Understanding Data Accessibility for People with Intellectual and Developmental Disabilities

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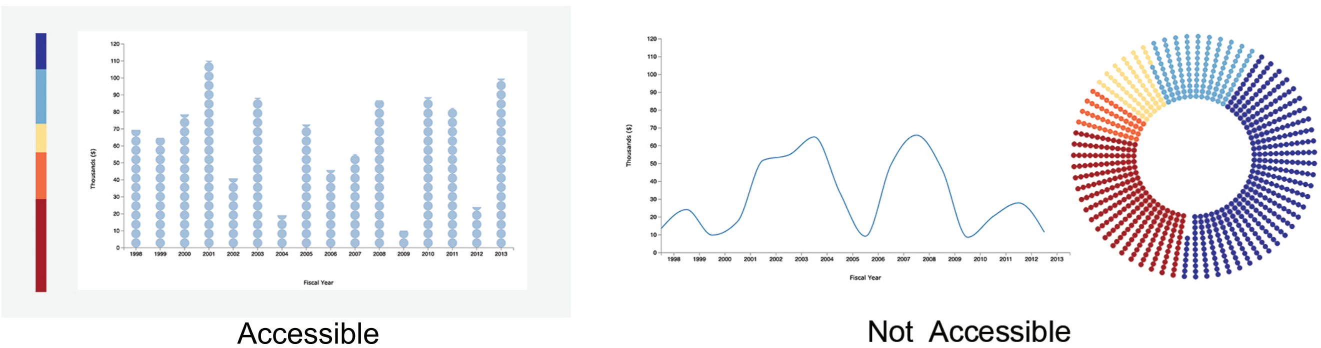

Figure 1: Designers can support accessibility for people with Intellectual and Developmental Disabilities (IDDs) by avoiding pie charts, encouraging natural metaphors and support for working memory, balancing semantics and simplicity, and using discretization with axis-aligned encodings.

ABSTRACT

Using visualization requires people to read abstract visual imagery, estimate statistics, and retain information. However, people with Intellectual and Developmental Disabilities (IDDs) often process information differently, which may complicate connecting abstract visual information to real-world quantities. This population has traditionally been excluded from visualization design, and often has limited access to data related to their well being. We explore how visualizations may better serve this population. We identify three visualization design elements that may improve data accessibility: chart type, chart embellishment, and data continuity. We evaluate these elements with populations both with and without IDDs, measuring accuracy and efficiency in a web-based online experiment with time series and proportion data. Our study identifies performance patterns and subjective preferences for people with IDDs when reading common visualizations. These findings suggest possible solutions that may break the cognitive barriers caused by conventional design guidelines.

CCS CONCEPTS

• **Human-centered computing** → **Visualization**; *Empirical studies in visualization*; **Accessibility**; *Accessibility design and evaluation methods.*

KEYWORDS

human-subjects quantitative studies, graphical perception & cognition

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1 INTRODUCTION

Over one billion people—about 15% of the world's population—lives with some form of disability [4]. About one in six children in the U.S. has one or more developmental disabilities [16], with Intellectual Disabilities (IDs), such as Down Syndrome, Fragile X Syndrome, and Develomental Delay, being the most common. Other common types of developmental disabilities include Autism Spectrum Disorder

(ASD) and Cerebral Palsy. People with Intellectual and Developmental Disabilities (IDDs) may learn about and make sense of abstract information differently from other people [35]. Students with IDDs often exhibit symptoms that directly or indirectly require changes to their exposure to mathematical and statistical reasoning skills in school. These symptoms may also shift the ways these students translate visual information into actionable knowledge [52]. Visualizations rely on these abilities to help people make sense of data. However, the design of such systems seldom considers people with intellectual and developmental disabilities (IDDs), leaving us with little insight into how well conventional mechanisms for data visualization, communication, and exploration support people with IDDs.

While abundant efforts have been made to establish guidelines for effectively communicating data [21, 42, 55], we have limited understanding of how well these guidelines hold for people with IDDs. The cognitive challenges imposed by these disabilities are not well understood, nor are the ways in which those challenges interact with visual and semiotic literacy. Experimental findings can provide both quantitative and qualitative evidence to inform guidelines on effective visualization design [19, 37]. However, the development of such guidelines often involves a limited set of human subjects, and the results might not generalize for people with IDDs. This population usually has inadequate access to information and has been excluded from effectively using visualizations to investigate and understand data related to their well-being. Our goal in this work is to understand how effective visualization design for people with IDDs may differ from conventional guidelines in order to identify potential barriers to data use.

Accessible visualization research has traditionally been focused on developing techniques rather than guidelines, mainly for color vision deficiency and visual impairment [18, 20, 39, 43]. Current understanding of visualization accessibility for people with IDDs is grounded in anecdotal evidence and implications drawn from experimental results in education and disability studies [58]. In this paper, we instead focus on providing empirical insight into aspects of visualization design that may support or inhibit people with IDDs. We build on findings from disability studies and first-hand experiences of relevant practitioners to identify three facets of visualization design that may influence data accessibility: chart type, chart embellishment, and data continuity. Drawing on clinicians' experiences, we expect that the optimal mapping of tasks to chart types like line charts, pie charts, and treemaps will differ for people with IDDs. IDDs often inhibit connecting abstract mathematical values to the real world quantities these numbers represent [52]. However, semantically meaningful pictorials like icons and chart junk can improve memorability [11] and may reinforce the connection between data and meaning [61]. Using discrete, countable representations, such as isotype visualizations [27], may provide further links between visual quantities and the abstract concepts they represent and benefit working memory [61].

To evaluate these design elements, we conducted a mixed-method web-based remote experiment with participants with and without IDDs using time-series and proportion data related to self-advocacy. Although comparing these populations is not standard practice in accessibility research, we use non-disabled participants as a baseline to identify potential barriers to effective visualization use. While our experimental design drew on experiences of clinicians and practitioners, we noted the subjective preferences of people with IDDs alongside standard measurements of task completion accuracy and efficiency to generate participatory insight into effective practices and new directions for accessible visualization design [53]. We used these instruments to identify performance differences across four tasks and two data types: trend estimation and extrema identification in time series data, and value estimation and value comparison in proportion data.

Our results indicate that IDD populations are more sensitive to design choices than non-disabled populations and that their needs at times contradict conventional design wisdom. While the benefits of explicit semantic information are mixed, chart types that mirror real world metaphors, simple imagery, and discretizations of axis-aligned representations can all enhance data accessibility. Our findings illuminate several new opportunities for accessible visualization design.

Contributions: The primary contribution of this work is a set of design guidelines for making visualization accessible to people with Intellectual and Developmental Disabilities. We collected both quantitative performance data and qualitative feedback from populations with and without IDDs. The findings of this study enhance our understanding of visual analytics for people with IDDs and challenge us to reflect on how best practices for visualization design extend to various populations. The results of our study provide preliminary guidance for how to break cognitive barriers caused by conventional design guidelines.

2 RELATED WORK

Intellectual and Developmental Disabilities (IDDs) can take many forms, and people with IDDs are different in many ways. Instead of taking IDD as an umbrella term, we focus on individuals with an intellectual disability (ID) and/or with autism spectrum disorder (ASD) in our study to understand their unique needs for data analyses. We surveyed literature and consulted domain experts to expand our knowledge of this population and situations and limitations to their use of data. Building on the knowledge of mathematical and special education, we identified cognitive aspects of visualization sensemaking that may differentiate these individuals from the non-disabled population. We revisited conventional visualization design guidelines related to these aspects to develop our preliminary hypotheses. We also reviewed progress on cognitive-friendly assistive technology and web accessibility to seek practical solutions.

2.1 Intellectual Disability and Neurodiversity

According to American Association on Intellectual and Developmental Disabilities (AAIDD), an intellectual disability is a disability that is broadly related to thought process, characterized by significant limitations both in intellectual functioning (reasoning, learning, problem solving) and in adaptive behavior, which covers a range of everyday social and practical skills. This disability originates before the age of 18 and is likely to be lifelong [3]. Neurodivergent [57], as opposed to neurotypical, usually refers to a person who has a developmental disorder and/or a mental illness.

Several recognized types of neurodivergence, include autism, Asperger's syndrome, dyslexia, dyscalculia, epilepsy, hyperlexia, dyspraxia, ADHD, obsessive-compulsive disorder (OCD), and Tourette syndrome (TS). As neurodiversity still lacks a clear medical definition, we include and only include individuals with autism in our investigation. Autism, or autism spectrum disorder (ASD), is a developmental disability that can cause significant social, communication, and behavioral challenges. The learning, reasoning, and problem-solving abilities of people with ASD can range from gifted to severely challenged [7].

Intellectual and other developmental disabilities often co-occur, and their symptoms usually vary from person to person. As of the most recent prevalence study [40] conducted by the Centers for Disease Control (CDC), which reported the co-occurring intellectual disability among children aged 8 years, 33% of children with ASD had intellectual disability; 24% of children with ASD were considered in the borderline range in terms of intellectual ability (an IQ of 71âĂŞ85); 42% had IQ scores over 85, considered average or above average. Given the range and diversity of abilities within the IDD community, it is both difficult to link design guidelines to specific abilities and to design universal solutions for all people within this population. However, due to the shared characterization that both intellectual disability and autism frequently cause differences in cognitive abilities related to sensemaking and to the high prevalence of their co-occurrence, we restrict our scope to individuals with intellectual disabilities and ASD. These groups represent a strong use case as there is an increasing trend in these groups of using data for self-advocacy and decision-making, as evidenced by the CDC's Autism Data Visualization Tool [6], the *State of the States* project,[1] and ASAN.[2] This grouping is also inline with established practices adopted by domain specialists in AAIDD (American Association on IDD). Insights into cognitive behaviors of these individuals may enhance our understanding of designing accessible visualization for more general classes of cognitive disabilities, but we leave this hypothesis to future work.

2.2 Mathematical Reasoning & Cognitive Disabilities

Visualizations help people rapidly recognize patterns and trends in data [29]. Reading and interpreting visualizations, however, take significant cognitive effort, including quantitative reasoning, statistical estimation, and information retention [9, 46]. These mechanisms typically function differently for people with IDDs. For example, studies in education have identified variations in how people with cognitive disabilities approach mathematical reasoning through images. Monague [41] found that students with learning disabilities used different strategies to solve mathematical problems than non-disabled populations, leading to challenges transforming abstract numerical information in word problems into mathematical operations. Van Garderen [52] confirmed a prior positive correlation between the use of spatial visualizations and higher mathematical problem-solving performance for non-disabled students. However, students with IDDs struggled to use spatial visualizations, instead using significantly more semantically-meaningful pictorials when solving word problems. Zhang et al. [61] extended these results to show that intelligently designed pictorial images could significantly improve performance on word problems for students with disabilities. These pictorials used fill color to slightly alter the visual representations based on theories about working memory processes and led to improved spatial reasoning.

These studies collectively show that students with cognitive disabilities often prefer using semantically-oriented images to make sense of mathematical concepts, and that figures carefully designed to operate independently of limitations in working memory could significantly improve abstract mathematical reasoning. These results provide preliminary evidence that the right kinds of visualization design cues may also lead to more accessible visualizations for people with cognitive disabilities. We connect these ideas to two concepts in visualization through our study: semantically-meaningful embellishments (i.e., chart junk and icons) to enhance semantic reasoning and discretization to support working memory.

People with disabilities also often face external obstacles to visualization use, including lack of visualization literacy due to variations in educational opportunities [35, 52] and inadequate representation in visualization research studies. Recent efforts towards understanding visualization literacy offer frameworks for developing and assessing people's abilities to read and construct data visualizations. For instance, the data visualization literacy framework (DVL-FW) works towards developing standards for teaching and assessing visualization literacy [14]. VLAT provides an instrument to measure visualization literacy [38]. Other efforts explore optimal means for communicating data to populations with different expected levels of data literacy, including both objective performance and emotional valence [24]. However, these studies focus on non-disabled populations. According to the U.S. Department of Education, only 17% of students with intellectual disabilities spend most of the school day inside general classes [1], lowering exposure to traditional mathematical and statistical concepts, including basic visualization use and literacy. This lack of statistical exposure coupled with known differences in cognitive processing mean that we have little insight into how well traditional assessments of visualization literacy work for people with IDDs nor do we have insight into how visualizations may be designed to help overcome these challenges.

2.3 Guidelines for Visualization Design

Guidelines for visualization design are based on how people process visual information. Empirical studies grounded in perception and cognition map chart types to the data types and analysis tasks they best support [8, 47]. For example, people tend to make comparative judgments between values using bar charts but focus on trends in line charts [60]. Scatterplots allow for precise estimates of correlation [28]. However, these guidelines are derived from experiments with neurotypical populations and may not hold for viewers with IDDs. For example, prior work shows that part-to-whole comparisons are more effective with pie charts than with stacked bars [48]. However, discussions with experts who design informational materials for IDD self-advocacy suggest that individuals with IDDs tend to understand stacked bars better than pie charts. Experiments in mathematical studies indicate that students with disabilities use

[1] https://stateofthestates.org/
[2] https://autisticadvocacy.org/

different strategies to translate math problems into corresponding visualizations [52]. These conflicts suggest that traditional mappings between chart types and tasks may not directly translate to viewers with IDDs.

Further, heuristic guidance about visualizations may also make assumptions that introduce accessibility barriers to individuals with IDDs. For example, visualizations are encouraged to maximize the data-ink ratio, encoding data using minimalist designs to maximize the focus on data [51]. However, this minimalism may make it difficult for people to connect data to meaning [25, 33]. Meaningful embellishment may create cognitive benefits for visualization [13, 32]. Hullman et al. found that introducing extra visual images may better engage the user to read information and improve their comprehension and recall [32]. Borkin et al. found that pictorial cues could enhance memorability when used appropriately [13]. Haroz et al. found that isotypes—discrete visualizations using pictorial icons—have positive effects on working memory and the speed of finding information [27]. The increased semantic connection and support for working memory found in these studies aligns well with preferences for pictorial cues [52] and working memory aids [61] used by students with IDDs in mathematical reasoning. The cognitive benefits of such design components, while controversial for traditional populations, may significantly improve usability for people with IDDs.

While these studies offer tacit design hypotheses about accessible visualization, empirical studies can provide direct insight into understanding accessible visualizations [23, 31, 59]. For example, Delogu et. al. [23] found that integrating sonification into maps could negate performance differences between sighted and non-sighted users. Yang et. al. [59] measured how tactile graph representations support different tasks for BLV users. Despite changes in abilities and media, they generally found similar mappings between task and visualization for sighted and non-sighted users. However, we lack substantial insight into how well visualization designs can support viewers with IDDs. This study builds on the above evidence to test how visualizations may begin to address challenges for cognitively accessible visualizations and craft preliminary empirical guidelines for more inclusive practices.

2.4 Web Accessibility & Assistive Technology for Cognition

The web is an important platform for interactive visualizations. The World Wide Web Consortium (W3C) and the Web Accessibility Initiative (WAI) have outlined several standards, tools and techniques to enhance web accessibility. For example, the W3C Cognitive Accessibility User Research [5] describes the challenges of using web technologies for people with learning disabilities or cognitive disabilities, particularly in the areas of attention, executive function, knowledge, language, literacy, memory, perception, and reasoning. This document suggests that people with intellectual disabilities usually have far stronger visual memory compared to verbal memory, but notes that they can experience visual-processing difficulties, such as when extracting meaning from written material, or struggle with mental overload that comes from large amounts of text or unfamiliar content or design elements. To remedy these challenges, guidelines from these agencies recommends using added visual elements like flow charts to break down procedures and pictograms and graphics to communicate location information. For people with autism, who frequently have affected visual comprehension and unusual sensory reactions, guidelines include avoiding distractions, presenting information in smaller units, and pairing icons or graphics with text to provide contexual cues to help with content comprehension.

Unlike screen readers and magnifiers for vision impairment or alternative input devices for mobility impairment, few assistive technologies directly support cognitive disabilities. The WAI introduces adaptive strategies and accessibility features [54] that may help people with IDDs interact with the web. For example, designers can use progressive disclosure techniques to manage visual complexity, showing the minimal information or functions necessary for a given task or use icons instead of text to represent words or concepts. However, these guidelines and techniques focus on general web content and provide limited insight into less standard content such as visualizations.

Research on designing accessible web visualizations has historically emphasized two main areas: color vision deficiency (CVD) and vision impairment. Color vision deficiency affects roughly 8% of the global population [12]. The W3C has developed comprehensive guidelines to make color-coded content distinguishable for people with color blindness and impaired vision[22]. Daltonization algorithms adjust digital images to make colors more distinguishable (see Simon et al. [49] for a survey), and tools exist for understanding and addressing CVD challenges using these algorithms and related approaches [18]. Solutions for blind and low-vision (BLV) analysts tend to focus on incorporating sonification and voice-based interactions into visualizations. For example, Choi et al. interviewed visualy impaired users and proposed an algorithm to automatically extract key information from online charts and read that information to users [20]. Charting libraries like amChart integrate compatibility with screen readers to better serve visually impaired users [2].

Insights into cognitive-friendly web accessibility and accessible features can help develop accessible web-based visualizations; however, it will require user-centered processes to be truly effective [53]. For example, Lundgard et al. introduced a set of sociotechnical considerations for accessible visualization research grounded in a case study of a design workshop in collaboration with the blind [39]. We see the development of such guidelines as a necessary longitudinal and multifaceted effort to examine visualization accessibility through a variety of lenses. To offer preliminary insight into the need to explicitly design for people with IDDs, we seek to understand how the ways people with IDDs read visualizations may differ from the traditional populations used to generate and verify visualization design guidelines. We conducted a preliminary mixed methods study designed in collaboration with self-advocacy experts and with feedback from community members. We additionally draw on both quantitative and qualitative information reflecting the experiences of people with IDDs in analyzing the results of the study.

3 MOTIVATION & HYPOTHESES

Data visualization is increasingly important in many aspects of life, from education and employment, to health care and finance. Despite the growing demand and availability of data, visualization literacy is relatively low among people with IDDs, and data accessibility remains a major challenge.

Discussions with domain experts, including people with IDDs, psychiatrists, and caretakers, revealed that conventional visualization designs are often inaccessible to people with IDDs. People who design data-oriented materials for use by the IDD community have developed heuristics based on their own experiences but feel these heuristics are often ad-hoc solutions that vary across organizations. For example, experts consistently noted that people with IDDs face significant challenges in reading pie charts—when two values are very close, people find it impossible to tell which slice is bigger—but feel more comfortable with stacked bar charts. They noted that popular visualization tools lack visual guidance for connection data to meaning. Experts expressed a strong desire for evidentiary support in designing accessible visualizations for people with intellectual and developmental disabilities. Using these discussions as guides, we aimed to understand whether (a) design guidelines for non-disabled populations generalize to viewers with IDDs and (b) if not, how we might make visualizations more accessible.

In collaboration with a psychiatric expert specializing in IDDs and self-determination, we identified the two important data types to ground our investigation—time-series budgetary data and proportion demographic data—and four associated analysis tasks—trend estimation and extrema identification in time series data and value estimation and value comparison in proportion data. Building on expert guidance and findings from disability studies and visualization research, we identified three elements that might contribute to the design of cognitively accessible visualization: chart type, chart embellishment, and data continuity. We defined chart types as those commonly used with our target data types and largely reflected in our collaborators' current efforts: **bar charts**, **line charts**, **pie charts**, **stacked bar charts** and **treemaps**. Building on observations about pictorial use in education [52, 61], chart embellishments test the effects of semantically meaningful pictorials including **icons** and **chart junk**, compared to classic **abstract** marks. Finally, drawing from observations about working memory and spatial reasoning [27, 61], we measure continuity using data represented through either **continuous** (e.g., a stacked bar) or **discrete** (e.g., a stacked isotype) marks.

Drawing on prior literature and discussions with domain experts, we hypothesize that:

H1–The best chart type for a given task will differ between people with and without IDDs.

Studies from education indicate that people with IDDs may process visual information differently for mathematical reasoning tasks [52, 61]. We anticipate that these differences will lead to different mappings between tasks and visualization designs.

H2–Semantically meaningful chart embellishments will enhance data interpretation for people with IDDs.

Both studies and conversations with experts note a heavy reliance on pictorials to facilitate mathematical reasoning for people with IDDs [52]. Meaningful semantic information can improve visualization interpretation and recall [13, 32] and may likewise serve to scaffold better connections between data and meaning.

H3–Discrete data representations will lead to more accurate performance for people with IDDs.

Haroz et. al. found that discrete isotype visualizations could improve analyses and interact with working memory in beneficial ways [27]. Given that pictorials annotated to support limited working memory improve geometric reasoning for people with IDDs [61], visualizations leveraging similar mechanisms may enable similar improvements.

4 METHODS

We tested our hypotheses using a mixed methods study to investigate how visualization design needs differ for people with IDDs. This study coupled a formal experiment measuring performance across different visualization designs with semistructured interviews to elicit subjective preference and insight into potential differences in the ways the two populations read visualizations. The experimental design team consisted of both visualization experts and a psychiatrist with extensive experience in designing data-oriented material for self-advocacy in the IDD community. Several factors in the study design were adjusted to accommodate the needs of our target population. We explicitly indicate those considerations below.

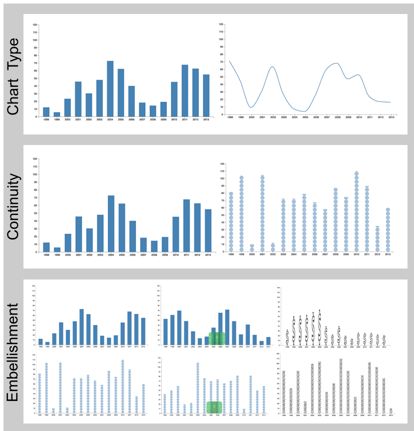
Our experiment was divided into two phases—one using time series data framed as budgetary analysis and a second with proportion data framed as demographic analysis—with interview sessions interleaved between. We used these semantic framings to ground our investigation in known data for self-advocacy [17]. The two phases followed the same general procedure with specific differences explicitly noted below. We tested four independent variables—chart type, chart embellishment, data continuity, and ability level—and two dependent variables—task completion accuracy and response time—across four different analysis tasks.

4.1 Stimuli

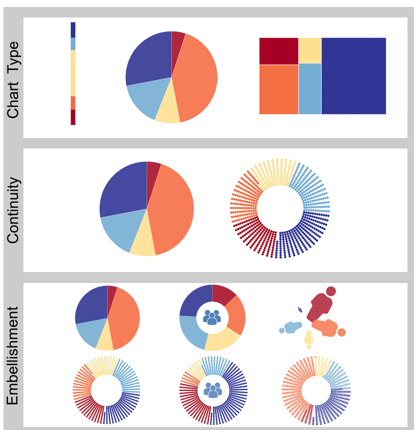
Each trial consisted of one visualization rendered on a white background using D3 [15]. All visualizations were scaled to fill a 900×550 pixel canvas. Above each visualization was a title corresponding to the context of the chart (e.g.,"Spending on Family Supports from 1996 - 2015"). The task question was displayed beneath the visualization along with radio buttons containing each response option.

To encourage engagement with the data over the duration of the study, we grounded the data in tasks oriented towards the community [45]. Time series data consisted of 18 datapoints (one per year) between 1996 and 2015, with total expenditures in dollars on the y-axis, reflecting budgetary information commonly used in self-advocacy scenarios. Proportion demographic data simulated the number of people in the United States with one of five cognitive disabilities drawn from *The State of the States* report [17]. Each stimuli used a simulated dataset (c.f., §4.2.1), with the mapping between datasets and visualizations randomized for each participant.

Each visualization was constructed using a configuration of one of the five target chart types, three embellishment types, and two continuity types. Each participant saw all thirty visualizations twice: once for each analysis task (c.f., §4.2). While we cannot describe



(a)



(b)

Figure 2: Stimulus examples from each trial type. Visualizations in (a) represent extrema identification and trend estimation tasks for time series data, and those in (b) represent value comparison and value estimation in proportion data. Each row displays variations in visualization design factors: chart type, continuity, and embellishment.

each combination of design factors in detail here, we discuss specific instantiations and important exceptions for each level of our independent variables, and show a subset of visualizations in Figure 2. A full set of experimental stimuli and their implementations are available at https://osf.io/vp4ac/.

4.1.1 Chart Types. Our selection of chart types largely reflects the design decisions made in current data visualization efforts targeting populations with IDDs [6, 17]. We tested two common time series chart types—line graphs and bar charts—and three proportion chart types—pie charts, stacked bar charts, and treemaps. These selections additionally mirror chart types compared in prior graphical perception studies focused on similar analysis tasks [34, 60].

Time Series (line graphs and bar charts): Time series visualizations displayed marks on a pair of black axes with no gridlines. Axes had tickmarks indicating each year on the x-axis and 1-step intervals representing units of 10 on the y-axis. The x-axis was labeled as "Fiscal Year", and the y-axis was labeled as "Thousands." Line graphs displayed data using a 2-pixel wide blue line. Bar chart marks consisted of 5-pixel wide blue bars.

Proportion (pie charts, stacked bar charts, and tree maps): Proportion visualizations displayed five categories of data using color: Intellectual Disability as red, Severe and Persistent Mental Illness as orange, Brain Injury as yellow, Stroke as light blue, and Alzheimers as dark blue. We opted for the chosen color palette for three reasons: it is color-blind safe, follows best practices for categorical color, and has a vibrant look that might enhance overall aesthetics and participants' engagement. Pie charts arrayed data using a radial layout; stacked bars as a single vertical bar; and treemaps using a rectangular layout. Each visualization had a color-coded legend rendered immediately to the right of the visualization.

4.1.2 Embellishments. Imagery used to test embellishments consisted of simple cartoon-style SVG graphics selected to maximize their relevance to the target data while minimizing any potentially extraneous information that could cause false associations with the data [10]. Embellishments for time series data focused on emphasizing connections to dollars by primarily encoding a United States dollar sign (all participants were recruited within the United States, §4.4). Embellishments for proportion data focused on demographics (number of people with a particular disability) and were represented using simplified human silhouettes. Embellishments were applied to visualizations in three different levels:

Abstract: Abstract marks consisted of traditional visualization marks with no added semantic embellishments. For example, an abstract bar chart contained only rectangular bar marks.

Chart Junk: While chart junk can involve complex imagery and even shape the data layout [32], we implemented chart junk as a simple, single hue background image aligned with the basic meaning of the data. We used a green cartoon stack of money labeled with a dollar sign for financial time series and a set of three blue human silhouettes for demographics data (Figure 2). This choice reflects a desire to integrate familiar semantic content into the visualization while avoiding potential perceptual confounds introduced by more complex imagery, such as shifting axis alignments when the chart junk guides the visualization layout [21] or significantly increasing the visual complexity of the visualization when the chart junk has high contrast or complex geometries.

Chart junk is overlaid in the center of each visualization as a semitransparent image, rendered behind marks whenever possible. The transparency, size, and layout of the chart junk was manually adjusted in piloting to minimize occlusion with marks while still providing salient visual cues. For treemaps and bar charts, the image was placed in front of the marks with its transparency adjusted such that all bars were clearly visible through the image. Because donut charts and pie charts rely on similar perceptual mechanisms [50], we place chart junk in the center of a donut chart for the pie chart condition to eliminate high-frequency visual artifacts that would otherwise arise from overlaying chart junk at the intersection of multiple wedge marks.

Icons: In icon conditions, each mark is mapped to a single image. To preserve the one-to-one mapping between marks and data, we used either a single dollar sign or a single human silhouette as our imagery for each icon. Icons use the same color schemes as abstract marks and are scaled to match the same dimensions as abstract marks where possible. For example, in bar charts, the height of the icon corresponded to the value of the datapoint while bar width remain fixed.

Icon implementation varied slightly for continuous line graphs and for continuous proportion visualizations. For line graphs, we mapped icons to sample points along the line and rendered a line behind the icons at the same thickness as the icons. In piloting, aspect ratio distortions in treemaps and pie charts interfered with people's abilities to recognize that the figure was a human silhouette. As our goal was to use icons to probe the role of semantic information in accessible visualization design, we preserved the original aspect ratio of icons in proportion visualizations during scaling (Figure 2).

4.1.3 Continuity. The selected chart types use continuous channels to encode data by default. For example, bar charts use the height of a bar while pie charts use the angle of a wedge. To assess the role of continuity in accessibility, we replaced the equivalent space for each continuous mark with an array of 10-pixel wide circular marks (for abstract marks) or images (for icons) arrayed at regular intervals. We used d3-iconarray[3] to implement discrete pie charts and d3-waffle[4] for discrete treemaps.

While we were able to use full icons in line graphs, tree maps, and pie charts without significant loss of information due to the uniform geometric structures of these visualizations, using full icon arrays in bar charts and stacked bars introduce significant imprecision due to rounding errors. We applied masks at partial values in discrete bars and stacked bars to match the length of the icon array to the corresponding data value. The effect led to the top icon being clipped at a level corresponding to the top of a continuous bar in discrete bar charts and to icons of multiple colors in discrete stacked bar charts.

4.2 Experimental Tasks

We evaluated two tasks for each dataset type: extrema identification and trend estimation for time series data and value comparison and value estimation for proportion data. The extrema tasks required participants to find the largest value. Trend tasks asked participants to assess the overall direction of the data (upward or downward). Value comparison tasks asked participants to compare the proportions of three categories. Value estimation tasks asked participants to estimate the interval that a target category's value fell into.

We blocked our experiment by datatype, with block order fixed (time series then proportion) and tasks randomly ordered within blocks. We used a fix block order based on feedback from our collaborators to help participants with IDDs start with what they anticipated would be a more familiar task to build confidence before progressing into the proportion tasks. We analyzed responses from each task separately.

[3]https://github.com/tomgp/d3-iconarray
[4]http://jkunst.com/d3-waffle/

These tasks were crafted based on discussions with experts in the field and based on the collaborating psychiatrist's extensive experience with self-advocacy initiatives among the IDD community. We chose to use trend estimation and extrema identification tasks for time series data as they can help estimate relative values and overall spending patterns for financial advocacy and policy making. Similarly, we chose value comparison and value estimation tasks for proportion data because they measure people's abilities to reason about the prevalence of certain quantities, grounding arguments for funding distributions and similar policy decisions based on relative community populations.

We framed each task using plain language with both wording and difficulty tuned in piloting. Experts worried that asking participants to choose a correct answer from too many options, such as finding the year where spending was highest from the 18 years visualized in the dataset, may lead to frustration amongst participants and high drop-out rates due to inaccessible visualization conditions. Based on this expert guidance and to control the total time needed to complete the experiment overall, we limited the set of possible responses per task to two (trend) to three (all other tasks) responses. The language and responses were as follows:

Extrema: ***Which year has the highest spending?***
Possible answers: The highest overall year, the second highest overall year, and a third year drawn at random

Trend: ***Is spending going up or down over time?***
Possible answers: "Going Up" and "Going Down"

Value Estimation: ***What percentage of the population have <disability name>?***
Possible answers: "Less than 33%," "33% - 66%," or "More than 66%," with the named disability specified according to the dataset.

Value Comparison: ***Which of the following groups has a larger population?***
Possible answers: Three of the named disabilities whose values differed by a fixed amount.

After finishing a task block, participants completed a semistructured interview expressing their preferences and strategies for using different visualization types. Interview sessions were each composed of six questions (three per task) structured hierarchically. Participants were first shown the three chart types as abstract, continuous visualizations and asked to choose the chart type they felt best supported a given task. They were then shown the continuous and discrete versions of their chosen chart type and asked about their preference. Finally, they were shown the different embellishment alternatives for the chosen chart and continuity level and asked their preference. Participants were encouraged to verbally discuss their preferences and thoughts for each question.

We designed the subjective interview hierarchically such that each participant did not have to comb through all thirty stimuli at once but could still provide feedback on each of the variables tied to our hypotheses. This approach helped mitigate concerns raised by IDD practitioners over fatigue effects and cognitive stress and allowed for more in-depth and direct feedback on each design consideration for the tested stimuli.

Design Consideration		Extrema		Trend		Value Estimation		Value Comparison	
		Accuracy	*RT*	*Accuracy*	*RT*	*Accuracy*	*RT*	*Accuracy*	*RT*
	Disability	**$\chi^2(1,32)=18.319, p<.001$**	**$\chi^2(1,32)=94.552, p<.001$**	**$\chi^2(1,32)=13.018, p<.003$**	**$\chi^2(1,32)=46.604, p<.001$**	**$\chi^2(1,32)=44.970, p<.001$**	**$\chi^2(1,32)=40.974, p<.001$**	**$\chi^2(1,32)=34.339, p<.001$**	**$\chi^2(1,32)=38.700, p<.001$**
H1	Chart Type	**$\chi^2(1,32)=5.362, p<.021$**	$\chi^2(1,32)=0.546, p<.460$	$\chi^2(1,32)=0.004, p<.948$	$\chi^2(1,32)=1.038, p<.308$	**$\chi^2(2,32)=9.025, p<.011$**	$\chi^2(2,32)=1.894, p<.388$	**$\chi^2(2,32)=9.179\ p<.010$**	$\chi^2(2,32)=3.094, p<.213$
	Chart Type x Disability	$\chi^2(3,32)=2.073, p<.150$	$\chi^2(3,32)=2.441\ p<.118$	$\chi^2(3,32)=0.050, p<.823$	$\chi^2(3,32)=0.002, p<.963$	**$\chi^2(5,32)=10.264, p<.006$**	$\chi^2(5,32)=0.821, p<.663$	$\chi^2(5,32)=0.131, p<.937$	$\chi^2(5,32)=2.218, p<.330$
H2	Embellishment	$\chi^2(2,32)=0.271, p<.873$	$\chi^2(2,32)=3.752, p<.153$	$\chi^2(2,32)=1.695, p<.428$	**$\chi^2(2,32)=7.953\ p<.019$**	$\chi^2(2,32)=2.395, p<.302$	$\chi^2(2,32)=1.319, p<.517$	$\chi^2(2,32)=3.577, p<.167$	$\chi^2(2,32)=1.202, p<.548$
	Embellishment x Disability	$\chi^2(5,32)=4.979, p<.083$	$\chi^2(5,32)=3.352, p<.187$	$\chi^2(5,32)=0.561, p<.756$	$\chi^2(5,32)=2.467\ p<.291$	$\chi^2(5,32)=1.498, p<.473$	$\chi^2(5,32)=1.039, p<.595$	$\chi^2(5,32)=1.010, p<.603$	$\chi^2(5,32)=2.245, p<.326$
H3	Continuity	**$\chi^2(1,32)=8.106, p<.004$**	$\chi^2(1,32)=0.081, p<.775$	$\chi^2(1,32)=0.414, p<.520$	$\chi^2(1,32)=3.446, p<.063$	$\chi^2(1,32)=0.981, p<.322$	$\chi^2(1,32)=0.636, p<.425$	$\chi^2(1,32)=0.094, p<.759$	**$\chi^2(1,32)=8.454, p<.004$**
	Continuity x Disability	**$\chi^2(3,32)=3.905, p<.048$**	$\chi^2(3,32)=0.021, p<.885$	$\chi^2(3,32)=0.641, p<.423$	$\chi^2(3,32)=3.460, p<.063$	$\chi^2(3,32)=0.083, p<.774$	$\chi^2(3,32)=0.095, p<.758$	$\chi^2(3,32)=0.332, p<.565$	$\chi^2(3,32)=1.281, p<.258$

Table 1: Results from generalized linear models for accuracy and response time for each of four tested tasks. Bolded cells indicate significant effects ($p < .05$); standard text indicates marginal effects ($p < .1$); grey text indicates non-significant effects.

4.2.1 Data Generation. Our data used a library of pre-generated synthetic datafiles structured to reflect the semantics of data used in the *State of the States* [17] while controlling for statistical properties to limit the tested difficulty level. We used synthetic rather than real-world data as the amount of available real world data was too small to generate a reliable set of trials reflecting the statistical constraints necessary to effectively measure performance differences. We first piloted different difficulty levels to find a range of settings that produced comparable performance while avoiding floor and ceiling effects across participants with and without IDDs. We generated one set of data files per task, with each set containing between 55 and 137 unique files. Tested data and generation code are available at https://osf.io/vp4ac/.

Extrema Identification: We generated extrema data by first generating a set of four uniformly-spaced pseudorandom values between 10 and 100 pixels. We interpolated these points using a cubic b-spline and added Perlin noise to introduce variations in the data. The magnitude of the noise was manually tuned to heuristically align with real world datasets [17]. We sampled the resulting curve at 18 regular intervals (one per year) and adjusted the largest sample value such that the difference between the largest and next largest value was between one and five pixels.

Trend Estimation: We generated each trend dataset by first sampling a linear function with a random slope and intercept at 18 equal intervals (one per year) and, if necessary, uniformly scaling the resulting samples to fall between 10 and 100. We then applied Perlin noise to these values to integrate noise into the signal, with noise level again adjusted heuristically to reflect patterns in corresponding real world data. We computed the new trend slope of the adjusted data using linear regression and filtered out any datasets that were too difficult or too easy, with difficulty thresholds tuned in piloting. Our final datasets included only those datasets with slopes whose absolute value fell between 0.18 and 3.2.

Value Comparison: Value comparison datasets consisted of five percentage values summing to 100%: a target proportion, two distractor proportions that were a fixed amount less than the target, and two random additional proportions. We generated these datasets by first assigning a random value for the target category between 14% and 30%. We then set the values for two distractor categories (the near distractor and far distractor) such that the values for the two distractors were:

$$near = value_{target} - \delta; far = value_{target} - \delta - \gamma \quad (1)$$

where δ was between 4% and 10% and γ was between 1% and 2% for each dataset. The values of the remaining two categories were set by randomly dividing the remaining percentages such that all categories were at least 10%.

Value Estimation: We created value estimation datasets by first randomly setting a target category to either 33% or 66%. We then adjusted the category to fall clearly into one of the three responses intervals that participants had to choose from ("Less than 33%," "33% - 66%," or "More than 66%") by either adding or subtracting a random value between 1% and 3%. We randomly divided the remaining percentages such that each category had a value of at least 5%.

For all tasks, we confirmed post-hoc that the above constraints were satisfied and removed any datasets failing to meet these constraints or falling outside of logical thresholds (e.g., percentages summing to more than 100%). Datasets were randomly mapped to stimuli without replacement.

4.3 Procedure

The study consisted of five phases: (1) Informed Consent, (2) Screening, (3) Tutorial, (4) Formal Study, and (5) Demographic Questionnaire. Due to constraints from COVID-19, we conducted each interview as a Zoom video meeting with one experimenter. Participants and, where applicable, their legal guardians received a consent form and PDF tutorial on how to join a Zoom meeting 24 hours prior to each interview. At the start of each interview, we informed participants that the video would be recorded and sent them a study link. We then asked them to open the link and share their screen to give shared context for any clarifying questions and for the interview. The screening phase confirmed whether participants did or did not have an IDD by asking them to self-report any cognitive disabilities.

Participants then received instructions about the study and completed 15 tutorial questions that reflected different visualization conditions seen in the study using easy datasets (i.e., those with lower difficulty levels than the actual study questions). Participants received feedback on whether they answered the tutorial questions correctly after they reported each answer. We encouraged participants to ask any questions they had when finishing these tutorials and noted that the official study would be more difficult. After the tutorial, participants had a chance to pause before proceeding to the formal study.

The formal study consisted of two blocks, one per dataset type. The first block tested time series datasets and contained 24 trials (2 chart types × 3 embellishment levels × 2 continuity levels × 2 tasks) presented in a random order. The dataset used to render each stimulus was randomly drawn from a central database.

Participants clicked a button to begin the formal trials, allowing them to read the instructions and ask any questions before continuing. For each question, they selected a radio button reflecting their answer and clicked "Next" to move to the next stimulus. Response time was measured between when the stimulus was rendered and when the button was clicked. After the last trial in a block, participants entered an interview session, and were asked about their thoughts on the visualizations they used for that dataset. This interview was composed of six questions arranged hierarchically and sequentially as described in §4.2, with each visualization shown as a clickable image button. After walking through the interview questions with the experimenter, participants started the second block. The second block had 36 trials (3 chart types × 3 embellishment levels × 2 continuity levels × 2 tasks). The procedure was otherwise the same as in the first block.

After completing the formal study, participants were directed to a demographic questionnaire and ended with an opportunity for participants to provide verbal or written feedback on our study. Upon submission, they were compensated with a $10 Amazon gift card for their participation.

4.4 Participants & Platform

We recruited 34 participants with normal or corrected-to-normal vision ($\mu_{age} = 30.3, \sigma_{age} = 9$, 19 female, 15 male) from populations with and without intellectual and developmental disabilities in the United States. Twelve of our participants had diagnosed IDDs: six had an intellectual disability and six had autism spectrum disorder. While we anticipate that people with IDDs represent a diverse range of abilities compared with standard populations, we group participants across these disabilities to generate preliminary insight into general accessibility challenges associated with IDDs. Disentangling effects for different IDDs can be challenging due to the co-morbity challenges discussed in §2 as well as ambiguities in diagnoses, variance within the same class of disability, and the size of the population [5]. While future work should strive to understand differences within this diverse group, we seek to instead establish preliminary differences associated with IDDs.

Accessibility studies seldom compare disabled and non-disabled participants. However, one of the primary goals of this study is to understand whether people with IDDs require different design considerations than non-disabled people, whose needs traditional visualization guidelines reflect. In line with prior studies focused on eliciting the unique circumstances of people with IDDs (e.g., [26, 30]), we recruited non-disabled participants to serve as a control population to help identify the unique needs of people with IDDs. Unlike visual or motor impairments, it is unclear whether traditional visualization guidelines hold for people with IDDs. Comparison against a control population allows us to determine whether design can influence accessibility to understand if people with IDDs process visualizations differently from the populations used to generate most visualization guidelines. However, future studies should carefully investigate whether such a comparison is necessary to effectively achieve their goals to avoid inadvertent harm.

5 RESULTS

We analyzed the results for each task using generalized linear models (GLiMs) with accuracy and response time as dependent variables and ability level, chart type, embellishment, and continuity as independent variables. We included interaction effects between the three main design variables and ability level. Though our data was normally distributed, we use GLiMs due to the numerical imbalance in populations sizes. We use contrast tests for post-hoc analyses. Table 1 summarizes our results. For legibility, we include all test statistics in the table, but only report means and 95% bootstrapped confidence intervals for significant effects in this section. Anonymized data is available at https://osf.io/vp4ac/.

People with IDDs performed significantly above chance on average for all tasks. We found significant interaction effects between ability level and all three design variables and performance for at least one task, indicating where performance differed between disabled and non-disabled participants as a function of visualization design. These results collectively suggest that visualizations can be designed to support users with IDDs, but that those designs may require a different set of guidelines. We explore the link between performance and each of our three design considerations in turn.

5.1 H1: Chart Type

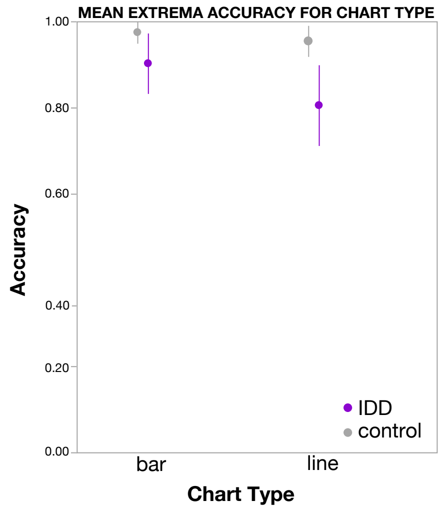
We tested two chart types for time series data—bar charts and line graphs—and three chart types for proportion data—pie charts, stacked bar charts, and treemaps. Figure 3 summarizes significant results.

Chart Type: Quantitative Results

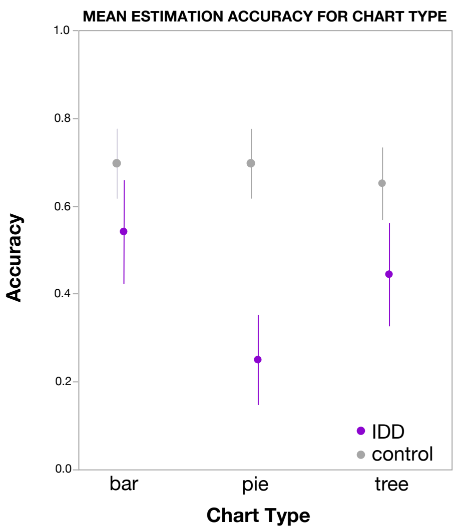
We found significant general differences between chart type and performance in three of our four tested tasks (extrema, value estimation, and value comparison). We found significant differences between participants with IDDs and our control population for extrema and value estimation. For time series data, people were significantly more accurate with bar charts (90.3% ± 7.0%) than with line graphs (80.6% ± 9.39%) in estimating the largest value, but we found no significant effects for trend estimation. When estimating values in proportion data, we found that people were generally better with stacked bars (64.2% ± 6.6%) than with pie charts (53.9% ± 6.9%, $\chi^2(2, 32) = 9.025, p < .011$), contrary to results from Simkin & Hastie [48]. However, this effect was exacerbated for people with IDDs. While chart type did not significantly affect performance for non-disabled users, people with IDDs were more than twice as accurate with stacked bar charts (54.2% ± 10.2%) than pie charts (25.0% ± 10.3%, $\chi^2(5, 32) = 10.264, p < .006$). People with IDDs using pie charts estimated value intervals at a rate less than chance.

Chart Type: Qualitative Results

Our interviews identified notable differences in preferences for chart types across tasks and visual strategies for reasoning over those chart types between people with IDDs and our control population. For extrema, participants from both populations preferred bar charts to line graphs. While the control population appreciated the discreteness of bars, people with IDDs found bars more visually appealing and felt it offered more detail. However, for trends, the control population consistently preferred line graphs while people



(a)



(b)

Figure 3: Mean accuracy across chart types for (a) extrema and (b) value estimation (grey = non-diabled population, purple = IDD population; error bars represent 95% confidence intervals). Bar charts afforded performance comparable between the two populations while line graphs, the conventional method of representing time series, led to worse performance differences. While treemaps offered generally lower performance for value comparisons, people with IDDs struggled to estimate quantities from pie charts.

with IDDs expressed mixed preferences. One participant with an IDD noted, "the rising bars are like steps and stairs and that helps me see where it goes *(P4-IDD)*." In contrast, a participant without an IDD commented that, "the line graph helps me connect those dots and shows the overall fluctuation in data. Though the bar graph is also doing the same thing, I find the line chart more concise and clear looking *(P10)*." These descriptions point to potential differences in sensemaking: while our control group preferred the minimal data-to-ink ratio of the line graph, participants with IDDs tended to prefer chart types that let them systematically progress through the values in the visualization.

Both populations showed a strong preference for pie charts over the stacked bar chart and treemap for proportion data. Non-disabled participants felt that treemaps had "just too much going on *(P11)*," noting that "it's just that the pie chart is bigger and gives me a lot more details than a skinny stripe [the stacked bar] *(P12)*." Participants in the control group also recognized pie charts from math courses. However, participants with IDDs tended to express their preferences for pie charts using analogs to real-world objects, as with the "stair" metaphor with bar charts noted for trends. One participant with IDDs found the pie chart easier to look at because "it's like a pizza or clock that comes with different colors, and I can easily break it down into slices *(P2-IDD)*."

Chart Type: Synthesis

Participants tended to prefer familiar representations in line with prior guidelines overall (bars for value, lines for trend, pies for proportion); however, people with IDDs had different preferences for trend estimation than non-disabled participants or prior studies [60]. While we found that the optimal mapping aligned across both populations for three of the four tasks, people with IDDs struggled to estimate quantities from pie charts despite an overall subjective preference for pie charts. These observations confirmed intuitions from our collaborators and other experts, who often use techniques like stacked bar charts in an effort to create accessible publications for self-advocacy [17]. Participants with IDDs also tended to reason about visualized data using real world metaphors based on the shape of the visual encoding. The conflict between subjective preference and objective performance indicates a novel design opportunity to understand how charts might map to familiar shapes or objects while still supporting accurate inference.

5.2 H2: Embellishment

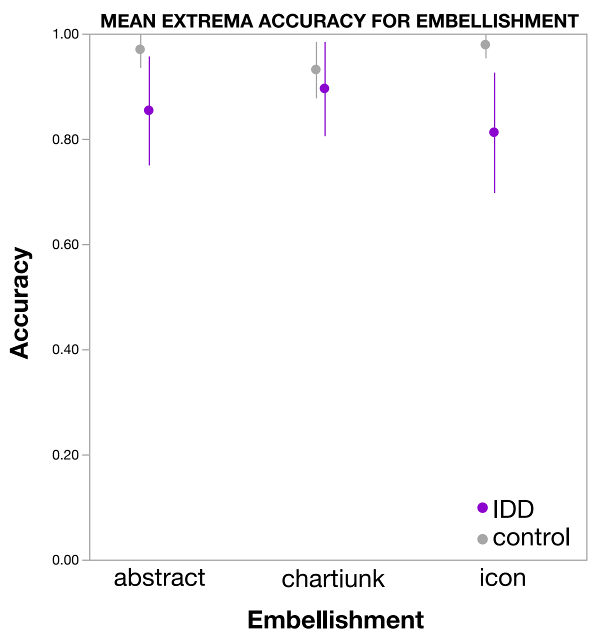
We tested three levels of embellishment across both data types: abstract marks, chart junk (a cartoon money stack with dollar sign logo or a set of stick figures), and icons (dollar signs or stick figures, §4.1). Figure 4 summarizes our findings.

Embellishment: Quantitative Results

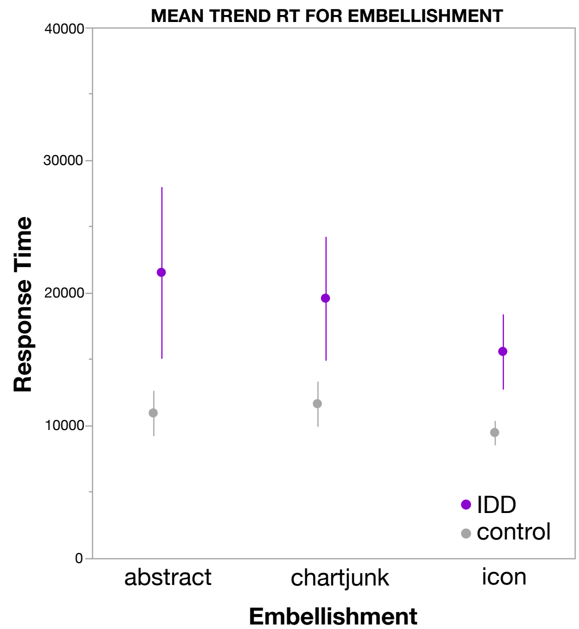
We found effects of embellishment for the two time series tasks (extrema and trend). Icons ($11.6s \pm 1.2s$) were significantly faster overall than chart junk ($14.6s \pm 2.0s$) or abstract marks ($14.7s \pm 2.6s$) for trend estimation. However, using icons marginally increased differences in error rates between participants with IDDs (81.3% ± 11.5%) and our control population (98.9% ± 2.2%) when estimating extrema.

Embellishment: Qualitative Results

Despite the decreases in accuracy for estimation, we found participants with IDDs had an overall stronger preference for icons than those without IDDs. Both populations found chart junk overlaid on a visualization distracting, but noted that it could also help. One participant with an IDD noted, "[an icon] adds a little variety and



(a)



(b)

Figure 4: Mean performances across embellishments for (a) extrema accuracy and (b) trend RT (grey = non-disabled population, purple = IDD population; error bars represent 95% confidence intervals). Icons significantly improved response time for people with IDDs, but introduced interpretation barriers in extrema tasks. Chart junk, however, may mitigate disparities between populations.

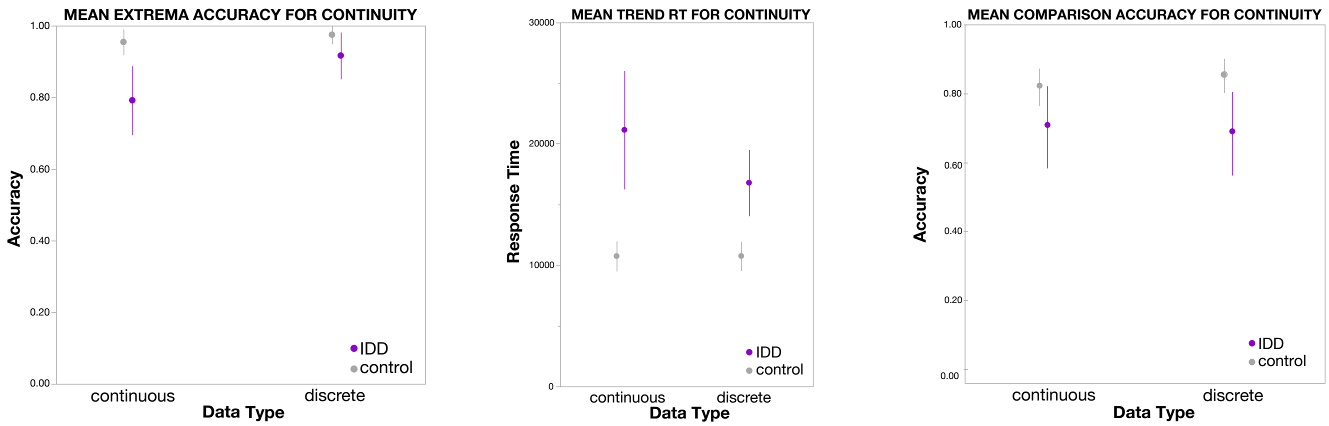
makes me feel much more engaged *(P2-IDD)*." However, the context semantic information is applied to may change preferences: one participant noted that "the dollar sign is universal and it's self-explanatory—the data is about money—but I didn't necessarily make that association between stick figure to people. It's easy to get overlooked *(P15)*." Participants saw imagery as a trade-off that could make values harder to compare. One participant noted, "this people chart looks interesting, however it's only helpful when the two people figures have dramatic differences; when they are small or close, I can't really tell the difference *(P20)*."

We also observed a difference within participants with disabilities: while people with intellectual disabilities tended to remark positively on embellishments, participants with austism tended to prefer abstract visualizations over embellished ones, in line with recommendations for visual simplicity from the W3C [5]. These effects manifested significantly more strongly with proportion charts than time series. One participant repeatedly noted that "clarity is important, the people chart is just not as clear as the solid pie *(P32-IDD)*." Another remarked that they "definitely [didn't] like the one with the people figure, it's confusing and it hurts my eyes. *(P14-IDD)*."

Embellishment: Synthesis

Our results present mixed support for observations from practitioners working with IDD populations and from prior research on pictorial use in mathematics [52, 61] that imagery can help people with IDDs better reason about data. While people were significantly faster at estimating values with icons generally, we found that icons could also degrade performance, and people found them both engaging and distracting. Interestingly, we found nearly identical performance for extrema when chartjunk was present. This apparent lack of difference may identify a case where design can help eliminate disparities between populations; however, given the high overall performance and existing controversy around chart junk [32], confirming the benefits of chart junk for accessible design is important future work. The tension in objective performance between time and accuracy indicates that visualization design knowledge may provide a different context for understanding mathematical reasoning for people with IDDs than word problems used in education research [52, 61]. Further investigating the intersection of math education and visualization literacy for data accessibility is key future work.

Our qualitative results indicate that embellishments may create higher engagement and interest, which aligns with previous findings [32]. Increased engagement may help address issues of limited attention that arise with many IDDs, as noted by our collaborators. While participants with IDDs were able to arrive at comparable answers across different embellishment types, having visual cues from semantic imagery helped them to arrive at the answer faster. However, our proportion results suggest that semantic images represent trade-offs depending on the image used [10]. In some cases, people build more natural associations between certain concepts (e.g., dollar sign and spending) than they do with others (e.g., stick figure and population) due to acquired familiarity. Further studies should explore how the kinds of pictorial cues used in different



(a) (b) (c)

Figure 5: Mean performances across data type for (a) extrema accuracy, (b) trend RT and (c) value comparison accuracy (grey = non-disabled population, purple = IDD population; error bars represent 95% confidence intervals). People with IDDs were faster and more accurate with discrete encodings in time series data, mitigating disparities with the control population.

visualization designs changes these results. Our qualitative observations also surfaced differences with participants with autism and participants with intellectual disabilities. While we found no notable patterns in individual differences for our objective measures, differences in subjective responses with regard to clarity and complexity indicate that analysts may have unique needs based on their own abilities and experiences.

5.3 H3: Continuity

We tested two levels of continuity across both data types: traditional continuous encodings (e.g., length or angle) and countable discrete marks (e.g., isotypes and scatterplots). Figure 5 summarizes our results.

Continuity: Quantitative Results

Performance was influenced by continuity for three of the four tasks (extrema, trend, and value comparisons). People were significantly more accurate at finding the largest of a set of values using discrete encodings (95.6% ± 2.9%) than continuous (89.7% ± 2.0%). They also estimated trends more quickly with discrete encodings (12.9s ± 1.3s) than with continuous encodings (14.4s ± 2.0s). However, these differences appear to driven by participants with IDDs. While performance in the control group was comparable across conditions, for people with IDDs, discrete encodings provided 20% faster trend detection on average (16.8s ± 2.7s) than continuous encodings (21.1s ± 4.9s). We found that discrete encodings also significantly improved extrema estimation accuracy for participants with IDDs (91.7% ± 6.5% for discrete encodings versus 79.2% ± 9.6% for continuous encodings), nearly eliminating overall performance differences between the two populations.

Continuity: Qualitative Results

Participants from both populations had a strong preference for discrete marks in bar charts and stacked bar charts, and but disliked discretized line graphs, pie charts and treemaps. Both groups felt that potentially being able to count elements making accurate judgments overall, but some participants found the charts too cluttered: one participant with IDDs noted, "it's up to how many dots you have. The sunshine looking chart [discrete pie chart] is just all over the place and looks overwhelming *(P4-IDD)*." With discrete line charts (scatterplots), people noted that they were still mentally trying to connect points to estimate values. People with IDDs noted that discrete marks could overencourage counting, noting that with treemaps, they found themselves counting marks rather than estimating as they felt that would lead to the most precise outcome.

Continuity: Synthesis

While classical studies in visualization suggest that continuous encodings are more intuitive for estimating trend and discrete for estimating values [60], our results suggest that the benefits of discrete representations provide more cognitive support, in line with observations about working memory from visualization [27] and education [61]. However, we did not see the same benefits for proportion judgments. This discrepancy leads us to believe that while axis-aligned discrete marks aid performance, people may focus too much on explicitly counting or other strategies that slow response times for non-axis aligned comparisons. Our subjective results support this conclusion: people found themselves counting and second-guessing themselves when discrete marks were not axis-aligned. Further exploration is needed to confirm this hypothesis; however, the mixed benefits of discretization suggest that discrete encodings can significantly support comprehension in time series data.

6 DISCUSSION

Conventional design knowledge in visualization focuses on traditional populations. However, people with IDDs process information differently, creating new challenges for visualization design. As first steps towards understanding cognitively accessible visualization, we measured how quickly and accurately people with and without IDDs interpret data with different chart types, embellishments, and continuity.

We found that people with IDDs were more sensitive to visualization design than non-disabled populations. The differences in performance show mixed benefits of pictorial cues and significant benefits of working memory aids, echoing findings from the education literature and somewhat contradicting conventional minimalistic design approaches. While designs could significantly improve performance for people with IDDs, we found that designs improving accessibility did not degrade performance for the control population. This discrepency indicates that developers can design for accessibility without reducing the universal communicative power of their visualizations. The success or failure of these designs varied as a function of the type of data being analyzed. We synthesize our results into the following design guidelines .

(1) Avoid pie charts: Experts consistently indicated that they avoid pie charts when designing accessible materials. Our results directly support this intuition: people with IDDs struggled to estimate quantities with pie charts and were more than twice as accurate with stacked bar charts and treemaps. However, they preferred pie charts and treemaps over stacked bar charts as currently employed in data materials for supporting IDD self-advocacy [17]. Our interviews revealed that people with IDDs felt that the familiar block shapes of treemaps helped them understand the data. Our results, as well as those from Kosara [34], suggest that treemaps have their own limitations for proportional comparisons. We instead posit that while stacked bars and treemaps are both significantly more accessible, alternative designs using large, regularly-shaped marks may also offer high preference and performance.

(2) Use familiar metaphors: People with IDDs often mentally reasoned about data through analogs to real world objects, such as stairs and pizzas. They preferred using chart types whose structures evoked real world shapes, and, for time series, these structures appear to scaffold reasoning about data in ways that significantly improve performance. These findings reflect the benefits of semantic pictorial information in supporting mathematical reasoning [52] and may help build familiarity with data that transcend differences in education [35] to instead build on differences in experience. These metaphors put performance and preference at odds with recommendations from traditional populations, such as suggesting a preference for bars over lines in estimating trends [47, 60]. Future work should explore the design space of visualizations whose physical structures reflect real world metaphors to enhance accessibility.

(3) Manage visual complexity: While the use of semantic embellishments remains controversial in visualizations generally [32], mathematics education noted substantial benefits for people with IDDs and such embellishments are frequently used by practitioners to enhance communication [5, 17]. However, we found mixed support for this hypothesis: while icons were quicker to use, they introduced performance gaps over other methods in identifying extrema. However, we found preliminary evidence that chart junk may significantly mitigate disparities introduced by visualization design. Participants noted that while visual embellishments could add interest and increase engagement, that they could also overwhelm. Collectively, these observations suggest that simple, meaningful imagery has the potential to support data access; however, such additions should be used intentionally and sparingly and in consultation with the target user group.

(4) Use discrete encodings for axis-aligned representations: Despite a preference for continuous encodings for proportion data, discrete encodings improved accuracy and response times for people with IDDs, significantly reducing disparities with the control group. Unlike the control group, participants strongly preferred discrete bar charts, especially abstract bars. They found that being able to count the points in bars with close values helped them compare values that were further apart. These findings align with prior work showing working memory benefits of "chunking" visual information [61]. However, participants also noted that discretization integrates the temptation to count and to second-guess their intuitions. This was especially problematic in visualizations where the dots in a group varied in more than one dimension (e.g., treemaps or pie charts). Differences in preference and performance by people with IDDs compared to our control population and conventional guidelines—both of which privilege continuous encodings—raise key considerations for how discretization and corresponding working memory benefits [27, 61] may enhance visualization accessibility. However, confirming this connection remains critical future work.

While the above recommendations provide preliminary insight into data accessibility, we note that there were no one-size-fits-all solutions. Instead, we find that the tested design factors illustrate key tensions between conventional guidelines and accessible data. Our results provide preliminary evidence that some design decisions may nearly eliminate performance disparities between the two populations. These recommendations offer new directions grounded in both the preferences and unique abilities of analysts with IDDs and offer preliminary qualitative insight into how the considerations designers make in creating visualizations may need to systematically shift. For example, instead of minimizing data-to-ink, designers may wish to maximize working memory or connections to familiar objects. We anticipate that cognitively accessible visualizations open a rich design space for innovation that removes barriers to data use.

6.1 Limitations & Future Work

We offer preliminary insight into accessible visualization. In doing so, we made several choices in the design and implementation of our study that offer opportunities for future work. For example, we aggregated several different disabilities into a single broad category to identify preliminary insight into the necessity of cognitively accessible visualization. IDDs are known to be difficult to diagnose and often co-occur with other learning or physical disabilities [36], limiting the benefits of more focused samples for design applications. While our sample size prevented us from reliably analyzing patterns in individual differences (we provide preliminary analyses of these differences in our OSF supplement), we anticipate that truly inclusive solutions will need to adapt to the needs of each user. Such techniques could further build on our results, methods from graphical perception, and measurement techniques from visualization literacy to create methods for measuring and adapting data displays to the unique abilities of different users.

When designing the tested visualizations, we chose a full-factorial approach to extensively examine our tested variables. However, some of the variables did not pair as intuitively as others. For example, icons did not map naturally to continuous pie charts without unreasonably distorting the shape of the icon. These mapping challenges led to some less conventional designs and small inequivalences between variable combinations. When possible, we used compromise representations that reflected choices used by designers in practice. Our results revealed no clear universal performance outliers and largely align with guidelines from visualization or education, indicating that less conventional designs did not unduly bias our findings. However, future work should explore a broader suite of designs and tasks to replicate our results.

We only examined a limited variety of designs tied to specific use cases. For example, chart junk focused on simple graphics tied to the semantic concepts they intended to reflect, which may limit the embellishment strategies to specific but familiar semantics. However, other imagery, such as less stylized silhouettes, may provide better cognitive anchors into the data. Future work should look more closely at the link between semantics and chart embellishment to expand these findings. We chose five common chart types and used their classical mapping to certain tasks. While this selection builds on known best practices for traditional users, it also may exacerbate existing educational inequities [1] and cause the familiarity biases we saw in our subjective results. However, participatory design initiatives may instead lead to innovative visualization solutions [39, 44]. Part of truly accessible visualization design will be determining how to create visualizations that make sense to each user to complement our empirical approach.

Finding visualizations that perform well for both populations can offer preliminary insight into universal design for visualization. Our quantitative results indicate that choices like continuous, unembellished stacked bars or discrete bar charts with minimal chartjunk provide generally accessible visualization designs. Although our results can help identify a quantitative middle ground for universal design; we found that people with IDDs had qualitatively very different views on the presented stimuli than those without. While we should ultimately aim to balance the needs of both populations with and without IDDs in visualization design either through adaptive approaches or by developing more universal design guidelines, we do not yet have sufficient evidence to do so effectively and with appropriate care for the special characteristics of this population as well as their individual differences. Substantially more work is necessary before these results could be translated into truly universal approaches to visualization design.

6.2 The Need for Data Accessibility

Our results only scratch the surface of data accessibility for people with intellectual and developmental disabilities. While the above directions represent potential next steps, our discussions with participants and practitioners illuminated both a desire to understand how to design visualizations that better serve people with IDDs and a frustration with the historical lack of inclusion of this population and subsequent feelings of invisibility. Our study indicates that effective designs differ for people with IDDs; however, our discussions with the community revealed broader needs for more inclusive visualization.

Participants noted that data accessibility is a matter of fairness and respect. Data analytics is about solving problems. Being able to make informed decisions using data is a critical skill for both personal and professional advancement. Without basic data access, people with IDDs rely on others to relay relevant personal and public information and make decisions using that data. People with IDDs have experienced these impacts directly, noting a desire to "speak up for yourself, whenever you can *(P26–IDD)*." Making data accessible will empower people with disabilities to discover new strengths and abilities. It will offer them new ways to be involved in their communities and afford greater independence in an increasingly data-driven world.

Our study is originally inspired by an onging effort that supports financial self-advocacy for people with IDDs [17]. This effort reflects a growing interest within AAIDD [56] in educating people with IDDs about data and using visualization in the disabled community. For example, public organizations are exploring means of using of visualization to enhance policy understanding amongst self-advocates with IDDs.[5] In order to develop effective tools, we must understand where current practices fall short and develop innovative co-designed solutions that truly reflect the needs and abilities of people with IDDs. As one of our participants noted, "Awareness is important, as someone with invisible disabilities, you have to make sure your voice is heard *(P26–IDD)*." Participants saw the lack of accessible visualization tools and inclusion in the design of these tools as a critical barriers towards effective self-advocacy.

7 CONCLUSION

Guidelines for visualization design emphasize non-disabled populations. The resulting designs inhibit people with IDDs from effectively engaging with data. To understand preliminary components of accessible visualization design, we conducted a two-phase web-based quantitative experiment to measure how accurately and quickly people with and without IDDs interpret visualized data. Our results led to four preliminary design suggestions for accessible visualization. With the proliferation of data-driven reasoning and decision making increasing across all aspects of life, making data accessible for self-determination is an increasingly critical challenge. We found that there is a desire from the IDD community for more accessible tools. Organizational partners expressed strong enthusiasm for improved communication tools, and self-advocates were excited to collaborate on tools to benefit the community. Making visualization cognitively accessible will not only help people with IDDs, but may also reveal new guidelines and designs for general understanding and decision making. We believe diversity and inclusion in visualization should also encompass designing visualizations that empower people with diverse abilities.

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[5]http://www.integratedsupports.org/

REFERENCES

[1] [n.d.]. 41st Annual Report to Congress on the Implementation of the Individuals with Disabilities Education Act.

[2] [n.d.]. Accessibility in amCharts 4. https://www.amcharts.com/accessibility/accessible-charts/

[3] [n.d.]. Frequently Asked Questions on Intellectual Disability. https://www.aaidd.org/intellectual-disability/definition/faqs-on-intellectual-disability

[4] 2011. *World Report on Disability*. World Health Organization, Geneva, Switzerland.

[5] 2015. Cognitive Accessibility User Research. https://www.w3.org/TR/coga-user-research/#research-on-cognitive-function/

[6] 2020. Autism Data Visualization Tool. https://www.cdc.gov/ncbddd/autism/data/index.html

[7] 2020. What is Autism Spectrum Disorder? https://www.cdc.gov/ncbddd/autism/facts.html

[8] Danielle Albers, Michael Correll, and Michael Gleicher. 2014. Task-Driven Evaluation of Aggregation in Time Series Visualization. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Toronto, Ontario, Canada) *(CHI '14)*. Association for Computing Machinery, New York, NY, USA, 551âĂŞ560. https://doi.org/10.1145/2556288.2557200

[9] Erik W Anderson. 2012. Evaluating visualization using cognitive measures. In *Proceedings of the 2012 BELIV Workshop: Beyond Time and Errors-Novel Evaluation Methods for Visualization*. 1–4.

[10] Adriana Arcia. 2019. Colors and Imagery in Tailored Infographics for Communicating Health Information to Patients and Research Participants. (2019).

[11] Scott Bateman, Regan L Mandryk, Carl Gutwin, Aaron Genest, David McDine, and Christopher Brooks. 2010. Useful junk? The effects of visual embellishment on comprehension and memorability of charts. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 2573–2582.

[12] Jennifer Birch. 2012. Worldwide prevalence of red-green color deficiency. *Journal of the Optical Society of America. A, Optics, image science, and vision* 29 (03 2012), 313–20. https://doi.org/10.1364/JOSAA.29.000313

[13] M. A. Borkin, Z. Bylinskii, N. W. Kim, C. M. Bainbridge, C. S. Yeh, D. Borkin, H. Pfister, and A. Oliva. 2016. Beyond Memorability: Visualization Recognition and Recall. *IEEE Transactions on Visualization and Computer Graphics* 22, 1 (2016), 519–528.

[14] Katy Borner, Andreas Bueckle, and Michael Ginda. 2019. Data visualization literacy: Definitions, conceptual frameworks, exercises, and assessments. *Proceedings of the National Academy of Sciences* 116 (02 2019), 201807180. https://doi.org/10.1073/pnas.1807180116

[15] Michael Bostock, Vadim Ogievetsky, and Jeffrey Heer. 2011. D3 Data-Driven Documents. *IEEE Transactions on Visualization and Computer Graphics* 17, 12 (Dec. 2011), 2301âĂŞ2309. https://doi.org/10.1109/TVCG.2011.185

[16] Coleen Boyle, Sheree Boulet, Laura Schieve, Robin Cohen, Stephen Blumberg, Marshalyn Yeargin-Allsopp, Susanna Visser, and Michael Kogan. 2011. Trends in the Prevalence of Developmental Disabilities in US Children, 1997-2008. *Pediatrics* 127 (06 2011), 1034–42. https://doi.org/10.1542/peds.2010-2989

[17] David Braddock, Richard Hemp, Amie Lulinski, and Emily Tanis. 2017. *The State of the States in Intellectual and Developmental Disabilities: 2017*.

[18] Alex Chaparro and Maria Chaparro. 2016. Applications of Color in Design for Color-Deficient Users. *Ergonomics in Design: The Quarterly of Human Factors Applications* 25 (11 2016). https://doi.org/10.1177/1064804616635382

[19] Chaomei Chen and Yue Yu. 2000. Empirical studies of information visualization: a meta-analysis. *Int. J. Hum. Comput. Stud.* 53 (2000), 851–866.

[20] Jinho Choi, Sanghun Jung, Deok Gun Park, Jaegul Choo, and Niklas Elmqvist. 2019. Visualizing for the Non-Visual: Enabling the Visually Impaired to Use Visualization. *Computer Graphics Forum* (2019). https://doi.org/10.1111/cgf.13686

[21] William S. Cleveland and Robert McGill. 1984. Graphical Perception: Theory, Experimentation, and Application to the Development of Graphical Methods. *J. Amer. Statist. Assoc.* 79, 387 (1984), 531–554. https://doi.org/10.1080/01621459.1984.10478080

[22] Michael Cooper, Alastair Campbell, and Andrew Kirkpatrick. 2020. *Web Content Accessibility Guidelines (WCAG) 2.2*. W3C Working Draft. W3C. https://www.w3.org/TR/2020/WD-WCAG22-20200227/.

[23] Franco Delogu, Massimiliano Palmiero, Stefano Federici, Catherine Plaisant, Haixia Zhao, and Olivetti Belardinelli. 2010. Non-visual exploration of geographic maps: does sonification help? *Disability and Rehabilitation: Assistive Technology* 5, 3 (2010), 164–174.

[24] Yu-Min Fang, Chun Lin, and Bo-Cheng Chu. 2019. Older Adults' Usability and Emotional Reactions toward Text, Diagram, Image, and Animation Interfaces for Displaying Health Information. *Applied Sciences* 9 (03 2019), 1058. https://doi.org/10.3390/app9061058

[25] Rhonda Faragher and Barbara Clarke. 2014. *Educating learners with down syndrome: research, theory, and practice with children and adolescents*. Routledge.

[26] E Gullone, RA Cummins, and NJ King. 1996. Self-reported fears: a comparison study of youths with and without an intellectual disability. *Journal of Intellectual Disability Research* 40, 3 (1996), 227–240.

[27] Steve Haroz, Robert Kosara, and Steven L. Franconeri. 2015. ISOTYPE Visualization: Working Memory, Performance, and Engagement with Pictographs. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (Seoul, Republic of Korea) *(CHI '15)*. Association for Computing Machinery, New York, NY, USA, 1191âĂŞ1200. https://doi.org/10.1145/2702123.2702275

[28] Lane Harrison, Fumeng Yang, Steven Franconeri, and Remco Chang. 2014. Ranking visualizations of correlation using weber's law. *IEEE Transactions on Visualization and Computer Graphics* 20, 12 (2014), 1943–1952.

[29] Jeffrey Heer, Michael Bostock, and Vadim Ogievetsky. 2010. A Tour through the Visualization Zoo. *ACM Queue* 8 (01 2010), 20. https://doi.org/10.1145/1794514.1805128

[30] Elizabeth Hensel, J Rose, B Stenfert Kroese, and J Banks-Smith. 2002. Subjective judgements of quality of life: a comparison study between people with intellectual disability and those without disability. *Journal of Intellectual Disability Research* 46, 2 (2002), 95–107.

[31] Leona Holloway, Kim Marriott, and Matthew Butler. 2018. Accessible maps for the blind: Comparing 3D printed models with tactile graphics. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–13.

[32] J. Hullman, E. Adar, and P. Shah. 2011. Benefitting InfoVis with Visual Difficulties. *IEEE Transactions on Visualization and Computer Graphics* 17, 12 (2011), 2213–2222.

[33] Ohad Inbar, Noam Tractinsky, and Joachim Meyer. 2007. Minimalism in information visualization: attitudes towards maximizing the data-ink ratio. In *ECCE '07*.

[34] Robert Kosara. 2019. The Impact of Distribution and Chart Type on Part-to-Whole Comparisons. In *21st Eurographics Conference on Visualization, EuroVis 2019-Short Papers*.

[35] Jan Kuhl, Daniel Sinner, and Marco Ennemoser. 2012. Training Quantity–Number Competencies in Students With Intellectual Disabilities. *Journal of Cognitive Education and Psychology* 11, 2 (2012), 128–142.

[36] Henry Kwok and Patrick WH Cheung. 2007. Co-morbidity of psychiatric disorder and medical illness in people with intellectual disabilities. *Current Opinion in Psychiatry* 20, 5 (2007), 443–449.

[37] H. Lam, E. Bertini, P. Isenberg, C. Plaisant, and S. Carpendale. 2012. Empirical Studies in Information Visualization: Seven Scenarios. *IEEE Transactions on Visualization and Computer Graphics* 18, 9 (2012), 1520–1536.

[38] Sukwon Lee, Sung-Hee Kim, and Bum Chul Kwon. 2017. VLAT: Development of a Visualization Literacy Assessment Test. *IEEE Transactions on Visualization and Computer Graphics* 23, 1 (Jan. 2017), 551âĂŞ560. https://doi.org/10.1109/TVCG.2016.2598920

[39] Alan Lundgard, Crystal Lee, and Arvind Satyanarayan. 2019. Sociotechnical Considerations for Accessible Visualization Design. arXiv:1909.05118 [cs.CY]

[40] Matthew Maenner, Kelly Shaw, Jon Baio, Anita Washington, Mary Patrick, Monica DiRienzo, Deborah Christensen, Lisa Wiggins, Sydney Pettygrove, Jennifer Andrews, Maya Lopez, Allison Hudson, Thaer Baroud, Yvette Schwenk, Tiffany White, Cordelia Rosenberg, Li-Ching Lee, R. Harrington, Margaret Huston, and Patricia Dietz. 2020. Prevalence of Autism Spectrum Disorder Among Children Aged 8 Years âĂŤ Autism and Developmental Disabilities Monitoring Network, 11 Sites, United States, 2016. *MMWR. Surveillance Summaries* 69 (03 2020), 1–12. https://doi.org/10.15585/mmwr.ss6904a1

[41] Marjorie Montague. 1997. Cognitive Strategy Instruction in Mathematics for Students with Learning Disabilities. *Journal of Learning Disabilities* 30, 2 (1997), 164–177. https://doi.org/10.1177/002221949703000204 arXiv:https://doi.org/10.1177/002221949703000204 PMID: 9066277.

[42] Tamara Munzner. 2014. *Visualization analysis and design*. CRC press.

[43] Jamie R. Nuñez, Christopher R. Anderton, and Ryan S. Renslow. 2018. Optimizing colormaps with consideration for color vision deficiency to enable accurate interpretation of scientific data. *PLoS ONE* 13 (2018).

[44] Sushil K Oswal. 2019. Breaking the exclusionary boundary between user experience and access: steps toward making UX inclusive of users with disabilities. In *Proceedings of the 37th ACM International Conference on the Design of Communication*. 1–8.

[45] Evan M Peck, Sofia E Ayuso, and Omar El-Etr. 2019. Data is personal: Attitudes and perceptions of data visualization in rural pennsylvania. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–12.

[46] Minna Reuhkala. 2001. Mathematical skills in ninth-graders: Relationship with visuo-spatial abilities and working memory. *Educational Psychology* 21, 4 (2001), 387–399.

[47] Bahador Saket, Alex Endert, and Çağatay Demiralp. 2018. Task-based effectiveness of basic visualizations. *IEEE Transactions on Visualization and Computer Graphics* 25, 7 (2018), 2505–2512.

[48] David Simkin and Reid Hastie. 1987. An information-processing analysis of graph perception. *J. Amer. Statist. Assoc.* 82, 398 (1987), 454–465.

[49] Joschua Simon-Liedtke, David R Flatla, and Eskild Narum Bakken. 2017. Checklist for Daltonization methods: Requirements and characteristics of a good recolouring method. *Electronic Imaging* 2017, 18 (2017), 21–27.

[50] Drew Skau and Robert Kosara. 2016. Arcs, angles, or areas: Individual data encodings in pie and donut charts. In *Computer Graphics Forum*, Vol. 35. Wiley Online Library, 121–130.
[51] Edward R. Tufte. 1986. *The Visual Display of Quantitative Information.* Graphics Press, USA.
[52] Delinda Van Garderen. 2006. Spatial Visualization, Visual Imagery, and Mathematical Problem Solving of Students With Varying Abilities. *Journal of Learning Disabilities* 39 (12 2006), 496–506. https://doi.org/10.1177/00222194060390060201
[53] Vanessa Vega, Katherine Exss, Izaskun ÃĄlvarez Aguado, Marcela Azagra, and Herbert Spencer. 2020. Including intellectual disability in participatory design processes: Methodological adaptations and supports. https://doi.org/10.1145/3385010.3385023
[54] W3C Web Accessibility Initiative (WAI). 2020. Tools and Techniques. https://www.w3.org/WAI/people-use-web/tools-techniques/#tools
[55] Colin Ware. 2019. *Information visualization: perception for design.* Morgan Kaufmann.
[56] Wikipedia. 2020. American Association on Intellectual and Developmental Disabilities — Wikipedia, The Free Encyclopedia. http://en.wikipedia.org/w/index.php?title=American%20Association%20on%20Intellectual%20and%20Developmental%20Disabilities&oldid=970390704. [Online; accessed 14-September-2020].
[57] Disabled World. 2020. What Is: Neurodiversity, Neurodivergent, Neurotypical. https://www.disabled-world.com/disability/awareness/neurodiversity/
[58] Keke Wu, Shea Tanis, and Danielle Albers Szafir. 2019. Designing Communicative Visualization for People with Intellectual Developmental Disabilities. (08 2019). https://doi.org/10.31219/osf.io/zbjhr
[59] Yalong Yang, Kim Marriott, Matthew Butler, Cagatay Goncu, and Leona Holloway. [n.d.]. Tactile presentation of network data: Text, matrix or diagram? *ACM Conference on Human Factors in Computing Systems* ([n. d.]).
[60] Jeffrey M. Zacks and Barbara Tversky. 1999. Bars and lines: A study of graphic communication. *Memory & Cognition* 27 (1999), 1073–1079.
[61] Dake Zhang, Yi Ding, Joanna Stegall, and Lei Mo. 2012. The effect of visual-chunking-representation accommodation on geometry testing for students with math disabilities. *Learning Disabilities Research & Practice* 27, 4 (2012), 167–177.