Who Do We Mean When We Talk About Visualization Novices?

Alyxander Burns
Mount Holyoke College, University of Massachusetts Amherst
Massachusetts, USA
ajburns@mtholyoke.edu

Christiana Lee*
Ria Chawla*
christianale@umass.edu
rchawla@umass.edu
University of Massachusetts Amherst
Massachusetts, USA

Evan Peck
Bucknell University
Pennsylvania, USA
evan.peck@bucknell.edu

Narges Mahyar
University of Massachusetts Amherst
Massachusetts, USA
nmahyar@cs.umass.edu

ABSTRACT

As more people rely on visualization to inform their personal and collective decisions, researchers have focused on a broader range of audiences, including "novices." But successfully applying, interrogating, or advancing visualization research for novices demands a clear understanding of what "novice" means in theory and practice. Misinterpreting who a "novice" is could lead to misapplying guidelines and overgeneralizing results. In this paper, we investigated how visualization researchers define novices and how they evaluate visualizations intended for novices. We analyzed 79 visualization papers that used "novice," "non-expert," "laypeople," or "general public" in their titles or abstracts. We found ambiguity within papers and disagreement between papers regarding what defines a novice. Furthermore, we found a mismatch between the broad language describing novices and the narrow population representing them in evaluations (i.e., young people, students, and US residents). We suggest directions for inclusively supporting novices in both theory and practice.

CCS CONCEPTS

• **Human-centered computing → Visualization**; *Visualization theory, concepts and paradigms*; *Visualization design and evaluation methods*.

KEYWORDS

data visualization, audience, critical analyses, research methodology

ACM Reference Format:
Alyxander Burns, Christiana Lee, Ria Chawla, Evan Peck, and Narges Mahyar. 2023. Who Do We Mean When We Talk About Visualization Novices?. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23), April 23–28, 2023, Hamburg, Germany*. ACM, New York, NY, USA, 16 pages. https://doi.org/10.1145/3544548.3581524

*Both authors contributed equally to this research.

CHI '23, April 23–28, 2023, Hamburg, Germany

ACM ISBN 978-1-4503-9421-5/23/04…$15.00
https://doi.org/10.1145/3544548.3581524

1 INTRODUCTION

As more people rely on visualization to inform personal and collective decisions in their everyday lives, visualizations researchers have focused on supporting a broader range of audiences. While visualizations were once largely used by analysts, they are now used by much broader audiences [57, 75, 104]. In particular, past work has emphasized the need to build bespoke visualizations for the "broadening audiences" of visualization which may find existing visualization techniques difficult to use or insufficient to meet their goals (e.g., in [47, 103, 113]). For brevity, we refer to this set of audiences ("novices," "non-experts," the "general public," or "laypeople") in this work as **novices**. However, successfully applying, interrogating, or advancing research in this area demands a clear understanding of exactly whom researchers mean by novice when they use the term in their work – What are the essential characteristics of a novice and how are they represented in studies?

Misinterpreting who is meant by the term "novice" could lead to designers misapplying guidelines and researchers overgeneralizing studies, which impacts the success of visualizations designed for novices. For instance, designing a visualization for novices who are *"users who have experience operating a computer, but no experience with programming in general"* [57] could result in visualizations which are entirely unusable if the novices who will actually interact with the visualization are *"users who create visualizations to support their primary tasks, but who are typically not trained in data analysis, information visualization, and statistics"* [47]. Despite both being referred to as "novices," the former group may be equipped to read or create visualizations that the latter has never seen, while the latter group may need to use visualizations in ways that are not relevant to the former.

In this paper, we qualitatively analyzed every visualization paper (n=79) that used "novice," "non-expert," "laypeople," or "general public" in their title or abstract and was published in one of seven influential venues which publish visualization research (TVCG, CHI, EuroVis, VAST, InfoVis, VIS, and BELIV). Driven by the desire to know what novice means to visualization researchers in theory and in practice, three coders qualitatively analyzed each of our selected papers. To investigate the theoretical uses of the terms, three coders collected descriptions of people and groups — described as either included or excluded — and applied thematic analysis to identify salient patterns among the descriptions. To see how novices are represented in practice, we collected information about the participants in studies (groups that they belonged to, ages, and geographic locations) as well as the type of evaluations conducted in the studies.

We found ambiguity within papers and disagreement between papers as to what defines a novice. Further, our results indicated a mismatch between the broad language describing novices and the narrow population representing them in evaluations; while novices were often defined broadly by what they lack and were defined in opposition to "experts," the participants recruited to represent them tended to be young people in their 20s, who were currently students, and/or were US residents. We conclude by providing suggestions and future directions for how to better design and evaluate visualizations intended for broader audiences like novices.

There are three main contributions of this paper. First, we contribute an analysis of what visualization researchers mean *in theory* when they refer to people as novices in research papers and who they describe as inside or outside of the novices group. We show that papers often use characteristics such as job titles, proximity to scientific fields, and/or a lack of expertise, knowledge, or skills to define who is inside or outside the group. Second, we contribute an analysis of how the theory is translated *into practice*, including the characteristics of participants in studies and characteristics of the studies themselves. In particular, we show that participants tend to come from a narrow set of backgrounds and take part in studies that are narrowly focused on user experience and performance. Finally, we reflect on opportunities and under-explored areas implied by our results: the need for inclusive definitions of novices in visualization research, opportunities to value audiences with alternative ways of knowing and doing, and the need for studies investigating a more diverse set of objectives and representative participants. Our work is a call to action emphasizing the need for the design and evaluation of visualizations to support populations beyond prototypical visualization users (often "analysts" [5]). By taking this action, visualization research can better inform inclusive and universal design principles [25] beyond those which primarily center and serve WEIRD (Western, Educated, Industrialized, Rich and Democratic) societies [45, 58, 65, 79].

2 BACKGROUND

In this section, we briefly describe varied interpretations of "novice" in current visualization literature and work done to meet the needs of novices in visualization research. Then we present conversations in Human-Computer Interaction research about representative sampling of participants and the gap in work in this area on visualization and novices which motivated our survey.

2.1 Considerations of Novices in Visualization Research

The notion of a "novice" as a person who is inexperienced or "new to [ones'] circumstances" predates the field of visualization and dates back to the 15th century, possibly stemming from a French word for "beginner" and a Latin word used to describe newly imported slaves [54]. Within visualization, there is no consensus around what a person needs to be new *to* in order to be considered a novice. For instance, Heer et al. defined novices in relation to their ability to program: *"users who have experience operating a computer, but no experience with programming in general"*[57], while Grammel's definition referred to *"users who create visualizations to support their primary tasks, but who are typically not trained in data analysis, information visualization, and statistics"*[47]. Understanding how these disparate definitions relate to each other is a critical component of understanding how the results of these works relate. This is possible on an individual level, but it remains difficult to get a holistic view of how the idea of a novice is being used across the field. We fill this gap through an analysis of how "novice" and related terms are used in visualization work in seven venues (defined in previous work as forming the "core" of visualization research [34]).

Visualization work about novices is often motivated by existing research on the barriers that they face in creating and using visualizations. For example, past work has found that novices may face difficulty deciding how to map values to visual channels when creating visualizations [47, 57], may have difficulty naming and interpreting visualizations such as network diagrams [11], and may flounder when their mental model of a visualization does not prove to be helpful [77]. Moreover, some estimate that difficulty interpreting and performing *"basic analyses of data and statistics in texts, tables and graphs"* may effect a great portion of the general public [129].

Past work meant to overcome these barriers has both taken the form of studies about novices and the creation of alternative visualizations and tools to meet their needs. For instance, past work identified how novices approach visualization creation [47], and tools have been built to help novices create visualizations, pulling design elements from art (e.g., DataQuilt [151]) and incorporating hand-sketched elements (e.g., DataInk [141]). Other work focused on the impact of design choices on how novices perceive and understand the content of visualizations (e.g., [14, 113, 143]). However, not all results are able to equally inform future design practices because the value of any result is inextricably linked to the experimental methodologies that were used to acquire it [90]. Therefore, it is also critical to examine how visualizations for novices have been evaluated and what kinds of participants represent novices in evaluations.

2.2 Sampling Participants for the Evaluation of Visualizations Designed for Novices

When a human-subject study is conducted, the characteristics of the audience that researchers want to study (here, novices) are translated into the criteria they use to select participants [74]. It is critical to select participants from a representative sample of the intended audience because a person's interpretation of and preference for particular design choices is informed by their experiences, background and knowledge [52, 53]. Prior work in Human-Computer Interaction explored the problem of participant representation – particularly as it pertains to the WEIRDness of participants (i.e., how Western, Educated, Industrialized, Rich, and Democratic participants are [45, 58]). For instance, past work by Linxen et al. and Sturm et al. found that a majority of participants in CHI papers were sampled from WEIRD countries (despite those countries representing a minority of the worlds' population) [79, 123]. This may, in turn, impact the quality and generalizability of the results of these works because visual preferences and needs of visualization readers vary worldwide [65, 107]. However, without a comprehensive survey of the participant demographics of novices in the evaluation of visualization work, it is yet unclear who participants are in this area and how recruitment and/or evaluation techniques may need to change to be more representative in the future. We fill this gap by examining the evaluation methods and how participants are described, their geographic locations, and their ages.

3 METHODOLOGY

To better understand current practices for defining *novice*, *non-expert*, *general public*, and *layperson*, we conducted a survey of all visualization papers published in seven "core" visualization venues.

3.1 Paper Selection

The focus of our search was papers from "core" visualization research venues during any year of their publication. Namely, we sampled papers published in the IEEE Transactions on Visualization and Computer Graphics (TVCG) journal or published as a part of IEEE VIS, InfoVis, VAST, EuroVis, BELIV, and the ACM Conference on Human Factors in Computing Systems (CHI). We selected these venues based on past work which similarly surveyed visualization research practices [34]. Our paper selection and data collection process is summarized in Figure 1.

We conducted a title and abstract keyword search within the publishers' respective digital libraries to retrieve relevant papers. The keywords we used were "novice," "non-expert," "general public," and "lay(man, men, person, people)[1]." We selected this set of terms because they are words that the authors have seen used to describe people who find existing visualization techniques difficult to use or insufficient to meet their goals. We used the IEEE, ACM, and Eurographics Digital libraries to obtain papers which possessed our keywords within the title or abstract. Because the Eurographics Digital Library does not allow users to search within the titles and abstracts directly, we conducted a full-text keyword search of EuroVis papers and then manually filtered the results to find those which satisfied the title and abstract requirement. Additionally, papers from CHI had to also include the word "visualization" in their title or abstract because CHI is not solely a visualization venue. To ensure we did not miss any related results from CHI, we manually skimmed through all CHI results which did not use the word "visualization" but included one of the other terms. Our inclusion criteria resulted in a total of 92 papers (89 + 3 from skim). Documentation of the specific queries used to retrieve the papers in our survey is available on our online repository: https://osf.io/rdcsf/?view_only=d638db5ca96945ed9765134ffa450d8a

From our list of 92 results, we excluded 13 results that were not visualization research papers. Namely, we excluded two speeches [30, 92] and eleven papers which focused solely on animation, virtual reality, or augmented reality (all published in TVCG). After applying our exclusion criteria, we ended up with a final set of 79 papers (see Figure 2 for a histogram of publication years). Note that our set of papers included papers of all lengths (e.g., full-length papers, short papers, extended abstracts). We did not apply any exclusion criteria based on the length of the paper because we wanted to get a holistic view of how these terms were being used. Further, restricting to only papers of a particular length would have been difficult given that the page layout and page limits vary between venues and may have changed.

[1]We use the word "layperson" or "laypeople" throughout to refer to any matches in this set of keywords.

3.2 Data Collection

A team of three coders (three of the co-authors) collected data from each paper with overlap to increase reliability. To begin, the coders created a codebook that described the information they wanted to collect, its purpose, and the process by which they would obtain it. For instance, coders used the keyboard function Control/Command-F to search for the terms novice, non-expert, general public, and lay(man, men, person, people). The entire codebook is available in our online repository. We investigated two central questions about novices in this work: How do visualization researchers talk about who novices are? and How are visualizations for novices evaluated?

How do visualization researchers talk about who novices are? To answer this question, we collected the following information from every paper:

- whether an explicit definition was provided for each keyword used
- descriptions of any group included in a keyword group
- descriptions of any group excluded from a keyword group

We began by collecting the explicit definitions provided for each of our keywords. After a small, initial pilot suggested that explicit definitions were infrequent. Therefore, we expanded our data collection to include people described as *included* or *excluded* based on work in social psychology on in- and out-groups (e.g., [16]). To collect these included and excluded groups, we collected the groups named and described within the same paragraph of any of the keywords. We restricted to within one paragraph to be more confident that the words were being used in relation to each other. A group were marked as **included** if they were given as an example (e.g., *"Such comparison tasks are challenging for novice ML practitioners who have primary but not comprehensive ML knowledge background ... For example, a medical school graduate student may want to adopt a CNN for disease detection"* [145]) or if the keyword group was described in terms of what they thought or did (e.g., *"Non-expert users have difficulties to comprehend the coherency of input, parameters, and output of these algorithms"* [13]). We did not count this kind of description as an explicit definition because it is unclear whether it is necessary for all novices to have this kind of thought or difficulty or whether it was supplied as an example. Alternately, a group was considered to be **excluded** if they were named in sequence with one of our keywords (e.g., *"Visualization of general relativity illustrates aspects of Einstein's insights into the curved nature of space and time to the expert as well as the layperson."* [48]) or were directly contrasted against them (e.g., *"While most of these systems are geared towards domain experts [...] CrowdLayout focuses on novice crowds"* [116]).

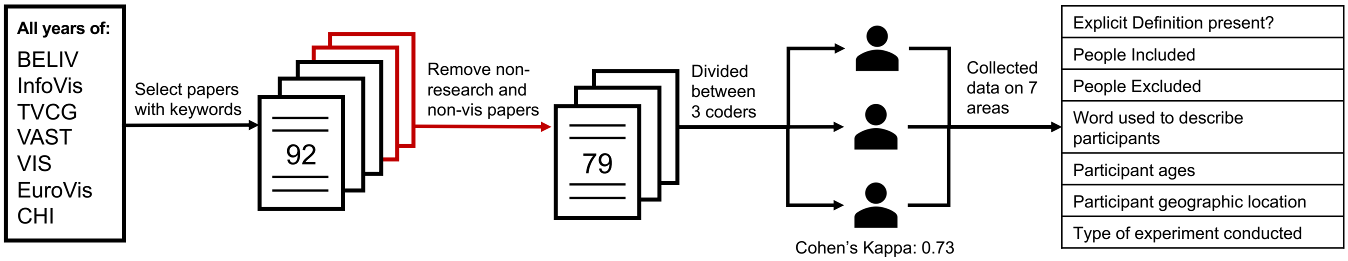


Figure 1: We selected all papers published in IEEE, ACM, and Eurographics visualization venues that contained "novice," "non-expert," "general public," or "layperson" in their title or abstract (n = 92). We then excluded 13 papers which were not visualization research papers, resulting in a final set of 79 papers. Three coders qualitatively coded the papers in seven areas shown here.

How are visualizations for novices evaluated? To answer this question, we collected information from papers that described at least one human-subject study where some or all participants were intended to be novices:

- which words the authors used to describe the participants (e.g., students, staff, crowdworkers, volunteers)
- the minimum, maximum, and mean age of participants
- the geographic location where participants were sampled from
- the type of study conducted (using the categorization scheme from [63])

We did not restrict which papers were included based on the *type* of human-subject study conducted; both papers with formal experiments and those with non-experiment studies (e.g., observation, interview) were included.

We collected information on participants and how they were selected because participants are supposed to accurately represent the intended audience. Furthermore, we collected information about the kinds of studies that were conducted to understand how researchers evaluate visualizations that are designed for novices.

3.2.1 *Data collection process.*

To ensure consistency between coders, we used an overlapping coding technique similar to one used by Mack et al. [86]. Using the codebook, coders independently coded the same set of 10 randomly selected papers. They then met to discuss their codes and differences, making any necessary changes to the code book in 3 iterations. Once the coders revised the data and reached a general consensus on the shared set of papers, the rest of the papers were divided among the coders (19 or 20 per coder). After all coders had coded half of their assigned papers, they all coded a second common set of 10 papers to double check that codes were consistent and provide an opportunity for the coders to discuss any difficulties which arose. The mean pairwise inter-coder reliability for the second set of papers was an average 0.73 (SD=0.06) as calculated using unweighted Cohen's Kappa. Once all differences had been settled, the coders coded the remainder of their papers and adjusted previously coded papers as needed.

4 HOW DOES THE VISUALIZATION COMMUNITY TALK ABOUT NOVICES?

4.1 How Do We Define Novices in Visualization Research?

4.1.1 *Explicit Definitions.*

We define an *explicit definition* of novice as one that is clear and precise enough that it leaves little doubt about which groups of people may included (or excluded). This kind of specificity is desirable because it means that the text directly and completely describes what is meant by a term, without room for misinterpretation [7].

Among the 79 papers we examined, our coding revealed that only 15 papers contained an *explicit definition* which clearly identified which people they referred to as novices, non-experts, members of the general public, or laypeople (see Table 2 for counts and example definitions). Two explicit definitions included "novice Vega users", which referred to people who were *"unfamiliar with Vega"* [59], and "novice ML practitioners", which were people with *"primary but not comprehensive ML knowledge background[s]"* [145]. The ambiguity in defining participants was prevalent both in research that used terms (such as "novice") sparingly and in research which relied heavily on the terminology throughout the paper.

4.1.2 *Implicit Definitions.*

In place of explicit definitions, authors provided *implicit definitions* in 56 papers by sharing examples of audience sub-groups or describing characteristics of audience processes or background (see Table 2 for counts). For example, "novices" were referred to as people with difficulty *"effectively utilizing GPU clusters"* [23] or those who *"lack the knowledge and expertise in data visualization"* [43]. "Non-expert" users were said to have difficulty *"managing the complexity of visual parameters"* of volumetric functions [110] and think that *"large network visualizations [were] overwhelming, confusing and contain[ed] too much detail"* [131]. Although these implicit definitions partially clarify the characteristics of terms used to describe novices, without the clarity and precision of explicit definitions, they leave room for ambiguity [138]. Further, not all examples are equally helpful — in order for an example to be effective, a reader must be able to identify that the example can generalize to a broader set of problems or rules [87]. Without sufficient context around the example, it may not be clear to the reader *what* should be generalized.

Table 1: An overview of the 79 articles we reviewed, sorted first by venue, then by year of publication. Where space allows, we have added publication year ranges. The filled boxes indicate that a keyword appeared in the paper (■), an explicit definition was provided for at least one keyword (■), and an implicit definition was provided via an example or counter-example (■). Explicit definitions were rare, though almost every paper defined their terms implicitly by providing examples or counter-examples, regardless of their publication year. The use of keywords seems to vary somewhat between publication venues (e.g., CHI papers seem to include multiple keywords more frequently than other venues).

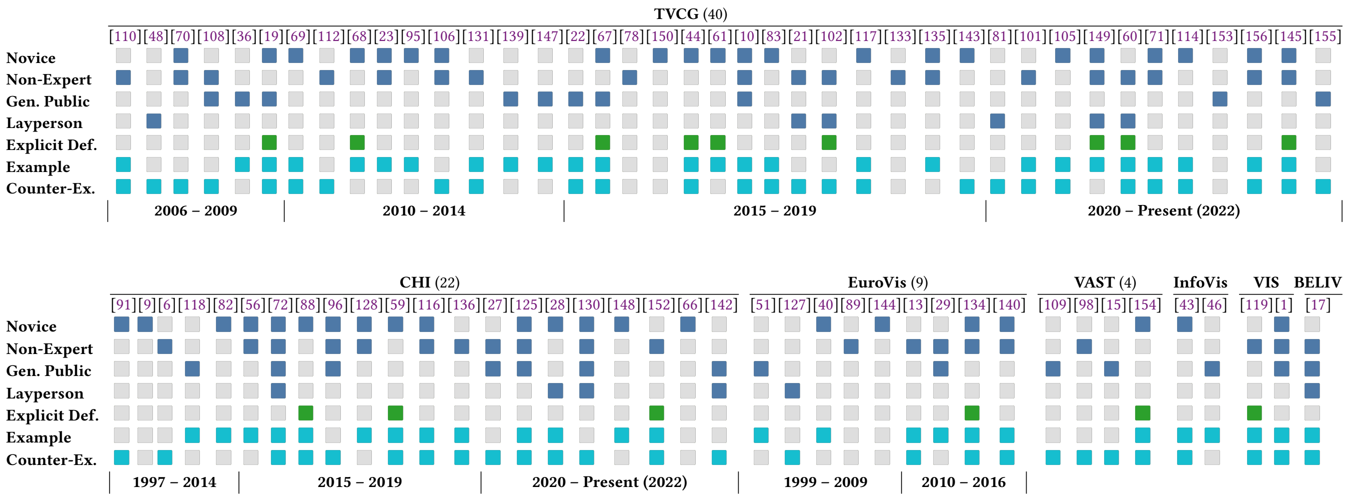


Table 2: Few of the papers we surveyed provided an explicit definition for at least one of the keywords used (15/79). Instead, terms were defined implicitly using examples (i.e., a sub-group or description) or counter-examples (i.e., by contrasting).

Definition Type	# Papers	Example	Source
Explicit Definition	15/79	*"None of the participants reported expertise in political debates or text visualization. We chose to use this population for our study because they represented the* ***non-expert****, general audience we want to use DebateVis."*	[119]
At least 1 Example	52/79	*"Since* ***novice users*** *of visualization systems lack the knowledge and expertise in data visualization, ..."*	[43]
At least 1 Counter-example	53/79	*"While pop music is intended to be friendly to the* ***general public*** *... [classical music is] usually only understood by music lovers, who have received extensive training in music theory and history.*	[19]

In 53 of 79 papers, authors used *counter-examples* to create implicit definitions by describing people who were *not* in the audience (see Table 2 for counts). In many papers, "experts" was used as a contrast to "novices" and "non-experts." For instance, "non-expert algorithm users" were contrasted against *"experts in data mining techniques (e.g., engineers or biologists)"* [13]. There were also more specific counter-examples provided such as in Chan et al., which contrasted people in the general public against *"music lovers, who have received extensive training in music theory and history"* [19]. We distinguish between "counter-examples" and "negative definitions" as such: "counter-examples" are cases where a group is named or described in a way that makes it ambiguous who else is included or excluded, while "negative definitions" refer to explicitly defining a group by what they are not. For example, *"Non-experts and engineers use visualizations"* is a counter-example, while *"Non-experts include anyone who is not an engineer"* is a negative definition.

4.2 Who is Included and Excluded from Novices?

4.2.1 Analysis of In/Out-Groups. To qualitatively analyze the descriptions of groups who were considered novices or were described in opposition to novices, we employed inductive thematic analysis [12]. We used an open coding scheme which generated 26 codes relevant to the combined set of inclusion and exclusion descriptions, then organized those codes into six themes (see Table 3 for all themes, codes, and code frequencies). Five themes pertained to the topics/nouns used in descriptions (*Who They Are, Specific Domain, Prior Exposure, What They Do, Technical Skill*) and one theme captured adjectives used in descriptions (*Modifiers*). We captured nouns and adjectives to analyze both **what** was relevant to novice definitions and **how** they were discussed. In the following section, we will discuss the six themes.

Table 3: We generated 26 codes using open, inductive coding to understand the descriptions of people who were included and excluded from novices category. We then inductively generated 6 themes from the codes. The final column of this table indicates the total number of descriptions that theme was applied to (131 total; 60 of people included, 71 of people excluded).

Themes	**Codes** (# of descriptions code was applied to)	Total
Who They Are	Expert (42), Profession (32), Resident (7), Novices (2)	84
Specific Domain	Visualization (21), Computing (20), Art/Design (16), Science/Research (16), Medicine (6)	79
What They Do	Use of A Technology (14), Task (10), Difficulty (5), Opinion (3)	31
Prior Exposure	Experience (11), Knowledge (9), Background (4), Familiarity (3), Training (2)	30
Technical Skill	Data (12), Analysis (4), Literacy (2)	18
Modifiers	Little Exposure (15), Expert (13), Professional (2), Novice (4), Other Modifier (9)	43

*Distinctions are based on who people are (Theme: **Who They Are**, 84/131 descriptions).* The most frequently applied theme captured broad categorizations of people — "Who they are." In this section, we discuss the codes we assigned within the theme to describe differences between people included in and excluded from novices. This theme was applied to 84 of the 131 descriptions we collected (23/60 about people included, 61/71 about people excluded).

Who are novices? At a high level, our coding revealed that authors use a range of categorical descriptors to specify which people are novices. Professions were most often used to identify novices (10/60 descriptions of people included), followed closely by geographical descriptions that used broad-sweeping terms like "residents" and "citizens" (7/60) (see Table 4 for examples of professions). A few papers included "experts" as part of defining novices. For example, Choi et al. [23] described "domain experts" as a subgroup of their target audience of "non-experts."

Who are not novices? Most descriptions of people not considered novices either directly described people as "experts" (38/71 descriptions of people excluded) or referred to a specific job title (23/71). Some papers provided more description about the nature of "experts" (e.g., *"experts in data mining techniques (e.g., engineers or biologists)"* [13]), while others referred to groups as "experts" without further explanation (e.g., *"wide audiences, including experts, policymakers, and lay people with different levels of data literacy."* [17]).

*4.2.2 Distinctions are connected to specific domains of knowledge (Theme: **Specific Domain**, 79/131 descriptions).* Many novice definitions mentioned at least one specific domain of knowledge (79/131 descriptions), suggesting the importance of domain-specific knowledge in visualization research for novices. Of the 79 descriptions that included domain information, many referred to scientific or technical fields, such as Visualization (21/131), Computing (20/131), Science/Research (16/131), and Medicine (6/131) (an important point of context is that a single paper and description may refer to *more than one* domain). For instance, Salama et al. [110] include *"scientists with only marginal knowledge of computer graphics"* and Tietjen et al. [127] exclude *"medical professionals."* A smaller set of papers referred to Art/Design knowledge (16/131), such as including people with *"limited intuitions to craft color ramps"* [117] or excluding graphic designers [21]. Finally, while domains were often used to contextualize novices, we find that they were rarely important in making distinctions between novices and non-novices — our analysis found very little difference between domains used to describe novices versus those used to describe non-novices. The frequency of assigned codes among descriptions of groups included and excluded from novices were similar, which could suggest that domains are salient to distinctions between who is and is not a novice, but are not, on their own, sufficient to distinguish between the in- and out-group.

*4.2.3 Distinctions are based on activities conducted (Theme: **What They Do**, 31/131 descriptions).* Both descriptions of people included and excluded mentioned activities that a person did or actions that a person took, though it was far more frequent in descriptions of those included (25/60) than excluded (6/71).

Who are novices? Descriptions of people who were included in novices more frequently mentioned tasks or goals, such as authoring visualizations [140], people who have difficulty *"effectively utilizing GPU clusters"* [23], or people who struggle to compare Convolutional Neural Networks [145]. These descriptions also mentioned use of specific tools or technologies (7/60). When descriptions were paired with modifiers, they often described a lack of exposure (e.g., users with no specific expertise in machine learning [60]) or a term like "amateur."

Who are not novices? On the other hand, when these codes were mentioned in descriptions of non-novices, they exclusively referred to a person's use of some tool or technology (6/71 descriptions of people excluded) and were almost always (5/6) paired with the modifier "expert" as in *"expert users"* or *"expert operators"* (e.g., [59, 131, 140]).

*4.2.4 Distinctions are based on prior exposure (Theme: **Prior Exposure**, 30/131 descriptions).* Descriptions of people who were included in novices sometimes focused on an individual's prior exposure. Researchers used different words to describe and quantify this exposure, most frequently referring to "knowledge" (9/131) or "experience" (11/131).

*4.2.5 Distinctions sometimes mention specific technical skills (Theme: **Technical Skill**, 18/131 descriptions).* Codes involving particular technical skills were mentioned infrequently overall and with a

Table 4: One of the codes that emerged during inductive coding was Professions when describing novices. This table provides examples of the specific professions mentioned in the papers (in alphabetic order).

Code	Examples Included	Examples Excluded
Professions	Crowdworkers [1, 116] Designers [61, 95] Forecasters [51] Medical graduate students [145] Policymakers [139] Visualization students [125] 3D Modelers [61]	Authors [156] Biologists [13] Data scientists [15] Designers [28, 117, 142] Engineers [13] Information workers [6] Medical professionals [127] ML practitioners [60] Musicians [61] Radiologists [67] Students [27, 125] Teachers [44, 70] Visualization experts/researchers [67, 108]

similar frequency among descriptions of novices (9/71) and non-novices (9/60). When technical skills were mentioned, they most frequently regarded a person's ability to work with or manipulate data (12/131), though explicit mentions of data analysis were infrequent (4/131). For instance, individuals with little to no background in data science were labelled novices, while data science experts were not [60].

*4.2.6 Modifiers (Theme: **Modifiers**, 43/131 descriptions).* Modifiers were used in both descriptions of people inside and outside of novices, though the specific modifiers used varied. Among descriptions of people excluded, the most common modifier was "expert" (11/71). The "expert" modifier was most often applied to "users" or "operators" (6/11), though it also appeared as a modifier to practitioner [69, 145], analyst [88], and designer [96]. This can be seen in direct contrast to descriptions of people who were included, where the most frequently applied modifier described how little of something novices had – appearing in a quarter of all inclusion descriptions (15/60). What exactly was lacking differed across papers. In 6 of the 15 papers, novices lacked knowledge in topics such as *"ontological models like [Knowledge Graphs]"* [152] and *"flood management"* [29]. In 4 other papers, novices lacked experience with areas like *"text analysis or text visualization"* [119] and process model analysis [149]. Other modifiers were present in descriptions of people who were included in novices, though novices were never described as "professional" as those excluded were.

4.3 How have Terms for Novices Been Used Over Time?

We can also ask how the usage of terms for novices has evolved over time. We collected papers from the entire history of the venues we sampled from. However, the papers that met our selection criteria were all published between 1997 and 2022. As summarized in Figure 2, although papers do span back to 1997, a majority of the papers were published between 2014 and 2022. The number of papers in which our keywords (novice, non-expert, general public, and layperson) appeared follow similar patterns, but differ in frequency. Namely, the terms "novice" and "non-expert" have consistently appeared in more papers than either general public or layperson, and began consistently appearing in abstracts and titles around 2014. These results may suggest that visualization community interest in novices emerged fairly recently.

5 HOW ARE VISUALIZATIONS FOR NOVICES EVALUATED?

In this section, we describe our findings regarding how visualizations for novices are evaluated. To do this, w e collected information on how participants are described, their geographic location, and age because those are details frequently reported in methodology sections and may be indicative of how visualizations are received (e.g., [107, 111]).

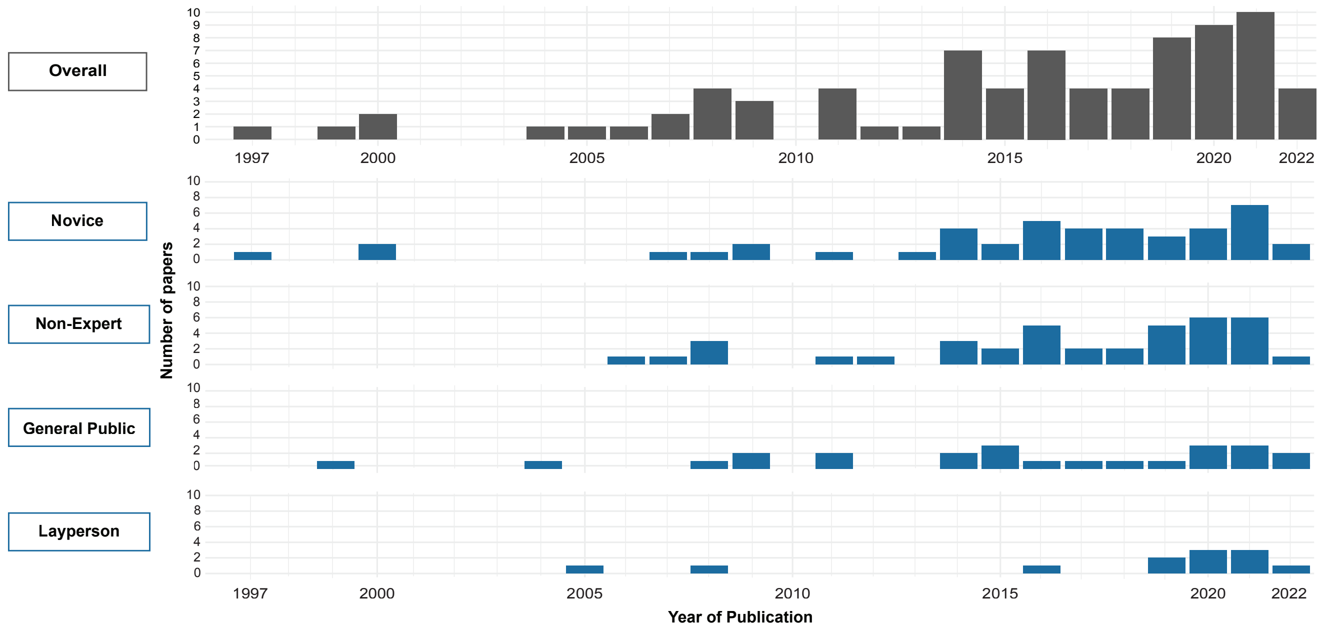
5.1 Where Do Participants Live?

We collected the countries where participants were sampled try to understand who participants are geographically. About half of the studies (24/49) did not explicitly state (or provide sufficient information to infer) which countries participants were sampled from. Among the papers which stated the location of the participants, a majority of studies sampled participants solely from the United States (15/25). Of the remaining 10 studies, 5 sampled participants from countries in Europe [9, 27, 40, 44, 81], 2 from Canada [10, 83], 1 from the United States and Canada [1], and 2 from China [19, 152].

5.2 How Old are Participants?

In our data collection, we collected the minimum, maximum, and mean of participant ages reported because it can help us understand what kinds of people the results for novices are based on. Of the 44 papers which included at least one study where participants were intended to represent novices, 19 provided no age information for one or more studies. When reporting ages, if papers reported a minimum participant age, they also always reported a maximum age (n = 24). While a majority of the papers reported the minimum and maximum ages numerically, 2 papers provided an age range instead (in both cases, 18-24 and 55-64 were the minimum and maximum respectively) [10, 27]. A smaller number of papers reported the

Figure 2: Although papers that met our selection criteria were published as early as 1997, most of the papers were published between 2014 and 2022. The terms "novice" and "non-expert" were consistently used more frequently than "general public" and "layperson."



mean age than the min/max ($n = 16$), though almost all of the papers reporting the mean also provided the min/max ($n = 15$).

Our results suggest that participants (in general) are fairly young, though most studies contain participants spanning several decades. The minimum age reported ranged from 6 [67] to 29 [127], though most of the papers reported the youngest participants as 18 ($n = 4$), 19 ($n = 5$), or 20 ($n = 5$) years old. Maximum ages were more evenly spread across the range from 23 to 72, with an approximately equivalent number of studies where the oldest participants were in their 20s, 30s, 40s, 50s, and 60s. Mean participant ages ranged from 20 to 43, with an average mean age of 30 and a median of 28.

5.3 How are Participants Described?

To analyze what kinds of participants were recruited in studies about novices, we collected descriptions of those participants from each paper. We inductively generated a set of exclusive description categories, and iterated upon that list until all descriptions fit into one of the categories. Ultimately, we ended up with eight categories of participants (see Table 5 for the categories, counts, and descriptions).

Our results indicated that over a quarter of studies used students as their only participants (15/49). This represents one and a half times the number of studies with participants from any of the other categories. Of the studies which solely recruited student participants, only [125] explicitly involved visualization students. An additional 5 studies utilized student participants, but combined them with another group of participants such as professors [88]. The second largest category of participants was crowdworkers, which were recruited in about 20% of studies (10/49).

5.4 What Types of Evaluations are Conducted?

To understand whether our current understanding of visualization novices might be influenced by our methods, we used Isenberg et al.'s taxonomy [63] (which itself is an extension of the taxonomy from Lam et al. [73]) to categorize papers which reported participant evaluations and also recorded their context (online or in-person).

Among the papers we surveyed, we observed 5 types of evaluations previously described by Isenberg et al.[63]: Communication Through Visualization, User Experience, User Performance, Understanding Environments and Work Practices, and Visual Data Analysis and Reasoning. Descriptions of all 5 types are provided in Table 6 along with the number of studies of each type we surveyed. Among the evaluations, User Experience and User Performance were by far the most common ($N_{UP} = 20$, $N_{UE} = 22$), but the types of studies differed among those conducted online and in-person. Our results indicated that more studies were conducted in-person (33 studies in 32 papers) than online (15 studies in 11 papers). Among the studies which took place online, almost all evaluated User Performance (11 of 15 studies). The tilt toward User Performance was not the same for in-person studies, where User Experience was evaluated twice as often as User Performance ($N_{UE} = 19$ of 33, $N_{UP} = 9$ of 33).

6 DISCUSSION

In this work, we explored how visualization researchers refer to novices in their work. Our qualitative analysis of 79 papers was guided by two central questions: *How do researchers talk about novices?* and *How are visualizations for novices evaluated?*. Our results revealed that in most of the papers we surveyed, it was ambiguous as to who should (not) be categorized as a novice. We

Table 5: We categorized the descriptions of participants for all 49 papers that reported a study into eight (exclusive) categories. The largest number of study participants were students followed by crowdworkers.

Type of Participants	# Studies	Description of Type
Students Only	15/49	All participants were students (undergraduate, graduate, or K-12).
Crowdworkers	10/49	Participants were crowdworkers recruited from platforms such as Amazon's MechanicalTurk or Prolific.
Students Plus One	5/49	Participants were a combination of students and one other group such as university staff or community members.
Volunteers	5/49	Participants were either directly described as volunteers or were sampled from attendees at a workshop or other event.
Mixed Skill	4/49	Participants are sampled to represent people of differing skills, experiences, or abilities.
Skill-based	3/49	Participants were recruited because they all possess a specific skill, experience, or ability.
Keyword	3/49	Participants are only described using one of our keywords (e.g., general public, novice, non-expert, layperson).
Unspecified	4/49	Participants were recruited, but they are not described.

Table 6: Among the papers which recruited participants to represent novices, we observed 5 types of evaluations described in Isenberg et al. [63]. Among all different types, User Experience and User Performance were the most frequent types of evaluations conducted.

Type of Evaluation	# Studies	Definition of Evaluation Type from [63]
User Experience	22/49	*"Evaluations that elicit subjective feedback and opinions on a visualization (tool)."*
User Performance	20/49	*"Evaluations in this category objectively measure how specific features affect the performance of people with a system."*
Understanding Environments and Work Practices	5/49	*"Evaluations that derive an understanding of the work, analysis, or information processing practices by a given group of people with or without software use."*
Communication Through Visualization	1/49	*"Evaluations that assess the communicative value of a visualization or visual representation in regards to goals such as teaching/learning, idea presentation, or casual use."*
Visual Data Analysis and Reasoning	1/49	*"Evaluations that assess how a visualization tool supports analysis and reasoning about data and helps to derive relevant knowledge in a given domain."*

found that novices are typically described in a non-inclusive manner: they are defined in opposition to "experts" and are described as lacking. Additionally, we found that researchers leverage features like professions and proximity to (largely scientific) fields to distinguish who is and is not a novice. Further, we found that despite the broad group of people who *might* be considered novices, the people who represent them in evaluations are rather narrow: participants tend to be people in their 20s, from the United States, and/or are students. In the following, we discuss the implications of our results, especially in light of inclusive design [25] arguing for the inclusion of a broader set of audiences in visualization practice.

6.1 Ambiguity in Defining Novices Imperils Generalizations

6.1.1 Implications: Our results indicated that there is often an ambiguity as to who is (not) a novice. In particular, our analysis suggested that authors rely on implicit definitions for novices in place of explicit definitions (e.g., by using examples or counter-examples). Although implicit definitions clarify some of the characteristics of the words being defined, they rarely provide the clarity and precision of explicit definitions [138]. Further, definition by example is difficult because not all examples are equally helpful — in order for an example to effective, a reader must be able to identify that the example can generalize to a broader set of problems or rules [87]. Without sufficient context around the example, it may not be clear to the reader *what* should be generalized.

Similarly, counter-examples can be a helpful for learning about the nature of some phenomena (e.g., as observed in [3, 18, 50]), but they must defy the reader's existing expectations in order to be beneficial [146]. In other words, in order to be helpful, a counter-example must (at least) teach the reader that their existing belief is wrong. In this way, specifying that "music lovers" are *not* in the general public may be helpful if the paper reader assumed that "music lovers" would be included, while stating that "experts" are not novices may not be helpful if the reader already assumed this was true. Nonetheless, counter-examples that violate a reader's expectations may still be unable to resolve the cognitive dissonance between what a reader previously believed and their new knowledge [146]. In other words, providing an effective counter-example may teach the reader that they are *wrong* about who belongs in an audience, but does not always help them understand what is *right*.

Given the broad implication of novices (ranging from novices in the field of visualization to novices in many other disciplines), the lack of consensus around the definition seems natural. However, the ambiguity in defining the targeted audience group and the lack of specificity can impede our understanding of the needs and challenges of broader audiences, and result in over-generalizing research outcomes for audiences that were never intended (or evaluated) in the original research. This, in turn, can misinform the future of visualization design for broader audience groups. We can see how this could occur for novices by examining how the pool of visualization "users" has shifted over time and how implied audiences may have shifted with it. As many authors have pointed out, analysts were once considered the dominant or sole audience for visualizations (e.g., [5, 57]). In that context, it is consistent within a paper for authors to use "novices" as a term for less experienced analysts. Today, this same group of people may be excluded from the novice category by authors using identical language — as the audience for visualizations has expanded, even inexperienced analysts may not be considered novices at all – and so results about and guidelines for novices 30 years ago might not be applicable to the novices of today.

6.1.2 Opportunities for Future Work: We propose that papers should clearly define what they mean by novice in their research context. In other situations, authors are expected to provide definitions when they introduce new terms or utilize a term that has multiple meanings. The terms used to refer to novices should be no different. For instance, in a paper exploring the impact of pictograph arrays on "causal sensemaking" processes for the general public, the authors defined the term "causal sensemaking" but did not define "general public" [14]. We suggest introducing a definition of general public such as "people who regularly use static, casual visualizations online or in-print to make decisions." We suggest that "clear" explicit definitions make it transparent what must be true about a person in order for them to be considered in the group (see Table 7 for examples of existing work with clear and explicit definitions).

If authors intend to define novices as a broad audience, it may be helpful to name people who are *excluded*. For instance, defining the "general public" as *"everyone who is not currently employed as a scientist"* clearly delineates who is in the general public and why. We suggest that authors who employ this approach note the difference between an explicit "negative" definition (e.g., *"The general public is everyone who is not currently employed as a scientist"*) and providing a counter-example (e.g., *"People who are currently employed as scientists are not in the general public"*). Notice that the former indicates that the *only* people excluded are people currently employed as scientists, while the latter suggests that scientists are *among* the group of people who are excluded.

6.2 Deficit Models and STEM-Centricity Exclude Broader Group of Novices

Our results show that researchers tend to describe novices by what they lack and in comparison to experts. Further, they rely on qualities like proximity to (largely scientific) domains of knowledge to define who is or is not a novice. Here, we discuss the potential implications of these results as they relate to deficit models and power.

6.2.1 Implications of Talking about Novices as Lacking. Definitions based on a perceived lack may indicate that a "deficit model" is being applied. In deficit models, people are ***"primarily (or even solely)*** *[conceptualized] in terms of their perceived deficiencies, dysfunctions, problems, needs, and limitations"* (emphasis added) [35]. Although not all of the papers we surveyed specifically used the language of deficits, we argue that comparing the lack of particular knowledge/experience/etc against experts who *do* possess that knowledge (and do not warrant further study or technological intervention) satisfies the definition of a deficit model posed in past work (i.e., the belief that a person lacks X and ought to have X) [35]. Deficit models have been critiqued for decades in fields such as education, disability studies, and philosophy on the bases that they can be de-humanizing, disproportionately punish minoritized people, and position one group as the "lesser" form of another [35, 55, 64]. Recognizing when and where deficit models are being applied is critical within the context of visualization research because they suggest different intervention goals than when groups are considered independent from one another. For example, if novices are viewed as lesser experts (in a deficit model), then the goal may be to change novices to make them more like experts; if novices are different from experts, then the goal may be to change the tool to meet the needs of novices.

6.2.2 Implications of Defining Groups Based on Proximity to Science. Many of the papers we surveyed used proximity to science and technology as a means to decide who is (not) a novice. For instance, Science/Research, Visualization, and Computing were among the most frequent codes applied to descriptions. In addition, although we did not code for it directly, we anecdotally noticed that many of the professions mentioned in descriptions seem to reflect a similar focus on science. The Science, Technology, Engineering, and Math (STEM)-centric framing may suggest that visualization applications for novices are largely focused on STEM applications. While there is certainly a broad group of people who use visualizations for STEM applications, there are many ways that people interact with visualizations which are *not* STEM related (e.g., in casual situations such as when procrastinating or listening to music socially [104, 120, 121]). This, in turn, may suggest that non-STEM applications may be under-represented in visualization research.

The preference for science-centric ways of describing novices may also reflect a preference for (or interest in) ways of knowing and doing which are similar to the researchers. People who have power define the knowledge or skills that are deemed valuable and valid [33, 53]. For example, colonial powers have systematically devalued Indigenous ways of knowing and doing in communities across the world in favor of Euro-centric knowledge and practices [115, 137]. Unchecked, this functions as a means to reassert *hierarchical* power

Table 7: Our results showed that novices were often defined ambiguously. To reduce ambiguity, authors should employ clear and explicit definitions that describe the dimensions they consider salient. This table contains examples from existing work which provide clear and explicit definitions.

Term	Explicit Definition	Source
Target Users	*"Our **target users** are people who want to understand their personal data with an aesthetically pleasing display, rather than to perform focused tasks in data analysis"*	[97]
General Public	*"The target audience of the science center is the **general public**, ages from six years and up, with no specific prior experience in computer usage."*	[67]
Non-expert	*"None of the participants reported expertise in political debates or text visualization. We chose to use this population for our study because they represented the **non-expert**, general audience we want to use DebateVis."*	[119]
Novice	*"All of our participants were **novice** Vega users (i.e., were unfamiliar with Vega)"*	[59]
Novice	*"... we are interested in '**novice users**' that can be defined as users who have seen a particular type of visualization for the first time."*	[77]

structures where those who have power perpetuate the idea that the things they have are the most important and inherently superior, and can block individuals who do not conform to behavioral norms from "rising up" [122].

6.2.3 Opportunities for Future Work. The qualities we saw mentioned in descriptions of novices focus on STEM-centric ways of knowing and doing. While a STEM-centric point of view may be appropriate for STEM-centric applications of visualization, it suggests that there are large groups of people who are not being imagined to interact with or use visualizations. We will now discuss a few opportunities for future work that we found under-represented in our data.

One opportunity for authors to value alternative ways of knowing and doing is to be curious about the perspectives of audiences who think about or use visualizations differently from researchers. For example, it could be fruitful to consider the perspectives of individuals who do *not* use or do not want to use visualizations, despite the pressures from an increasingly data-focused world [84, 100] to do so. Like the potential for examining who does not engage with particular media [49], considering the non-users of visualizations may be illuminating. One instance of engaging with people who use visualizations differently is present in recent work by Sultana et al. on visual communication practices in rural Bangladesh [124]. This project offered a look at ways of encoding and communicating information which do not conform to Euro-centric "modern" visualization techniques and values [124]. We argue that the visualization research community should proceed with caution when looking outside of "traditional" visualization audiences and values in that they do not exoticize and other those who are "out there" [126]. Instead, visualization researchers must actively recognize that they are "in here" – that is, that their knowledge and perspectives are actively shaped by their own experiences and perspectives [53, 126].

There may also be opportunities to anchor analyses to dimensions with weaker ties to unequal power structures (e.g., instead of attainment of formal education which is strongly correlated with wealth [42]). For example, literature in education and psychology has explored how "grit" (i.e., "perseverance and passion for long-term goals" [38]) impacts success and achievement (e.g., in [31, 38, 39]). Although the evidence is mixed on the effects of grit as a composite metric, a recent meta-analysis suggested that perseverance component may be positively correlated with academic performance [31]. Further, grit is theorized to differ little between demographic groups [38], though more empirical work needs to be done to clarify the mixed evidence on the relationship between grit scores and specific demographic variables (e.g., age [41], gender [2], ethnicity [20]) [31]. Within a visualization context, one might therefore ask: What strategies do audiences with high grit/perseverance, but little formal visualization training, utilize to accomplish tasks?

Valuing the perspectives of people who use visualizations differently and including skills or attributes which are less tied to institutional power could enable researchers to build visualizations that leverage the knowledge and skills that audience members already have (and therefore get away from a deficit-based point of view). Connecting visualization practices to the experiences and interests of audiences has been discussed in visualization work for years (e.g., [32, 47, 57, 93, 113]) and could take the shape of alternative visual metaphors (e.g., [93]) or entirely different ways to encode or represent data (e.g., [113]). In Science and Technical Communication, reframing communication messages in ways that connect with the audience's specific values and knowledge has been observed as an effective method to connect with people who were entirely excluded from the conversation before (e.g., [8, 85, 94]). For example, Nisbet and Scheufele observed that framing science as "anti-religion" meant that some religious communities felt that climate change conversations were irrelevant to their lives, but re-emphasizing the moral and ethical dimensions of climate change helped scientists such as E. O. Wilson to convince "religious leaders that environmental sustainability is directly applicable to questions of faith" [94]. There is evidence to support connecting visualizations to existing knowledge and interests for groups historically excluded from visualization research as well. For instance, Peck et al. observed that personal connections to the subject of a visualization influenced perceptions of its usefulness among individuals living in rural Pennsylvania [99]. Work in visualization rhetoric may be particularly helpful for future work in this area because it deals with the intricacies of tailoring messages to audiences in visualization (e.g., [26, 62]).

6.3 WEIRD Participant Pools Impede Understanding of Novices' Needs and Issues

Our results showed that the participants sampled to represent novices were largely people located in the United States, around 20 years old, and/or currently students. The result that mean and median participant ages clustered around 20 years of age is consistent with our other findings that revealed participants tend to be students or a mix of students and non-students (e.g., local community members, university staff). However, we ought to keep in mind that these narrow sets of participants may not be representative of broader audiences. The practice of using students as subjects has been a controversial debate for decades and, while not inherently wrong, can be problematic when students differ from the target population along dimensions which influence the magnitude or implications of the result [37]. Without a clear description of who novices are (within the context of a particular paper), it is difficult to accurately assess how students may represent novices as whole.

Further, over-sampling students could be a problem for the generalizability of visualization results because of the similarity between students and researchers. Media and communication theory tells us that when two parties are communicating, the similarity between the message sender (i.e., researcher) and receiver (i.e., participant) is an important factor in whether the intended message will be received [52]. If both visualization researchers and the students that they recruit tend to be similarly WEIRD (Western, Educated, Industrialized, Rich and Democratic [45, 58]), then it is possible students will be more likely to perceive the "intended" meaning of a visualization than novices as a whole. In this work, we did not specifically investigate *how* participants were recruited or compensated, but these factors may also impact who is considered an acceptable participant in visualization research and how they approach the visualizations. Future work may explore these design choices and their potential impacts on research outcomes.

6.4 Narrow Focus on User Experience and Performance Hinders In-Depth Evaluation with Novices

Our results indicate that human-subject studies motivated by novices tend to rely on evaluations of user experience or user performance on a visualization. These two experimental methods are helpful for establishing what works for people and how they feel about them, but there is some knowledge that cannot be established by these two types of evaluations alone. For instance, very few papers that we surveyed examined the *existing* practices of novices. Observing the ways that participants already use visualization in their daily lives may be helpful for better understanding what role visualization plays in novices' lives [4] and reveal topics that participants may not bring up in interviews or other types of evaluations in which they are asked for their perspectives on novel stimuli [24]. Although observations were largely absent from the papers we surveyed, there are several examples of visualization papers which have applied this approach and demonstrated how informative it can be (e.g., Grammel et al. and Liu et al. on visualization construction [47, 80], Lee et al. on coronavirus skeptics [76]). Future work may further utilize observation and explore alternative methods of exploring how novices interact with visualizations and utilize them in their decision-making processes. Together, this approach may inform how the field can address the needs of broader audiences beyond the typical user groups that are recruited today.

6.5 Limitations

There are several limitations to our work. First, our results may be influenced by the particular papers that we included in our survey. We selected papers which used one of our keywords in the title or abstract as a proxy for selecting papers which were "about" visualization for novices (following a similar selection method to the method used in [34]). However, this selection technique may have resulted in the inclusion of papers that did not center novices or the exclusion of papers which were about novices but either did not use one of our keywords in either their abstract or title or used another possibly related term such as "mass audiences" that we did not use (as in [132])). Future work could utilize alternative methods of collecting or filtering papers, such as using author-supplied keywords or full-text search. Similarly, our results may have been influenced by the number of papers which were included in our survey. Our set of papers represents all papers published within "core" visualization venues, but they are, by no means, all of the papers about novices and visualization. Finally, we utilized qualitative methods throughout our survey process. While this allowed us to collect nuanced information about the papers we read and we utilized techniques to ensure consistency between coders similar to those used in previous work (e.g., [86]), what data we collected and how we interpreted them was necessarily influenced by the authors' own perspectives and experiences.

7 CONCLUSION

In this paper, we investigated how visualization research conceptualizes novices in terms of both the language used to describe them and the participants who are recruited to represent them. Through a survey of 79 "core" visualization research papers that used the terms "novice," "non-expert," "general public," or "layperson" in their title or abstract, we revealed that researchers often used characteristics such as professions, proximity to scientific fields, and/or a lack of expertise, knowledge, or skills to define who is (not) a novice. Further, we found that the participants selected to represent novices in evaluations come from a narrow set of backgrounds and take part in studies that are narrowly focused on user experience and performance. Based on our results, we identified a series of potential consequences of generalizing results from a small subset of participants to a wide range of novices in visualization. We also discussed opportunities for future work, including the importance of engaging with individuals who have alternative ways of knowing and doing. Our suggestions are not intended to be exhaustive but instead meant to probe some of the assumptions made about people labeled novices and to call for action in which more diverse audiences are included and accounted for in the future.

ACKNOWLEDGMENTS

The authors would like to thank the anonymous reviewers for their thoughtful feedback and Michael Correll and members of the HCI-VIS lab for their feedback on early versions of the paper.

REFERENCES

[1] Jarryullah Ahmad, Elaine Huynh, and Fanny Chevalier. 2021. When Red Means Good, Bad, or Canada: Exploring People's Reasoning for Choosing Color Palettes. In *2021 IEEE Visualization Conference (VIS)*. IEEE, CA, USA, 56–60.

[2] Benita R Allen. 2014. *An analysis of student success predictors for technical college persistence*. Ph. D. Dissertation. Edgewood College.

[3] Dana Angluin. 1987. Learning regular sets from queries and counterexamples. *Information and computation* 75, 2 (1987), 87–106.

[4] Lynda Baker. 2006. Observation: A complex research method. *Library trends* 55, 1 (2006), 171–189.

[5] Eric P.S. Baumer, Mahmood Jasim, Ali Sarvghad, and Narges Mahyar. 2022. Of Course it's Political! A Critical Inquiry into Underemphasized Dimensions in Civic Text Visualization. (2022). To appear in the Proceedings of EuroVis 2022.

[6] Sebastian Baumgärtner, Achim Ebert, Matthias Deller, and Stefan Agne. 2007. 2D meets 3D: A Human-Centered Interface for Visual Data exploration. In *CHI'07 Extended Abstracts on Human Factors in Computing Systems*. ACM, NY, USA, 2273–2278.

[7] Nuel Belnap. 1993. On rigorous definitions. *Philosophical Studies: An International Journal for Philosophy in the Analytic Tradition* 72, 2/3 (1993), 115–146.

[8] David Bickford, Mary Rose C Posa, Lan Qie, Ahimsa Campos-Arceiz, and Enoka P Kudavidanage. 2012. Science communication for biodiversity conservation. *Biological Conservation* 151, 1 (2012), 74–76.

[9] Staffan Björk, Lars Erik Holmquist, Peter Ljungstrand, and Johan Redström. 2000. Powerview: structured access to integrated information on small screens. In *CHI'00 extended abstracts on Human factors in computing systems*. ACM, NY, USA, 265–266.

[10] Tanja Blascheck, Lindsay MacDonald Vermeulen, Jo Vermeulen, Charles Perin, Wesley Willett, Thomas Ertl, and Sheelagh Carpendale. 2018. Exploration strategies for discovery of interactivity in visualizations. *IEEE Trans. Vis. Comput. Graph.* 25, 2 (2018), 1407–1420.

[11] Katy Börner, Adam Maltese, Russell Nelson Balliet, and Joe Heimlich. 2016. Investigating aspects of data visualization literacy using 20 information visualizations and 273 science museum visitors. *Information Visualization* 15, 3 (2016), 198–213.

[12] Richard E Boyatzis. 1998. *Transforming qualitative information: Thematic analysis and code development*. Sage Publications, CA, USA.

[13] Sebastian Bremm, Tatiana von Landesberger, Jürgen Bernard, and Tobias Schreck. 2011. Assisted descriptor selection based on visual comparative data analysis. *Computer Graphics Forum* 30, 3 (2011), 891–900.

[14] Alyxander Burns, Cindy Xiong, Steven Franconeri, Alberto Cairo, and Narges Mahyar. 2021. Designing with Pictographs: Envision Topics without Sacrificing Understanding. *IEEE Trans. Vis. Comput. Graph.* (2021), 13 pages.

[15] Ángel Alexander Cabrera, Will Epperson, Fred Hohman, Minsuk Kahng, Jamie Morgenstern, and Duen Horng Chau. 2019. FairVis: Visual analytics for discovering intersectional bias in machine learning. In *2019 IEEE Conf. on Visual Analytics Science and Technology (VAST)*. IEEE, CA, USA, 46–56.

[16] Emanuele Castano, Vincent Yzerbyt, David Bourguignon, and Eléonore Seron. 2002. Who May Enter? The Impact of In-Group Identification on In-Group/Out-Group Categorization. *Journal of Experimental Social Psychology* 38, 3 (2002), 315–322.

[17] Damla Cay, Till Nagel, and Asım Evren Yantaç. 2020. Understanding User Experience of COVID-19 Maps through Remote Elicitation Interviews. In *2020 IEEE Workshop on Evaluation and Beyond-Methodological Approaches to Visualization (BELIV)*. IEEE, CA, USA, 65–73.

[18] Nicolas Cebron, Fabian Richter, and Rainer Lienhart. 2012. "I can tell you what it's not": active learning from counterexamples. *Progress in artificial intelligence* 1, 4 (2012), 291–301.

[19] Wing-Yi Chan, Huamin Qu, and Wai-Ho Mak. 2009. Visualizing the semantic structure in classical music works. *IEEE Trans. Vis. Comput. Graph.* 16, 1 (2009), 161–173.

[20] Winnie Chang. 2014. *Grit and academic performance: Is being grittier better?* Ph. D. Dissertation. University of Miami.

[21] Zhutian Chen, Yun Wang, Qianwen Wang, Yong Wang, and Huamin Qu. 2019. Towards automated infographic design: Deep learning-based auto-extraction of extensible timeline. *IEEE Trans. Vis. Comput. Graph.* 26, 1 (2019), 917–926.

[22] Luca Chittaro and Fabio Buttussi. 2015. Assessing knowledge retention of an immersive serious game vs. a traditional education method in aviation safety. *IEEE Trans. Vis. Comput. Graph.* 21, 4 (2015), 529–538.

[23] Hyungsuk Choi, Woohyuk Choi, Tran Minh Quan, David GC Hildebrand, Hanspeter Pfister, and Won-Ki Jeong. 2014. Vivaldi: A domain-specific language for volume processing and visualization on distributed heterogeneous systems. *IEEE Trans. Vis. Comput. Graph.* 20, 12 (2014), 2407–2416.

[24] Malgorzata Ciesielska, Katarzyna W Boström, and Magnus Öhlander. 2018. Observation methods. In *Qualitative methodologies in organization studies*. Springer, USA, 33–52.

[25] John Clarkson, Roger Coleman, Simeon Keates, and Cherie Lebbon (Eds.). 2013. *Inclusive Design: Design for the Whole Population*. Springer Science & Business Media, USA.

[26] Andrew Collins and D Ball. 2013. Philosophical and theoretic underpinnings of simulation visualization rhetoric and their practical implications. In *Ontology, epistemology, and teleology for modeling and simulation*. Springer, USA, 173–191.

[27] Shauna Concannon, Natasha Rajan, Parthiv Shah, Davy Smith, Marian Ursu, and Jonathan Hook. 2020. Brooke leave home: Designing a personalized film to support public engagement with open data. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 1–14.

[28] Sarah Cooney. 2021. Toward Co-Creative Tools for Tactical Urban Revitalization. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*. ACM, NY, USA, 1–5.

[29] Daniel Cornel, Artem Konev, Bernhard Sadransky, Zsolt Horvath, Eduard Gröller, and Jürgen Waser. 2015. Visualization of Object-Centered Vulnerability to Possible Flood Hazards. *Computer Graphics Forum* 34, 3 (2015), 331–340.

[30] Donna J Cox. 2015. VIS keynote address. In *2015 IEEE Conference on Visual Analytics Science and Technology (VAST)*. IEEE, CA, USA, 1–1.

[31] Marcus Credé, Michael C Tynan, and Peter D Harms. 2017. Much ado about grit: A meta-analytic synthesis of the grit literature. *Journal of Personality and social Psychology* 113, 3 (2017), 492.

[32] Yael De Haan, Sanne Kruikemeier, Sophie Lecheler, Gerard Smit, and Renee Van der Nat. 2018. When does an infographic say more than a thousand words? Audience evaluations of news visualizations. *Journalism Studies* 19, 9 (2018), 1293–1312.

[33] Catherine D'ignazio and Lauren F Klein. 2020. *Data feminism*. MIT press, MA, USA.

[34] Evanthia Dimara and John Stasko. 2021. A Critical Reflection on Visualization Research: Where Do Decision Making Tasks Hide? *IEEE Trans. Vis. Comput. Graph.* 28, 1 (2021), 1128–1138.

[35] Janette Dinishak. 2016. The deficit view and its critics. *Disability Studies Quarterly* 36, 4 (2016), 24 pages.

[36] Michael Douma, Grzegorz Ligierko, Ovidiu Ancuta, Pavel Gritsai, and Sean Liu. 2009. SpicyNodes: Radial layout authoring for the general public. *IEEE Trans. Vis. Comput. Graph.* 15, 6 (2009), 1089–1096.

[37] James N Druckman and Cindy D Kam. 2011. Students as experimental participants. *Cambridge handbook of experimental political science* 1 (2011), 41–57.

[38] Angela L Duckworth, Christopher Peterson, Michael D Matthews, and Dennis R Kelly. 2007. Grit: perseverance and passion for long-term goals. *Journal of personality and social psychology* 92, 6 (2007), 1087.

[39] Angela L Duckworth and Patrick D Quinn. 2009. Development and validation of the Short Grit Scale (GRIT–S). *Journal of personality assessment* 91, 2 (2009), 166–174.

[40] Niklas Elmqvist and Philippas Tsigas. 2007. TrustNeighborhoods: Visualizing Trust in Distributed File Sharing Systems. In *Eurographics/ IEEE-VGTC Symposium on Visualization*, K. Museth, T. Moeller, and A. Ynnerman (Eds.). The Eurographics Association, Switzerland, 8 pages.

[41] Lauren Eskreis-Winkler, Elizabeth P Shulman, Scott A Beal, and Angela L Duckworth. 2014. The grit effect: Predicting retention in the military, the workplace, school and marriage. *Frontiers in psychology* 5 (2014), 36.

[42] Deon Filmer and Lant Pritchett. 1999. The effect of household wealth on educational attainment: evidence from 35 countries. *Population and development review* 25, 1 (1999), 85–120.

[43] Issei Fujishiro, Yoshihiko Ichikawa, Rika Furuhata, and Yuriko Takeshima. 2000. GADGET/IV: a taxonomic approach to semi-automatic design of information visualization applications using modular visualization environment. In *IEEE Symposium on Information Visualization 2000. INFOVIS 2000. Proceedings*. IEEE, CA, USA, 77–83.

[44] Lynda Joy Gerry. 2017. Paint with me: stimulating creativity and empathy while painting with a painter in virtual reality. *IEEE Trans. Vis. Comput. Graph.* 23, 4 (2017), 1418–1426.

[45] Samuel D Gosling, Carson J Sandy, Oliver P John, and Jeff Potter. 2010. Wired but not WEIRD: The promise of the Internet in reaching more diverse samples. *Behavioral and Brain Sciences* 33, 2-3 (2010), 94.

[46] Nathan Gossett and Baoquan Chen. 2004. Paint inspired color mixing and compositing for visualization. In *IEEE Symposium on Information Visualization*. IEEE, CA, USA, 113–118.

[47] Lars Grammel, Melanie Tory, and Margaret-Anne Storey. 2010. How information visualization novices construct visualizations. *IEEE Trans. Vis. Comput. Graph.* 16, 6 (2010), 943–952.

[48] Frank Grave and Michael Buser. 2008. Visiting the Gödel universe. *IEEE Trans. Vis. Comput. Graph.* 14, 6 (2008), 1563–1570.
[49] Jonathan Gray. 2017. Reviving audience studies. *Critical Studies in Media Communication* 34, 1 (2017), 79–83.
[50] Norbert Gruenwald and Sergiy Klymchuk. 2003. Using counter-examples in teaching Calculus. *The New Zealand Mathematics Magazine* 40 (2003), 33 – 41.
[51] H Haase, M Bock, Elke Hergenröther, C Knöpfte, H-J Koppert, Florian Schröder, Andrzej Trembilski, and Jens Weidenhausen. 1999. Where weather meets the eye—A case study on a wide range of meteorological visualisations for diverse audiences. In *Computer Graphics Forum*. Springer, USA, 261–266.
[52] Stuart Hall. 2003. Encoding/decoding. In *Culture, media, language*. Routledge, England, UK, 127–137.
[53] Donna Haraway. 2020. Situated knowledges: The science question in feminism and the privilege of partial perspective. In *Feminist theory reader*. Routledge, England, UK, 303–310.
[54] Douglas Harper. 2019. Etymology of novice. https://www.etymonline.com/word/novice.
[55] Beth Harry and Janette Klingner. 2007. Discarding the deficit model. *Educational leadership* 64, 5 (2007), 16.
[56] Marti A Hearst, Paul Laskowski, and Luis Silva. 2016. Evaluating information visualization via the interplay of heuristic evaluation and question-based scoring. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 5028–5033.
[57] Jeffrey Heer, Frank van Ham, Sheelagh Carpendale, Chris Weaver, and Petra Isenberg. 2008. Creation and collaboration: Engaging new audiences for information visualization. In *Information visualization*. Springer, USA, 92–133.
[58] Joseph Henrich, Steven J Heine, and Ara Norenzayan. 2010. Most people are not WEIRD. *Nature* 466, 7302 (2010), 29–29.
[59] Jane Hoffswell, Arvind Satyanarayan, and Jeffrey Heer. 2018. Augmenting code with in situ visualizations to aid program understanding. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 1–12.
[60] Md Naimul Hoque and Klaus Mueller. 2021. Outcome-explorer: A causality guided interactive visual interface for interpretable algorithmic decision making. *IEEE Trans. Vis. Comput. Graph.* (2021), 13 pages.
[61] Yi-Jheng Huang, Wen-Chieh Lin, I-Cheng Yeh, and Tong-Yee Lee. 2017. Geometric and textural blending for 3d model stylization. *IEEE Trans. Vis. Comput. Graph.* 24, 2 (2017), 1114–1126.
[62] Jessica Hullman and Nick Diakopoulos. 2011. Visualization rhetoric: Framing effects in narrative visualization. *IEEE transactions on visualization and computer graphics* 17, 12 (2011), 2231–2240.
[63] Tobias Isenberg, Petra Isenberg, Jian Chen, Michael Sedlmair, and Torsten Möller. 2013. A Systematic Review on the Practice of Evaluating Visualization. *IEEE Transactions on Visualization and Computer Graphics* 19, 12 (2013), 2818–2827.
[64] Nancy Jay. 1981. Gender and dichotomy. *Feminist studies* 7, 1 (1981), 38–56.
[65] Amit Jena, Matthew Butler, Tim Dwyer, Kirsten Ellis, Ulrich Engelke, Reuben Kirkham, Kim Marriott, Cecile Paris, and Venkatesh Rajamanickam. 2021. The next billion users of visualization. *IEEE Computer Graphics and Applications* 41, 2 (2021), 8–16.
[66] Stine S Johansen, Timothy Merritt, Rune Møberg Jacobsen, Peter Axel Nielsen, and Jesper Kjeldskov. 2022. Investigating Potentials of Shape-Changing Displays for Sound Zones. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 1–12.
[67] Daniel Jönsson, Martin Falk, and Anders Ynnerman. 2015. Intuitive exploration of volumetric data using dynamic galleries. *IEEE Trans. Vis. Comput. Graph.* 22, 1 (2015), 896–905.
[68] Marta Kersten-Oertel, Sean Jy-Shyang Chen, and D Louis Collins. 2013. An evaluation of depth enhancing perceptual cues for vascular volume visualization in neurosurgery. *IEEE Trans. Vis. Comput. Graph.* 20, 3 (2013), 391–403.
[69] Aaron Kotranza, D Scott Lind, and Benjamin Lok. 2011. Real-time evaluation and visualization of learner performance in a mixed-reality environment for clinical breast examination. *IEEE Trans. Vis. Comput. Graph.* 18, 7 (2011), 1101–1114.
[70] Per Ola Kristensson, Nils Dahlback, Daniel Anundi, Marius Bjornstad, Hanna Gillberg, Jonas Haraldsson, Ingrid Martensson, Mathias Nordvall, and Josefine Stahl. 2008. An evaluation of space time cube representation of spatiotemporal patterns. *IEEE Trans. Vis. Comput. Graph.* 15, 4 (2008), 696–702.
[71] Yngve S Kristiansen, Laura Garrison, and Stefan Bruckner. 2021. Semantic Snapping for Guided Multi-View Visualization Design. *IEEE Trans. Vis. Comput. Graph.* 28, 1 (2021), 43–53.
[72] Bum Chul Kwon and Bongshin Lee. 2016. A comparative evaluation on online learning approaches using parallel coordinate visualization. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 993–997.
[73] Heidi Lam, Enrico Bertini, Petra Isenberg, Catherine Plaisant, and Sheelagh Carpendale. 2011. Empirical studies in information visualization: Seven scenarios. *IEEE transactions on visualization and computer graphics* 18, 9 (2011), 1520–1536.
[74] Jonathan Lazar, Jinjuan Heidi Feng, and Harry Hochheiser. 2017. *Research Methods in Human-Computer Interaction*. Morgan Kaufmann, MA, USA.
[75] Bongshin Lee, Eun Kyoung Choe, Petra Isenberg, Kim Marriott, and John Stasko. 2020. Reaching broader audiences with data visualization. *IEEE Computer Graphics and Applications* 40, 2 (2020), 82–90.
[76] Crystal Lee, Tanya Yang, Gabrielle D Inchoco, Graham M Jones, and Arvind Satyanarayan. 2021. Viral visualizations: How coronavirus skeptics use orthodox data practices to promote unorthodox science online. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 1–18.
[77] Sukwon Lee, Sung-Hee Kim, Ya-Hsin Hung, Heidi Lam, Youn-ah Kang, and Ji Soo Yi. 2015. How do people make sense of unfamiliar visualizations?: A grounded model of novice's information visualization sensemaking. *IEEE transactions on visualization and computer graphics* 22, 1 (2015), 499–508.
[78] Sukwon Lee, Sung-Hee Kim, and Bum Chul Kwon. 2016. Vlat: Development of a visualization literacy assessment test. *IEEE Trans. Vis. Comput. Graph.* 23, 1 (2016), 551–560.
[79] Sebastian Linxen, Christian Sturm, Florian Brühlmann, Vincent Cassau, Klaus Opwis, and Katharina Reinecke. 2021. How weird is CHI?. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 1–14.
[80] Zhicheng Liu, John Thompson, Alan Wilson, Mira Dontcheva, James Delorey, Sam Grigg, Bernard Kerr, and John Stasko. 2018. Data Illustrator: Augmenting vector design tools with lazy data binding for expressive visualization authoring. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 1–13.
[81] Anna-Pia Lohfink, Simon D Duque Anton, Hans Dieter Schotten, Heike Leitte, and Christoph Garth. 2020. Security in process: Visually supported triage analysis in industrial process data. *IEEE Trans. Vis. Comput. Graph.* 26, 4 (2020), 1638–1649.
[82] Weiquan Lu, Chenchen Sun, Timo Bleeker, Yingdan You, Shintaro Kitazawa, and Ellen Yi-Luen Do. 2014. Sensorendipity: a real-time web-enabled smartphone sensor platform for idea generation and prototyping. In *Proceedings of the Second International Symposium of Chinese CHI*. ACM, NY, USA, 11–18.
[83] Zhicong Lu, Mingming Fan, Yun Wang, Jian Zhao, Michelle Annett, and Daniel Wigdor. 2018. Inkplanner: Supporting prewriting via intelligent visual diagramming. *IEEE Trans. Vis. Comput. Graph.* 25, 1 (2018), 277–287.
[84] Michael Luca and Max H Bazerman. 2021. *The power of experiments: Decision making in a data-driven world*. MIT Press, MA, USA.
[85] María José Luzón. 2013. Public Communication of Science in Blogs: Recontextualizing Scientific Discourse for a Diversified Audience. *Written Communication* 30, 4 (2013), 428–457.
[86] Kelly Mack, Emma McDonnell, Dhruv Jain, Lucy Lu Wang, Jon E. Froehlich, and Leah Findlater. 2021. What do we mean by "accessibility research"? A literature survey of accessibility papers in CHI and ASSETS from 1994 to 2019. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 1–18.
[87] John Mason. 2006. *What makes an example exemplary: Pedagogical and didactical issues in appreciating multiplicative structures*. Routledge, England, UK, 41–68.
[88] Matthew Louis Mauriello, Ben Shneiderman, Fan Du, Sana Malik, and Catherine Plaisant. 2016. Simplifying overviews of temporal event sequences. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems*. ACM, NY, USA, 2217–2224.
[89] Kevin T McDonnell and Klaus Mueller. 2008. Illustrative parallel coordinates. *Computer Graphics Forum* 27, 3 (2008), 1031–1038.
[90] Joseph E McGrath. 1995. *Methodology matters: Doing research in the behavioral and social sciences*. Morgan Kaufmann, USA, 152–169.
[91] Kevin Mullet, Christopher Fry, and Diane Schiano. 1997. On your marks, get set, browse! In *CHI'97 Extended Abstracts on Human Factors in Computing Systems*. ACM, NY, USA, 113–114.
[92] Brad A Myers. 2017. SIGCHI Lifetime Research Award Talk–RUBY: Reminiscing about User interfaces by Brad over the Years. In *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems*. ACM, NY, USA, 10–11.
[93] Adam Nieman. 2012. Concrete vs abstract visualisation: the real world as a canvas for data visualisation. In *Proceedings of ADS-VIS2011: Making visible the invisible: Art, design and science in data visualisation*. University of Huddersfield Press, UK, 49–56.
[94] Matthew C Nisbet and Dietram A Scheufele. 2009. What's next for science communication? Promising directions and lingering distractions. *American journal of botany* 96, 10 (2009), 1767–1778.
[95] Peter O'Donovan, Aseem Agarwala, and Aaron Hertzmann. 2014. Learning layouts for single-pagegraphic designs. *IEEE Trans. Vis. Comput. Graph.* 20, 8 (2014), 1200–1213.
[96] Stefano Padilla, Thomas S Methven, David A Robb, and Mike J Chantler. 2017. Understanding Concept Maps: A Closer Look at How People Organise Ideas.. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 815–827.
[97] Ji Hwan Park, Arie Kaufman, and Klaus Mueller. 2018. Graphoto: Aesthetically pleasing charts for casual information visualization. *IEEE computer graphics and applications* 38, 6 (2018), 67–82.
[98] Ji Hwan Park, Saad Nadeem, Seyedkoosha Mirhosseini, and Arie Kaufman. 2016. C 2 A: Crowd consensus analytics for virtual colonoscopy. In *2016 IEEE Conf. on Visual Analytics Science and Technology (VAST)*. IEEE, CA, USA, 21–30.
[99] Evan M Peck, Sofia E Ayuso, and Omar El-Etr. 2019. Data is personal: Attitudes and perceptions of data visualization in rural pennsylvania. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 1–12.

[100] Alex "Sandy" Pentland. 2013. The Data-Driven Society. *Scientific American* 309, 4 (2013), 78–83.
[101] Laura J Perovich, Sara Ann Wylie, and Roseann Bongiovanni. 2020. Chemicals in the Creek: designing a situated data physicalization of open government data with the community. *IEEE Trans. Vis. Comput. Graph.* 27, 2 (2020), 913–923.
[102] Hermann Pflüger, Dennis Thom, Anna Schütz, Daniela Bohde, and Thomas Ertl. 2019. VeCHArt: visually enhanced comparison of historic art using an automated line-based synchronization technique. *IEEE Trans. Vis. Comput. Graph.* 26, 10 (2019), 3063–3076.
[103] Catherine Plaisant. 2005. Information visualization and the challenge of universal usability. In *Exploring geovisualization.* Elsevier, Netherlands, 53–82.
[104] Zachary Pousman, John Stasko, and Michael Mateas. 2007. Casual information visualization: Depictions of data in everyday life. *IEEE Trans. Vis. Comput. Graph.* 13, 6 (2007), 1145–1152.
[105] Chunyao Qian, Shizhao Sun, Weiwei Cui, Jian-Guang Lou, Haidong Zhang, and Dongmei Zhang. 2020. Retrieve-Then-Adapt: Example-based automatic generation for proportion-related infographics. *IEEE Trans. Vis. Comput. Graph.* 27, 2 (2020), 443–452.
[106] Peter Rautek, Stefan Bruckner, M Eduard Gröller, and Markus Hadwiger. 2014. ViSlang: A system for interpreted domain-specific languages for scientific visualization. *IEEE Trans. Vis. Comput. Graph.* 20, 12 (2014), 2388–2396.
[107] Katharina Reinecke and Krzysztof Z Gajos. 2014. Quantifying visual preferences around the world. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 11–20.
[108] Paul Rosen, Voicu Popescu, Christoph Hoffmann, and Ayhan Irfanoglu. 2008. A high-quality high-fidelity visualization of the September 11 attack on the World Trade Center. *IEEE Trans. Vis. Comput. Graph.* 14, 4 (2008), 937–947.
[109] Scott D Rothenberger, John E Wenskovitch, and G Elisabeta Marai. 2011. Pexel and heatmap visual analysis of multidimensional gun/homicide data. In *2011 IEEE Conf. on Visual Analytics Science and Technology (VAST).* IEEE, CA, USA, 297–298.
[110] Christof Rezk Salama, Maik Keller, and Peter Kohlmann. 2006. High-level user interfaces for transfer function design with semantics. *IEEE Trans. Vis. Comput. Graph.* 12, 5 (2006), 1021–1028.
[111] Timothy A Salthouse, Renee L Babcock, Eric Skovronek, Debora RD Mitchell, and Roni Palmon. 1990. Age and experience effects in spatial visualization. *Developmental Psychology* 26, 1 (1990), 128.
[112] Michael Sedlmair, Annika Frank, Tamara Munzner, and Andreas Butz. 2012. Relex: Visualization for actively changing overlay network specifications. *IEEE Trans. Vis. Comput. Graph.* 18, 12 (2012), 2729–2738.
[113] Hong Shen, Haojian Jin, Ángel Alexander Cabrera, Adam Perer, Haiyi Zhu, and Jason I Hong. 2020. Designing alternative representations of confusion matrices to support non-expert public understanding of algorithm performance. *Proc. of the ACM on Human-Computer Interaction* 4, CSCW2 (2020), 1–22.
[114] I-Chao Shen and Bing-Yu Chen. 2021. Clipgen: A deep generative model for clipart vectorization and synthesis. *IEEE Trans. Vis. Comput. Graph.* (2021), 15 pages.
[115] Edward Shizha. 2006. Legitimizing indigenous knowledge in Zimbabwe: A theoretical analysis of postcolonial school knowledge and its colonial legacy. *Journal of Contemporary Issues in Education* 1 (2006), 20–35.
[116] Divit P Singh, Lee Lisle, TM Murali, and Kurt Luther. 2018. Crowdlayout: Crowdsourced design and evaluation of biological network visualizations. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 1–14.
[117] Stephen Smart, Keke Wu, and Danielle Albers Szafir. 2019. Color crafting: Automating the construction of designer quality color ramps. *IEEE Trans. Vis. Comput. Graph.* 26, 1 (2019), 1215–1225.
[118] Henricus Smid, Patrick Mast, Maarten Tromp, Andi Winterboer, and Vanessa Evers. 2011. Canary in a coal mine: monitoring air quality and detecting environmental incidents by harvesting Twitter. In *CHI'11 Extended Abstracts on Human Factors in Computing Systems.* ACM, NY, USA, 1855–1860.
[119] Laura South, Michail Schwab, Nick Beauchamp, Lu Wang, John Wihbey, and Michelle A Borkin. 2020. DebateVis: Visualizing political debates for non-expert users. In *2020 IEEE Visualization Conference (VIS).* IEEE, CA, USA, 241–245.
[120] David Sprague and Melanie Tory. 2012. Exploring how and why people use visualizations in casual contexts: Modeling user goals and regulated motivations. *Information Visualization* 11, 2 (2012), 106–123.
[121] David W Sprague and Melanie Tory. 2009. Motivation and procrastination: Methods for evaluating pragmatic casual information visualizations. *IEEE Computer Graphics and Applications* 29, 4 (2009), 86–91.
[122] Eftychia Stamkou, Gerben A van Kleef, Astrid C Homan, and Adam D Galinsky. 2016. How norm violations shape social hierarchies: Those who stand on top block norm violators from rising up. *Group Processes & Intergroup Relations* 19, 5 (2016), 608–629.
[123] Christian Sturm, Alice Oh, Sebastian Linxen, Jose Abdelnour Nocera, Susan Dray, and Katharina Reinecke. 2015. How WEIRD is HCI? Extending HCI principles to other countries and cultures. In *Proc. of the 33rd Annual ACM Conf. Extended Abstracts on Human Factors in Comput. Sys.* ACM, NY, USA, 2425–2428.
[124] Sharifa Sultana, Syed Ishtiaque Ahmed, and Jeffrey M. Rzeszotarski. 2021. Seeing in Context: Traditional Visual Communication Practices in Rural Bangladesh. *Proc. ACM Hum.-Comput. Interact.* 4, CSCW3, Article 214 (jan 2021), 31 pages.
[125] Uzma Haque Syeda, Prasanth Murali, Lisa Roe, Becca Berkey, and Michelle A Borkin. 2020. Design Study" Lite" Methodology: Expediting Design Studies and Enabling the Synergy of Visualization Pedagogy and Social Good. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 1–13.
[126] Alex S Taylor. 2011. Out there. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.* ACM, NY, USA, 685–694.
[127] Christian Tietjen, Tobias Isenberg, and Bernhard Preim. 2005. Combining Silhouettes, Surface, and Volume Rendering for Surgery Education and Planning.. In *EuroVis.* The Eurographics Association, Switzerland, 303–310.
[128] Cesar Torres, Jasper O'Leary, Molly Nicholas, and Eric Paulos. 2017. Illumination aesthetics: Light as a creative material within computational design. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 6111–6122.
[129] U.S. Department of Education. 2017. *Highlights of the 2017 U.S. PIAAC Results Web Report.* Technical Report. Institute of Education Sci., National Center for Education Statistics. https://nces.ed.gov/surveys/piaac/current_results.asp.
[130] Niels Van Berkel, Jorge Goncalves, Daniel Russo, Simo Hosio, and Mikael B Skov. 2021. Effect of information presentation on fairness perceptions of machine learning predictors. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 1–13.
[131] Stef Van den Elzen and Jarke J Van Wijk. 2014. Multivariate network exploration and presentation: From detail to overview via selections and aggregations. *IEEE Trans. Vis. Comput. Graph.* 20, 12 (2014), 2310–2319.
[132] Fernanda B Viegas, Martin Wattenberg, Frank Van Ham, Jesse Kriss, and Matt McKeon. 2007. Manyeyes: a site for visualization at internet scale. *IEEE Trans. Vis. Comput. Graph.* 13, 6 (2007), 1121–1128.
[133] Manuela Waldner, Alexandra Diehl, Denis Gračanin, Rainer Splechtna, Claudio Delrieux, and Krešimir Matković. 2019. A comparison of radial and linear charts for visualizing daily patterns. *IEEE Trans. Vis. Comput. Graph.* 26, 1 (2019), 1033–1042.
[134] Jagoda Walny, Samuel Huron, and Sheelagh Carpendale. 2015. An exploratory study of data sketching for visual representation. *Computer Graphics Forum* 34, 3 (2015), 231–240.
[135] Yong Wang, Zhihua Jin, Qianwen Wang, Weiwei Cui, Tengfei Ma, and Huamin Qu. 2019. Deepdrawing: A deep learning approach to graph drawing. *IEEE Trans. Vis. Comput. Graph.* 26, 1 (2019), 676–686.
[136] Gesa Wiegand, Matthias Schmidmaier, Thomas Weber, Yuanting Liu, and Heinrich Hussmann. 2019. I drive-you trust: Explaining driving behavior of autonomous cars. In *Extended abstracts of the 2019 CHI conference on human factors in computing systems.* ACM, NY, USA, 1–6.
[137] Angela Cavender Wilson. 2005. *Reclaiming our humanity: Decolonization and the recovery of Indigenous knowledge.* Rowman & Littlefield Lanham, CA, 255–263.
[138] John A Winnie. 1967. The implicit definition of theoretical terms. *The British Journal for the Philosophy of Science* 18, 3 (1967), 223–229.
[139] Jo Wood, Roger Beecham, and Jason Dykes. 2014. Moving beyond sequential design: Reflections on a rich multi-channel approach to data visualization. *IEEE Trans. Vis. Comput. Graph.* 20, 12 (2014), 2171–2180.
[140] Tiffany Wun, Jennifer Payne, Samuel Huron, and Sheelagh Carpendale. 2016. Comparing bar chart authoring with Microsoft Excel and tangible tiles. *Computer Graphics Forum* 35, 3 (2016), 111–120.
[141] Haijun Xia, Nathalie Henry Riche, Fanny Chevalier, Bruno De Araujo, and Daniel Wigdor. 2018. DataInk: Direct and Creative Data-Oriented Drawing. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 1–13.
[142] Cindy Xiong, Ali Sarvghad, Daniel G Goldstein, Jake M Hofman, and Çagatay Demiralp. 2022. Investigating Perceptual Biases in Icon Arrays. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 1–12.
[143] Cindy Xiong, Lisanne Van Weelden, and Steven Franconeri. 2019. The curse of knowledge in visual data communication. *IEEE Trans. Vis. Comput. Graph.* 26, 10 (2019), 3051–3062.
[144] Songhua Xu, Wenxia Yang, and Francis CM Lau. 2009. A visualization based approach for digital signature authentication. *Computer Graphics Forum* 28, 3 (2009), 935–942.
[145] Xiwei Xuan, Xiaoyu Zhang, Oh-Hyun Kwon, and Kwan-Liu Ma. 2022. VAC-CNN: A Visual Analytics System for Comparative Studies of Deep Convolutional Neural Networks. *IEEE Trans. Vis. Comput. Graph.* 28, 6 (2022), 2326–2337.
[146] Rina Zazkis and Egan J Chernoff. 2008. What makes a counterexample exemplary? *Educational Studies in Mathematics* 68, 3 (2008), 195–208.
[147] Wei Zeng, Chi-Wing Fu, Stefan Müller Arisona, Alexander Erath, and Huamin Qu. 2014. Visualizing mobility of public transportation system. *IEEE Trans. Vis. Comput. Graph.* 20, 12 (2014), 1833–1842.
[148] André Zenner, Hannah Maria Kriegler, and Antonio Krüger. 2021. Hart-the virtual reality hand redirection toolkit. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems.* ACM, NY, USA, 1–7.
[149] André Zenner, Akhmajon Makhsadov, Sören Klingner, David Liebemann, and Antonio Krüger. 2020. Immersive process model exploration in virtual reality.

IEEE Trans. Vis. Comput. Graph. 26, 5 (2020), 2104–2114.

[150] Fang-Lue Zhang, Jue Wang, Eli Shechtman, Zi-Ye Zhou, Jia-Xin Shi, and Shi-Min Hu. 2016. Plenopatch: Patch-based plenoptic image manipulation. *IEEE Trans. Vis. Comput. Graph.* 23, 5 (2016), 1561–1573.

[151] Jiayi Eris Zhang, Nicole Sultanum, Anastasia Bezerianos, and Fanny Chevalier. 2020. DataQuilt: Extracting visual elements from images to craft pictorial visualizations. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 1–13.

[152] Shengchen Zhang, Zixuan Wang, Chaoran Chen, Yi Dai, Lyumanshan Ye, and Xiaohua Sun. 2021. Patterns for Representing Knowledge Graphs to Communicate Situational Knowledge of Service Robots. In *Proc. CHI Conf. Hum. Factors Comput. Sys.* ACM, NY, USA, 1–12.

[153] Jian Zhao, Shenyu Xu, Senthil Chandrasegaran, Christopher James Bryan, Fan Du, Aditi Mishra, Xin Qian, Yiran Li, and Kwan-Liu Ma. 2021. ChartStory: Automated Partitioning, Layout, and Captioning of Charts into Comic-Style Narratives. *IEEE Trans. Vis. Comput. Graph.* (2021), 15 pages.

[154] Zengsheng Zhong, Shuirun Wei, Yeting Xu, Ying Zhao, Fangfang Zhou, Feng Luo, and Ronghua Shi. 2020. SilkViser: A visual explorer of blockchain-based cryptocurrency transaction data. In *2020 IEEE Conf. on Visual Analytics Science and Technology (VAST)*. IEEE, CA, USA, 95–106.

[155] Mengdie Zhuang, David Concannon, and Ed Manley. 2022. A framework for evaluating dashboards in healthcare. *IEEE Trans. Vis. Comput. Graph.* 28, 4 (2022), 1715–1731.

[156] Alexandra Zytek, Dongyu Liu, Rhema Vaithianathan, and Kalyan Veeramachaneni. 2021. Sibyl: Understanding and addressing the usability challenges of machine learning in high-stakes decision making. *IEEE Trans. Vis. Comput. Graph.* 28, 1 (2021), 1161–1171.