 3 | 2 | 2 | 5 | | 12 |
| | enclosure–connector–color | | 4 | | 2 | | 6 |
| | enclosure–connector–text | 3 | 10 | | 4 | 3 | 20 |
| | enclosure–enclosure–color | | 2 | 2 | | | 4 |
| | enclosure–enclosure–connector | | 1 | | | | 1 |
| | enclosure–text–color | 1 | | | | | 1 |
| | text–mark–color | | 8 | 4 | 1 | 1 | 14 |
| 4–Annotation Ensembles | enclosure–connector–text–color | | 1 | 6 | 2 | | 9 |
| | enclosure–text–mark–color | 2 | 2 | 2 | 2 | 1 | 9 |

**Figure 6.** Summary of annotation ensembles observed in our study, detailing the ensembles used by participants across different categories and their frequencies for various visual analytic tasks. Box colors represent the frequency of different ensembles used for distinct tasks and the overall usage of each ensemble: 1-4 5-9 10-14 15+ and 1-4 5-14 15-24 25+.

collaboration (i.e. as ensembles) with mark- and enclosure-based annotations. For example, in Figure 2(a), four colors are used for the date enclosures. The *question*-based color annotates the different questions (e.g. Q1, Q2, etc.) used in coordination with mark-based annotations. For example, the roman numerals used in Figure 4(b) are colored. From Figure 3, color-based annotations were used heavily for all tasks, except sort, whereas highlights were used only for the filter task.

*Other* The other category comprises some special symbols used in the annotation. We found plus (+) used for denoting the addition operation of different values for the CDV task, delta (Δ) for differentiating groups of bars, and pound (#) used with an enclosure bracket for the CDV task.

## Ensemble annotations

When coding the annotated charts, participants frequently used multiple individual annotations together. For example, in Figure 7, half-box–text (i.e. enclosure–text) was used to denote filter, bracket–pound (i.e. enclosure–other) was used to denote CDV, and arrow–text (i.e. connector–text) was used to denote a sorting task. In Figure 8, line–text–color (i.e. connector–text–color) was used to denote RV, and ellipse–line–text (i.e. enclosure–connector–text) was used to denote filter. The use of multiple annotations happened for two reasons. For one, multiple annotations would be used when the task itself was complicated to describe with individual annotations (e.g. the filter task). Secondly, when visual elements interfere with the annotation (e.g. when annotating an RV task for a single bar), multiple annotations, almost always including connectors, would be used.

The resulting ensembles are divided into three categories based on the number of individual annotations used in the ensembles, which we identify as 2-annotation, 3-annotation, and 4-annotation ensembles. Figures 5 and 6 summarize the ensembles we identified.

*2-Annotation Ensembles* When participants used two different annotations in a combined manner to denote a single task, we named them 2-annotation ensembles.

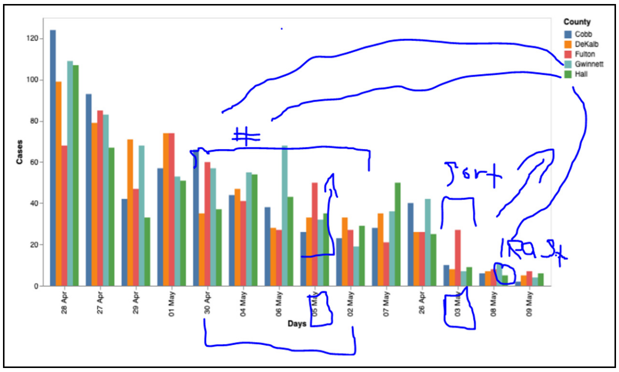


**Figure 7.** An example of 2-annotation ensembles shows how one participant used half-box-text (i.e. enclosure–text) for filtering the date, May 3 for sorting, bracket–pound (i.e. enclosure–other) for computing the total number of COVID cases for Gwinnett and Hall from April 30to May 2, and arrow–text (i.e. connector–text) for sorting counties on May 3.

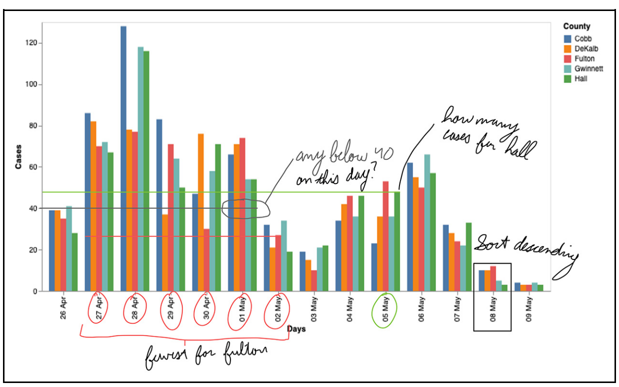


**Figure 8.** An example of 3-annotation ensembles where the participant used ellipse–bracket–text (i.e. enclosure–enclosure–text) for filtering the dates from April 27 to May 2, ellipse–line–text (i.e. enclosure–connector–text) to filter the counties with >40 COVID cases on May 1, and line–text–color (i.e. connector–text–color) to find out the total number of COVID cases for Hall on May 5.

We further classified 2-annotation ensembles into two categories based on the dependency relationship between the individual annotations used in the ensembles.

*One-way* When in a 2-annotation ensemble, one of the annotation types can stand independently, but the other one cannot, then the latter one is dependent on the previous one. Therefore, they have a one-way dependency relationship between them. In this particular case, although the dependent annotation type cannot stand by itself, it complements the independent one to accomplish the task. For example, in Figure 7, a half-box was used to filter the bars for sorting on May 8, but the half-box was accompanied by text to denote the filter task in a clearer way. Similarly, a bracket for the bars from April 30to May 2 was used to denote CDV, but the pound on top of the bracket was used to denote the computation needed to accomplish the overall task. So, in both these cases, the half-box and the bracket can stand independently to denote filter and CDV tasks, respectively, whereas text and pound cannot stand independently, but by accompanying half-box and bracket, respectively, they made the overall annotation clearer.

*Two-way* When in a 2-annotation ensemble, neither of the annotations can stand independently without the help of the other, then they are mutually dependent on each other. In other words, both annotation types are required to accomplish the task. Therefore, they have a two-way dependency relationship between them. For example, in Figure 7, arrow–text (i.e. connector–text) is used to denote the sort task. Here, without the arrow, the text fails to denote the direction of the sorting task. Similarly, without the text, the arrow does not clearly indicate the sorting. Thus, the text and the arrow are both dependent on each other in this case.

*3-Annotation Ensembles* When participants used three annotation types in a combined manner for a single task, we named them 3-annotation ensembles. Due to the complex relationship of 3-annotations, we do not differentiate dependencies between the annotations. For example, in Figure 8, line–text–color (i.e. connector–text–color) is used to retrieve the total value of Hall on May 5. The horizontal colored line was used primarily for retrieving the desired value. Another line from the horizontal line pointing to the text was used to clarify the overall annotation. Line-ellipse-text (i.e. connector-enclosure-text) is used to denote the task that filters counties with fewer than 40 COVID cases on May 1.

*4-Annotation Ensembles* When participants used four annotation types in a combined manner for a single task, we named them 4-annotation ensembles. Again, dependencies are ignored. For example, in Figure 9, rectangle–text–mark–color (i.e. enclosure–text–mark–color) is for filter, FE, and RV. For each of those tasks, colored rectangles were used to filter out the dates, and colored rectangular-shaped marks with text were used to match the selection. In other submissions, rectangle–arrow–text–color (i.e. enclosure–connector–text–color) was used for filter, CDV, and FE (see individual 9 in the supplement), and rectangle–line–text–color (i.e. enclosure–connector–text–color) was used for CDV (see individual 27 in the supplement).

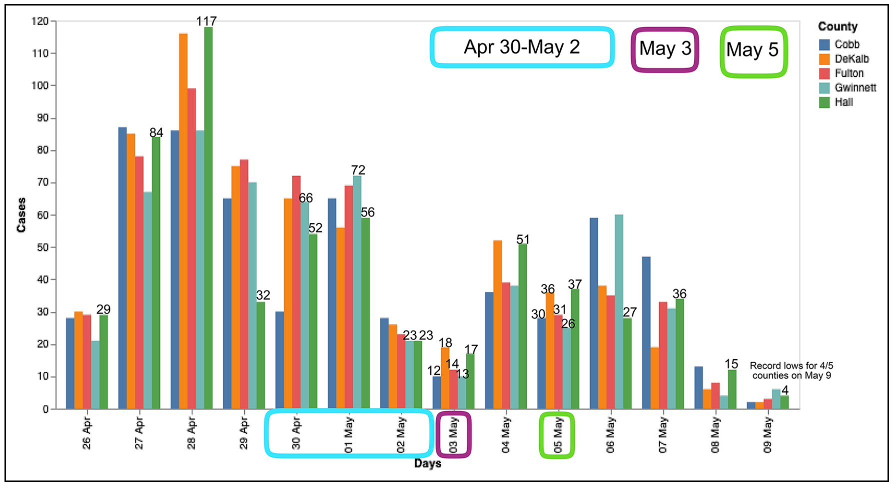


**Figure 9.** An example of 4-annotations uses rectangle–text–mark–color (i.e. enclosure–text–mark–color) for filtering different dates, finding out the extremum values, and retrieving specific values.

## Discussion

One of the key insights we are interested in remains gaining a better understanding of the design space for annotations. We frequently use annotations, knowingly or unknowingly, in our daily lives. For example, in a presentation, annotations enable a presenter to draw the attention of the viewers to an important point of focus.[63] Our participant population of current visualization students provided us with graphical-literate audience who also were not experts. The students were sufficiently well versed in visualizations to know how to use them effectively but not so experienced as to have a set of standard practices to draw upon for annotation. The freedom to use open-ended annotations ultimately enabled us to capture a diverse picture of the potential design space available for annotations.

Within this design space, whether intentional or not, the annotations we observed participants using seemed closely linked to the idea of encoding semantics.[81] Our evaluation of the design space looks at both the most commonly used annotations and annotation ensembles and the low-level tasks those annotations were used for.

### *Frequent uses of individual and ensemble annotations*

*Individual Annotations* There was a surprising balance in the usage of different individual annotation categories (see Figure 3). Overall, participants used most in high amounts (enclosure: 144 instances, connector: 201 instances, text: 156 instances, and color: 194 instances), except mark (33 instances).

- *Enclosure* Ellipses and rectangles were frequently used for RV and filtering tasks. Participants would use these enclosures to highlight an individual or set of data items for those tasks. For FE tasks, we sometimes saw ellipses drawn on the top of the bar of interest.
- *Connector* Connectors were also heavily used for RV, filter, and FE tasks. Oftentimes, the participants used a horizontal line to filter or retrieve a value. Similarly, the participants used vertical lines or arrows to point out the specific bar of interest.
- *Text* Text was used for almost all the tasks in our study. During the analysis, we noticed the frequent use of descriptions when participants could not find an appropriate alternative annotation to use or if they wanted to provide more information than a graphical annotation alone could convey.
- *Color* Color was often used to clarify or separate information in the visualization. For example, participants used colors for separating the annotations they drew for different tasks or high-level questions. For CDV, in particular, we observed a pattern of using colors to filter out the bars or dates of interest. For example, in Figure 9, participants used different colored rectangles to filter out and separate the dates of interest.
- *Mark* Marks were infrequently used, but we observed them mostly used as identifiers for filtering tasks. For example, in Figure 4(b), T-shaped and circular marks were used to filter different dates. We believe their infrequent use was probably caused by the fact that better

substitutes (e.g. enclosure and color) were available to serve the same purpose.

*Ensemble Annotations* For ensemble annotations, we can see in Figure 5 that the participants used a variety of 2-annotation, 3-annotation, and 4-annotation ensembles. Generally speaking, ensembles were used when individual annotations could not easily stand on their own due to complex tasks, for example, sorting, or clutter issues, for example, the text might need a connector for spacing reasons.

- *2-Annotation Ensembles* Connector–color was the most frequently used 2-annotation ensemble for almost all the tasks except for sort. Participants tended to use colored lines or arrows for filtering out the bar of interest from other bars or for pointing to the bar of interest. One of the common scenarios is using colored arrows or lines filtered the data so that a CDV task could be performed on it. Connector–text was another commonly used ensemble, mostly for RV and filter tasks. Participants used the connector to point to the bar of interest and then used the associated text to explain what they were to do. For example, in Figure 8, the participants used the line to point to the green bar for Hall on May 5 and then used text to explain the task (i.e. "how many cases for hall"). The same usage pattern was seen for enclosure–text for CDV and filtering tasks. Participants enclosed a specific area of interest on the charts and then used the associated text.
- *3-Annotation Ensembles* 3-annotation ensembles were used in a variety of situations. The most frequently used 3-annotation ensemble, enclosure–connector–text, was used for multiple tasks, including RV, filter, FE, and sort. Other commonly used 3-annotation ensembles were as follows: for RV was connector–text–color, for CDV was text–mark–color, for FE was connection–text–color, and for filter was text–color–mark. The commonality of most of these 3-annotations was that they appeared in more compound tasks, such as having one or more annotation types for identifying the data (e.g. color or a connector) and others for directly completing a task (e.g. text).
- *4-Annotation Ensembles* 4-annotation ensembles were used in a similar regard to 3-annotation ensembles. Participants used enclosure–connector–text–color and enclosure–text–mark–color 4-annotation ensembles for denoting all five tasks, though the CDV task was the most frequent recipient (see Figure 9). Note the commonality of color, enclosure, and text used in both of the 4-annotation ensembles that we observed.

One final important observation is that many three-annotation and four-annotation examples contained redundant or unnecessary encodings. In other words, it is possible that a two-annotation ensemble could have been used instead of three-annotation and similarly four-annotation ensembles.

## Low-level task support of annotations

When evaluating individual low-level tasks, it became clear that there was non-uniform support from different annotation types.

- *Retrieve Value (RV)* The RV task saw broad support from individual annotation types, excluding marks, as well as from several annotation ensembles. In particular, connector and color seemed to be used frequently to identify (i.e. using color) and draw attention to the data (i.e. using the connector). Given the many options available, RV seems to be one of the easier tasks to annotate.
- *Filter* The filter task saw universal support from individual annotation types and most annotation ensembles. Similar to RV, filter seems to be one of the easier tasks to annotate. Because one of the main goals of annotation is highlighting particular data (i.e. filtering), it makes sense that the types of annotations participants chose would generally be useful for filtering.
- *Compute Derived Value (CDV)* For CDV, participants used text, color, and enclosure most frequently. In many cases of CDV tasks, the participants had to filter the data according to the dates and then compute something (e.g. add, average, etc.) on the filtered data. For example, in Figure 9, dates from April 30 to May 2 were filtered first, then the number of COVID cases for Gwinnett and Hall were filtered, and then finally, these numbers were added and compared. To denote all these steps, the participant used enclosure (i.e. rectangle), color, and text to indicate the compound nature of the CDV task.
- *Find Extremum (FE)* For FE tasks, text and connector annotations were the ones the participants used most frequently. The annotation usage for FE closely mirrors that of RV because, on bar charts, FE is just a special case of RV.
- *Sort* The sorting task appeared to be challenging to annotate. Some participants used connectors

for the sorting task (see Figure 4(a)), but most often, participants relied upon some text to describe the part of the charts that needed to be sorted. We also observed the use of connectors and text together to annotate sorting tasks, but that can still be challenging when data are dense, or the number of data to sort is large.

### Further design space observations

*Usage of Legends* We frequently observed participants adding legends to the visualizations. They used legends for two reasons. First, they wanted to identify the annotations based on different dates or questions separately. Second, they wanted to denote CDV tasks that involved retrieving data for multiple dates. For example, in Figure 9, rectangular marks were used as a legend to identify different dates.

*Within Subject Variations* The participants tended to use the same set of annotations in all three charts given in the assignment. For example, one participant applied only rectangle, text, and color for annotating their charts; another participant annotated their chart using rectangle, text, and mark only; another one utilized text, arrow, and brackets for most of their annotations. This consistency in using a limited subset of annotation types is a general pattern seen in almost all the submissions, where participants restricted themselves to a limited subset of the annotation types.

*Non-chronological* versus *Chronological Ordering* Many of our high-level questions required identifying ranges of dates. Participants had difficulty annotating the range when the chart contained non-chronological dates because the dates were not adjacent. To overcome this difficulty, the participants used a variety of approaches, including no annotations used in seven instances, enclosures used in eight cases, marks used in eight instances, and ensembles used in two instances. When the participants used enclosures for denoting the non-chronological dates, they had to separately annotate each (see Figure 2(a)), whereas, for chronological dates, they used only a single enclosure for all the dates (see Figure 2(b)). Reflecting these differences, the data show a variation in annotation frequency: participants applied an average of 16 annotations per chart for the 29 non-chronological charts and 14 annotations per chart for the 31 chronological charts. This increased use of annotations suggests that dealing with non-chronological charts may involve a higher cognitive load, potentially leading to the increased need for annotations.

*Digital* versus *Hand-written Annotation* We identified eight digital annotations, seven handwritten annotations, and four used both digital and handwritten annotations simultaneously in their submission. However, we did not observe any trend in the types of annotations used in hand-written submissions versus those used in digital submissions.

### Limitations and future research directions

Our research provides initial insights into grouped bar chart annotations and aims to establish a preliminary framework rather than a comprehensive taxonomy applicable to all visualization types. We acknowledge limitations due to our primary focus on visualization students, which may not reflect the broader user base, including general audiences and experts. This student-centric focus could restrict the applicability of our findings across various demographic and professional backgrounds. Furthermore, by concentrating solely on grouped bar charts, our insights may not be fully applicable to other types of charts, each posing unique annotation challenges.

Future research should involve a wider range of participants, including data visualization researchers, industry practitioners, and professionals from various fields, to enhance our understanding of how different groups use annotations. Studies should also cover more than just grouped bar charts and include various chart types to help develop a detailed taxonomy of annotations for bar charts and establish a taxonomy for all visualization types. Conducting research across different visualization formats, focusing on various annotation styles and approaches, is also essential to determine the most effective strategies for improving user engagement and understanding.

Future research should also incorporate cognitive frameworks, such as Cognitive Load Theory[82] and Cognitive Fit Theory,[83] to assess annotation effectiveness, optimizing cognitive efficiency. Educational frameworks, such as Multiple Representations theory,[84] should similarly be integrated to accommodate different learning styles relating to annotations. Additionally, studies should explore the role of visual literacy in understanding annotations, guided by relevant frameworks.[38,85]

## Conclusion

Our study highlights the critical role of bar chart annotations in enriching data visualization, serving as a vital tool for hypothesis formation, disseminating information, enhancing user comprehension and engagement, and facilitating collaborative data analysis. We have developed a two-level taxonomy for bar chart annotations, organizing them into five main categories: enclosure, connectors, text, marks, and colors, which was derived through analyzing bar charts annotated by visualization students. Our proposed taxonomy is vital as it provides a structured framework for understanding and categorizing chart annotations. By defining clear categories and associating them with specific tasks, the taxonomy aids visualization designers, practitioners, professionals, and researchers in systematically considering the range of annotation options available. Furthermore, our research opens avenues for future research that could potentially expand our understanding of annotations in various visualization contexts.


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## Supplemental material

Supplemental material for this article is available online: https://osf.io/vup8r/

## Note

1. The students had previously been exposed to encoding semantics in a single lecture slide several weeks before the assignment. Therefore, we suspect that the relationship was unintentional.

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