Visual Task Performance and Spatial Abilities: An Investigation of Artists and Mathematicians

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ABSTRACT

This study builds on past research to present a domain-specific empirical investigation of artists and math & computer scientists on their respective relationships to, perceptions of, and interactions with data visualization. We conducted a three-phase study utilizing mixed-methods to investigate performance on visual and text representations of data between domains. Our findings evidenced how math & computer scientists are proficient utilizing text representations of data while artists benefit more from visual chart representations. Finally, we present perspectives from artists to gain an understanding of their approach to visual and mathematical tasks. Our findings indicate that artists are especially adept at statistical visual tasks and that development of cognitive skills could be fostered by individuals to potentially benefit visualization task performance.

CCS CONCEPTS

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

KEYWORDS

Human-subjects quantitative studies, mixed-methods, perception, bar charts, text representation, education, domain-specific, visual artists, spatial ability, cognitive abilities

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1 INTRODUCTION

Information visualization marries data properties and visual form; visualization research often aims to empower audiences to understand and reason with data through accessible and engaging communication [60]. However, complex cognitive activities are at work decoding visual structure to interact with underlying data [86]. Visualization research has recently demonstrated that interpretation and interaction with data visualization is affected by the interplay of domain background/experiences with cognitive abilities, specifically spatial visualization [32, 74] (i.e., abilities involving retention, manipulation, and rotation of visual images [51]).

We build on this past research to dive into two domains with comparable, rather than disparate, levels of spatial visualization that are representative of the marriage of information visualization: math & computer science and the visual arts. Science and art have a long history of interwoven development, with both applying mathematical intuition and creative interpretation in numerous ways [26]. In the early 20th century, enthusiasm for visualization was supplanted by the rise of formal quantification and statistical reporting [26] – data visualization became closely tied to statistics and technological communication with a decreasing focus on aesthetics that has been re-introduced to the field in the last few decades [45, 64]. Lack of interdisciplinary cooperation between mathematics and the arts contributed to domain silos despite congruent content [5, 9, 76]. We aim to capitalize on the cognitive similarities and domain expertise of visual artists and mathematicians and their combined application to statistical data visualization.

In this paper, we present past research related to spatial visualization in psychology and visualization that motivated us to study the relationship between these domains and data visualization. We conducted a three-phase study to meet our aims (see Fig. 1). Phase 1 included established methods of evaluating spatial visualization, domain motivations, and their combined effect on performance of common data visualization tasks. In Phase 2, we provide perspectives of expert visual artists on their relationship with, and approach to, visual and mathematical tasks, and an assessment of data visualization familiarity and preferences. Finally, in Phase 3 we test performance between math & computer scientists and visual artists in text representations of data to examine how domain differences and spatial abilities affect interaction with data in various forms. The results we collected demonstrate how communities, with similar spatial visualization ability, perform visual and text-based tasks given their expertise.

2 BACKGROUND

Our investigation builds on research in spatial visualization, psychology, and information visualization. We move beyond exploring domains with differing capabilities to capitalize on the cognitive similarities of two domains often held at odds [11, 29, 85]; we aim to understand if, and how, visual task performance differs between them.

2.1 Spatial Visualization

Spatial visualization relates directly to the internal process of manipulation or transformation of a visual stimulus – it allows an individual to remain unconfused by varying orientations or rotational positions in which a spatial object or pattern may be presented and has measurable outcomes when interacting with external visualizations [15, 34, 51].

Spatial abilities are considered a key cognitive factor in interpretation of visual information; elevated spatial visualization specifically can correlate with higher recall, understanding, and increased task performance around data visualization [32, 40, 74, 77]. High spatial abilities have been tied to increased performance and recall of values on line up tests, parallel coordinate plots, tables, and written descriptions of data [40, 77, 81]. Speed can also be a dominant indicator of lower spatial abilities and understanding compared to accuracy [17, 71, 78, 81]. However, Wenhong [81] noted that individuals are often unaware of their own cognitive style, but still prefer visual representations of data.

Additionally, the differing experiences of disciplines around data visualization will bias and affect performance on visual tasks in a measurable way [20, 41, 67]. Dasgupta et al. [20] suggest that domain expert's performance on visual tasks is similar between charts regardless of familiarity – this may be because cognitive abilities influence interactions as much as experience. Hall et al. [32] and Tandon et al. [74] explore how spatial visualization and domain experiences come together to explain performance on information visualization tasks. Hall et al. confirmed spatial visualization and correlated performance differences amongst Education, Chemistry and Computer Science disciplines. Tandon et al. further confirmed spatial visualization, motivations, and visual task performance are correlated on rotated bar charts between Business, Law & Political Science, and Math & Computer Science domains.

There are established ties between spatial visualization, domain, and visualization performance. However, these previously studied domains have varying levels of spatial visualization – we aim to use established methods to study a community with increased levels of spatial visualization and visual task expertise.

2.2 Why Might Artists be Different?

Spatial abilities have often been tested in educational settings as an indicator of increased performance in STEM subjects [4, 24, 37, 54, 65, 68, 84]. Some have suggested testing and development of spatial abilities to directly affect student performance on numeracy and mathematical subjects – noting interpretation of graphics is fundamental to numeracy skills [46, 59]. However, research also indicates visual artists display elevated levels of spatial abilities that are equally imperative to their work [29, 68, 79]. Further, Angelone et al. [2] demonstrate superiority of quick and accurate visual encoding by visual artists over novices – a direct skill involved in spatial visualization [51]. These studies confirm the development of visual-spatial skills in visual artists over time but have not extrapolated to studying performance on information visualization tasks, often involving numeracy.

Research indicates artists pursue creative endeavors due to intrinsic (e.g., inner drive, therapeutic benefits, understanding of self) and extrinsic (e.g., renown, contribution to society) factors [19, 35]. In education systems, arts are presented as an outlet for creative, imaginative, and emotive expression, while mathematics is stereotypically presented as small skill pieces with strong memorization ability as a prerequisite for learning [5, 19, 39]. These methods can foster anxieties around both mathematics and creativity, limiting engagement and full realization of both domains [5, 18]. However, math and technology experts display increased performance in data visualization literacy and tasks [47, 74], while visualization processing requires cognitive skills visual artists use in daily practice [77, 79]. We set out to compare performance between these domains as there is too much math in art and art in math to consider one without the other [5].

3 PHASE 1: VISUAL TASK PERFORMANCE

Inspired by previous work, we chose to use established methodologies in information visualization that allowed us to test spatial visualization, visual task performance, and domain motivations of visual artists versus mathematicians and computer scientists (MCS). Neither cognition nor domain motivations alone can fully explain task performance as individuals approach visuals as whole persons shaped by their background [32, 74]. We use methods in accordance with [74] for Phase 1, enabling us to directly compare visual artists' spatial visualization ability and domain motivations to MCS, while expanding to implications of how visual artists might perform with respect to previously studied domains.

3.1 Motivation & Hypothesis

We chose to compare visual artists to MCS as the latter are often "standard participants" for many studies on task performance and design choices in visualization research; the field of information visualization is associated with, created by, and studied by those in MCS related fields [13, 14, 45, 77]. Additionally, research shows that MCS out-performs other domains in visual task performance [47, 74]. Meanwhile, research suggests that artists approach problem solving differently to scientists [11, 35, 85] while exhibiting high spatial abilities [68, 79]. The modern juxtaposition between the visual arts and MCS makes artists an interesting group for the focus of a data visualization study – as visual artists work with similar, if not identical, mediums to data visualization designers, do their increased spatial abilities mitigate differences in visual task performance?

In line with visualization domain-needs research, we believe these domains' differing experience around data visualization will bias and affect performance on visual tasks in a measurable way [20, 41, 67]. We utilized methods from psychology and information visualization to measure motivational differences around data visualization that might affect visual interaction [28, 74]. As spatial

Figure 1: Three phases of our research. In the spatial visualization assessment (under Phase 1), the paper is folded and punched above the line. Participants are given five multiple-choice responses to choose between. Scores are the number answered correctly out of 10 in 3 minutes.

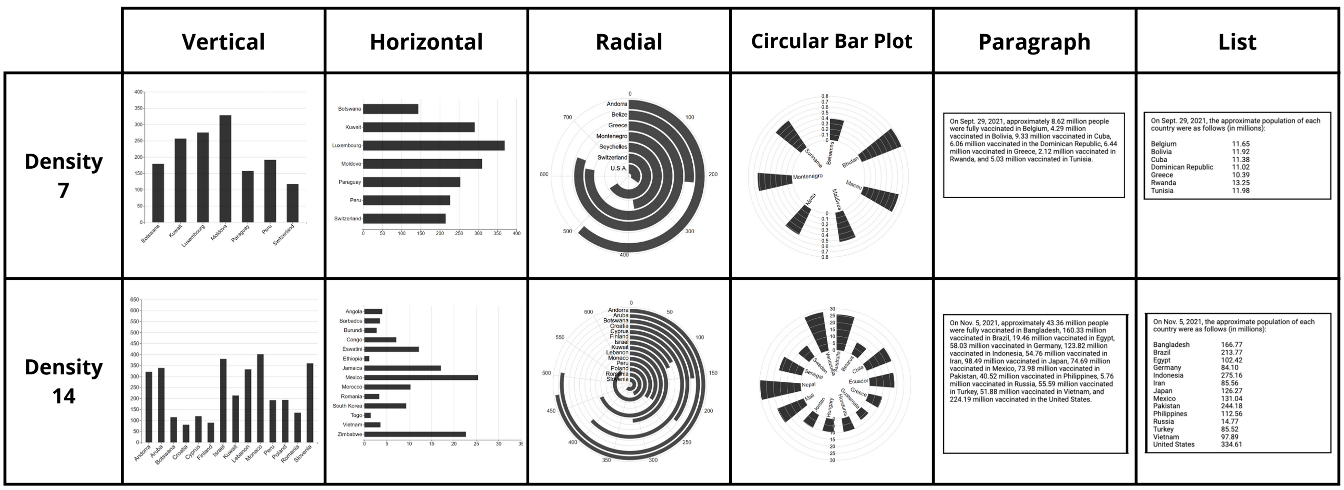


Figure 2: Stimuli examples across densities from Phase 1 and Phase 3. The same data was used in Phase 1 and 3 for direct comparison of text vs chart performance; Phase 3 was conducted ~5 months after Phase 1 to reduce confounding factors. See sec 3.2.6, Fig. 3, and Fig. 8 for question examples and supplementary material for complete sets.

visualization is similarly high between MCS and visual artists [79], differences that arise may be due to domain motivations around data visualizations. To claim differences in performance correlate with domain, we ensured a balanced sample from both domains for statistical integrity. We aim to confirm if spatial visualization ability is similar between MCS and visual artists and explore how domain background interacts with spatial visualization to affect performance in a quantitatively significant way. We explore these questions by investigating the following hypotheses.

H1: Spatial visualization level will be comparable between visual artists and MCS. Research has demonstrated systematic similarities in spatial abilities between visual artists and MCS [68, 79]. Drawing from these findings, we anticipate MCS and visual artists will have similar levels of spatial visualization.

H2: Artists’ motivations around data visualization will differ from MCS given domain differences. Art and information visualization, though connected, are fundamentally different [42]. We anticipate marked differences in motivations around data visualization between MCS and visual artists given the domains’ varying levels of interaction, creation, and consumption of information visualization (i.e., domain experience).

H3: Task performance (accuracy and time) will differ between visual artists and MCS according to domain differences. High spatial individuals tend to have higher accuracy and reduced response times [32, 77]. However, visualization research demonstrates that needs, knowledge, bias, and experience differ by domain and that these factors can affect performance of tasks and visualization design [20, 31, 41, 67, 70, 83]. We expect to see analogous results, emphasizing the role of spatial visualization in performance and use of visualizations. However, we expect domain differences will affect performance of visual artists such that questions involving mathematics will be negatively affected while performance will be similar on Easy and Medium questions due to spatial visualization level.

3.2 Methodology

We conducted a two-part online study to address our hypotheses. The methods described below are congruent to [74] to ensure consonant results of visual artists to MCS and further domains; our work can corroborate and increase application of psychologically grounded methods in information visualization, bringing together cognition and individual background/experience. Part 1 of the study consisted of a brief spatial visualization psychometric test, known as a paper folding or punch test. Part 2 consisted of stimuli and questions asking individuals to draw conclusions from visualizations. A short motivation and perception of difficulty assessment followed Part 2. We intentionally chose methods with familiar data, chart types, and tasks to increase relevancy and mimic common data visualization interactions for individuals in both domains. We provide the study structure and stimuli design below (see supplementary material for complete stimuli set).

3.2.1 Recruitment. Participants were recruited through a research focused crowdsourcing platform called Prolific [58]. Prolific was chosen for this study due to its reputation of connecting a pool of diverse and high-quality participants to researchers around the world at fair wages. Participants were pre-screened to our meet our educational and professional requirements, 18 years and older, and fluent in English. We were able to recruit a balanced sample of 30 participants in each domain with valid data, for a total of 60 participants (details below). Participants were paid £7.71/hour in accordance with Prolific's fair pay policy. The average response time was 34 minutes and 8s.

3.2.2 Study Format. The online study was created using a Flask Web App with D3.js for chart generation. A trigger warning was presented to participants before agreeing to take part in the study as the data related to case, hospitalization, death, and vaccination statistics of the COVID-19 pandemic. The trigger warning acknowledged that COVID-19 data might personally affect participants and they should gauge for themselves if they could interact with the data to the best of their ability. Additionally, participants were explicitly told they could leave the study at any time, ending their participation. No identifiable data was collected, and all data was stored and maintained on a private server at the author's institution.

After consent and demographics collection, the study process consisted of two parts with an additional page of 5-point Likert scale questions, assessing perceived difficulty and personal motivations regarding data visualization (see Section 3.2.8). Participants were asked to confirm readiness to move to the next block between each step to allow for breaks as needed. Part 1 began with training from the Kit of Factor Referenced Cognitive Tests [22] on the spatial visualization assessment – including a sample question participants had to answer correctly to move forward. Active training for Part 2 consisted of 4 sample questions displaying the various charts participants would see throughout the study. Additionally, a break is integrated halfway through Part 2, consisting of a catch question wherein users were encouraged to take a break, answer with a specific response, and move on when they were ready. The catch question was not analyzed (other than ensuring all respondents answered correctly for quality assurance) and was not included in response time data analysis.

3.2.3 Screening. Following consent, participants completed 7 demographic questions, collecting information about gender, age, education history, profession, and countries of origin and influence. Prolific offers a participant score that is based on the quality of an individual's past submissions on their site: our participants had scores of 97% or higher.

We ensured alignment between profession and education background to account for any spatial abilities gained during education [79]. We gathered data until we achieved balanced samples with high quality data between visual artists and MCS.

3.2.4 Part 1 Spatial Visualization Assessment. Part 1 consisted of the spatial visualization assessment from the Kit of Factor Referenced Cognitive Tests [22], a well-established 2D psychometric assessment [1, 51] largely utilized in previous data visualization studies evaluating spatial visualization [40, 50, 56, 74]. In line with evaluation of the assessment, we gathered both the response time and selected answer for each of the 10 questions. Questions consist of an image of a paper being folded and hole-punched; participants must then choose from 5 options what the paper will look like when unfolded (see Fig. 1 for a sample). The spatial visualization score is calculated as the number of correct answers out of 10. See supplementary material for complete set.

3.2.5 Part 2 Stimuli Design. Visual task performance was analyzed over the three manipulated elements in the stimuli: data density, chart type, and task difficulty.

Data. The data was inspired by the vast amount of COVID-19 Pandemic visualizations and dashboards disseminated by organizations, universities, news outlets, and tech companies since 2020 [3, 33, 52, 73, 82]. We utilized COVID-19 Pandemic data (from a comprehensive world statistics site [63]) for this study as the scale of the ongoing global pandemic allowed an assumption of a basic level of familiarity with the data, regardless of domain, and no need for training or expert knowledge [7]. The data reflects actual case, vaccination, hospitalization, and death statistics from March 2020–January 2022 across 95 countries.

The data is displayed across two levels of density to ensure differing cognitive load: 7 and 14 points. The limit of the span of absolute judgement and immediate memory sits at about 7 points [53] – this implies that moving sufficiently beyond 7 data points will increase cognitive load; thus 14 is the second set size. Across stimuli, data was ordered alphabetically by country, each displaying a unique group of countries to reduce familiarity. Conventionally, visual search studies vary the number of objects, visual targets, and/or visual distractors present over sub-conditions [23] – we varied the two set sizes amongst the four chart types and three questions detailed below, while maintaining the same density for side-by-side charts.

Chart Types. The stimuli were formed keeping in mind that spatial visualization directly affects ability to compare visual encodings and layouts quickly and accurately [51], and that the assessment in Part 1 uses 2D rotated stimuli on a Euclidean plane [22]. Charts were designed to systematically target spatial rotation over multiple coordinate systems, clearing out any confounding factors such that spatial position is the major influence on performance. These charts were additionally inspired by the common usage of rotated bar charts of varying densities in COVID-19 pandemic data dashboards and in health data presentation [3, 33, 44, 52, 73, 82]. Each question displays a vertical bar chart with a spatially rotated chart side-by-side to assess performance as participants utilize both

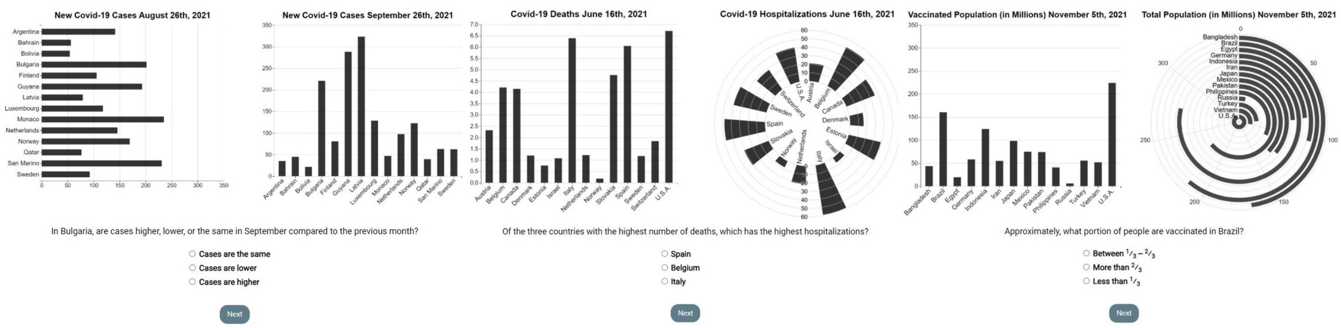


Figure 3: Density 14 charts with question examples: Easy, Medium, and Hard.

charts to respond to a given question. Using two spatially rotated charts side-by-side simulates the cognitive processes involved in spatial visualization assessments. Charts utilized in this assessment are a vertical bar chart paired with a horizontal bar chart (rotated along Cartesian coordinates), a radial bar chart, or a circular bar plot (both rotated along polar coordinates - see Fig. 2). We varied all four chart types amongst the two set sizes and three questions.

3.2.6 Part 2 Task Design. The basic task paradigm used in this study was a simple conjunctive-visual search process across two charts and densities. Visual search is a vital element to visualization interpretation [6]; simple conjunctive-visual search involves search over two channels (in this case, two spatially re-arranged charts with no distinct differences from the target) and increases in difficulty as object density increases [69, 75]. Conjunctive-search of two chart types, across two levels of density, is paired with three 3-alternative forced-choice multiple-choice questions increasing in difficulty to evaluate performance over: questions were categorized as Easy, Medium, and Hard. The three response options were randomized across all questions. Fig. 3 shows three examples of questions. Supplementary material provides a comprehensive overview of all the combinations.

Easy Question: The easy question displays two charts with case numbers from the same set of countries across two months. Participants are asked to search for a given country in the first chart and compare case numbers of that country to the second chart to respond if cases were higher, lower, or the same as the previous month. This question is classified as easy, as it consists of a search for the same singular target variable across both displayed charts. Easy question example: *In Bulgaria, are cases higher, lower, or the same in September compared to the previous month?* Easy Responses: *Cases are higher, cases are lower, cases are the same.*

Medium Question: The medium question displays two charts, the left with death rates, the right with hospitalization rates of the same set of countries on a given date. Participants are asked to search for the *three* countries with the highest number of deaths in the first chart and responded with which of the three countries had the highest hospitalizations from the second chart. This question is classified as medium as it increases the variables for search and comparison to three targets across both charts.
Medium question example: *Of the three countries with the highest number of deaths, which has the highest hospitalizations?* Medium responses consisted of the correct response, one of the countries with the highest number of deaths, but not the highest hospitalizations, and one random country (see Fig. 3).

Hard Question: The hard question displays two charts, the left with the raw number (in millions) of vaccinated people, the right with the raw population (in millions) of the same set of countries on a given date. In this question, participants are required to estimate the vaccinated portion of people in a target country. This question is classified as hard as after search for one target variable across charts, participants are asked to perform a mathematical computation to estimate a derived variable.
Hard question example: *Approximately what portion of people are vaccinated in Brazil?* Hard responses: *less than* $\frac{1}{3}$, *between* $\frac{1}{3} - \frac{2}{3}$, *more than* $\frac{2}{3}$.

3.2.7 Part 2 Measures. Part 2 had a total of 42 multiple-choice questions: four possible chart pairings, two possible layouts (e.g., Vertical or Radial chart on either right or left), two levels of data density, with three question types/difficulty levels. To assess performance, we recorded the selected answer and the response time (RT) of each question. Stimuli were shown randomly to participants to minimize learning effects.

3.2.8 Data Visualization Motivations Assessment. To gain a complete picture of how visual artists and MCS approach and think about data visualization, we included an assessment from [74], grounded in prominent theories of academic motivation, that encompasses many of the motivational factors found to influence performance in STEM [4, 28]. We expect domain differences in motivation due to differing experiences and expectations around data visualization and mathematics between visual artists and MCS [11, 26]. The assessment includes 5 questions targeting various motivations and are rated by participants on a 5-point Likert scale (see Table 1 and supplementary material).

3.2.9 Participants. We successfully gathered 30 participants with reliable data in each target domain for 60 total participants. We followed a strict rule of balanced samples across groups to support our between subject design. The demographic statistics as a whole and across each domain were as follows. Gender participation overall: 53% male, 47% female. MCS: 77% male, 23% female. Visual artists: 30% male, 60% female. These are consistent with known educational domain gender differences across Europe [21]. Additionally, research demonstrates high spatial females are more

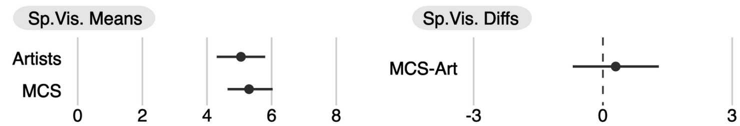


Figure 4: H1: Spatial visualization per domain, with the CI of means (left) and of mean differences (right). Error bars represent 95% Bootstrap confidence intervals.

likely to pursue artistic domains while high spatial males are more likely to pursue STEM education [57, 79]. The average age (± standard deviation) of all participants was 24 ± 5, 23 ± 4 for MCS, and 25 ± 6 for visual artists.

3.3 Results

We analyzed differences in performance and spatial visualization using sample means, hypothesis (p-value) testing, and 95% confidence intervals. Confidence intervals (CIs) were constructed in Python using bias-corrected and accelerated bootstrapping (BCa) with 5000 iterations. We utilized BCa to create confidence intervals along with hypothesis testing using the Monte Carlo permutation test, Welch's t test, Student's t test, and Mann-Whitney U test to obtain multiple test statistics and p-values for further validation as recommended in recent reviews [30, 38, 55, 61]. Below we report on our high-level findings; detailed means, test statistics, p-values, and stepwise analysis are reported in the supplementary material.

3.3.1 H1: Spatial Visualization. We hypothesized that spatial visualization ability would be comparable between visual artists and MCS. The spatial visualization score (out of 10) for MCS was 5.33 while visual artists had a mean score of 5.03 – there is no statistical evidence of difference between them with $p > 0.5$. See Fig. 4.

⇒ We confirmed **H1**, spatial visualization is analogous between visual artists and MCS such that there is no statistical detection of difference between them. This finding is consistent with previous research into spatial abilities of these domains [68, 79]. As our psychometric tests align with [74], these scores demonstrate visual artists and MCS have increased spatial visualization compared with average abilities and to other domains. This furthers previous research demonstrating spatial abilities are elevated and advanced by involvement in both STEM and the visual arts [2].

3.3.2 H2: Motivations. The final tasks of the study were to rate perceived difficulty of each section along with rating personal motivations regarding data visualization. We hypothesized that domain experience would result in motivational differences around interaction with data visualization. Each motivation response corresponded to a score from 1-4, rating agreement with the statement. The statement measuring anxiety (*I become anxious when math is involved in data visualization*) was reverse-scored so that higher scores correspond to lower anxiety – thus, we refer to this construct as low math anxiety. See Table 1 for motivation ratings and significant differences.

MCS has significantly higher overall motivation scores compared to visual artists. Specifically, MCS outranked visual artists in extrinsic motivation, self-efficacy, and had lower math anxiety than artists. This indicates both data and information visualization are

Table 1: Motivation scores and significant differences between MCS and Artists.

Motivation	Mean Score	Significant Differences
Overall (out of 20)	MCS - 12 Artists - 9.23	MCS>Artists: CI$(1, 4)$, $p < 0.001$
Intrinsic (out of 4) Spend my own time learning about data visualization	MCS - 1.77 Artists - 1.60	None
Extrinsic (out of 4) My career or studies involve data visualization	MCS - 2.57 Artists - 1.57	MCS>Artists: CI$(0.6, 1)$, $p < 0.001$)
Self-Determination (out of 4) I put effort into learning about data visualization	MCS - 2.23 Artists - 1.97	None
Self-Efficacy (out of 4) I am confident I will perform well on data visualization tasks	MCS - 2.80 Artists - 2.20	MCS>Artists: CI$(0.2, 1)$, $p < 0.01$
Low Math Anxiety (out of 4) Note: higher score indicates lower anxiety	MCS - 2.63 Artists - 1.90	MCS>Artists: CI$(0.2, 1)$, $p < 0.05$

more prevalent in MCS than in the visual arts, thus there may be a higher value placed on accuracy in visualization tasks. Further, the increased confidence of MCS in visualization and math performance may also lead to increased performance [16, 27].

⇒ Our results partially confirm **H2** that domain differences affect motivations around interacting with data visualization. As MCS interacts with data visualization and mathematics more often than visual artists and have increased confidence, we might expect to see increased performance in statistical visualization tasks by MCS [8, 11, 47]. However, current research demonstrates that artists have high levels of creativity, openness to new experiences, extroversion, and problem solving skills compared to non-artists [11, 35], all of which lead to increased performance in scientific tasks [2, 29, 87] – not to mention artists' elevated levels of spatial visualization.

3.3.3 H3: Performance by Domain. Cognition interacts with domain motivations and experiences such that performance between domains is measurable [32, 74]. We hypothesized that performance (accuracy and response time) would differ between disciplines, with MCS performing better on Hard questions involving math computation due to domain differences.

Looking at overall mean differences (Fig. 5), we found that visual artists were faster than MCS by 4.1s (CI$(2, 6)$, $p < 0.001$). No difference was detected in the overall mean accuracy between MCS (89%) and visual artists (87%). We detail results of our analysis of

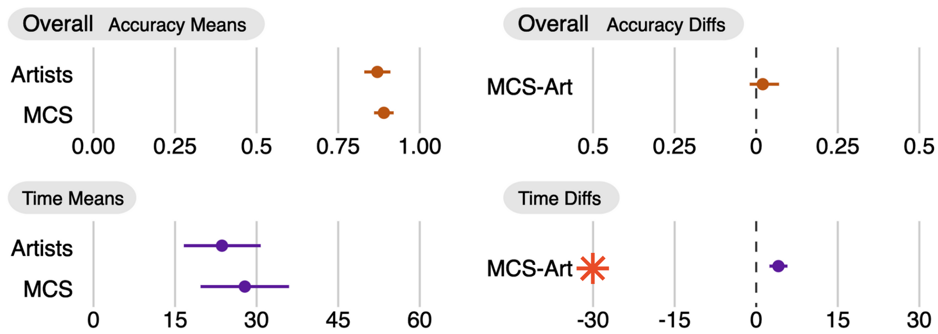
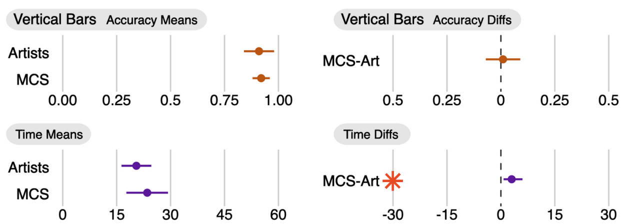
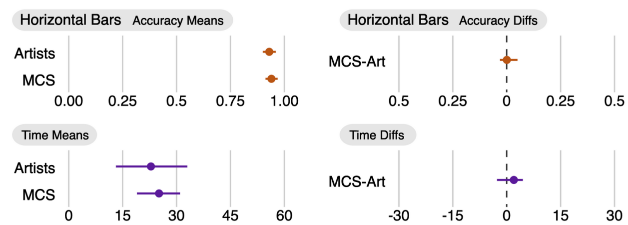


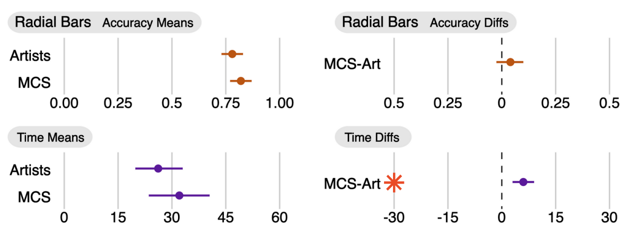
Figure 5: H3: Overall performance means (left) and mean differences (right), for Accuracy and Response Time. Time in seconds. Stars indicate evidence of significant differences.



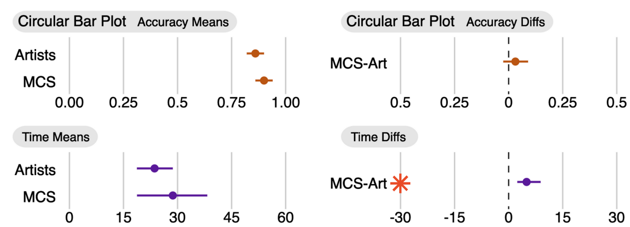
(a) Vertical Bars Performance Differences



(b) Horizontal Bars Performance Differences



(c) Radial Bars Performance Differences



(d) Circular Bar Plot Performance Differences

Figure 6: H3: Performance means (left) and mean differences (right), for Accuracy and Response Time. Time in seconds.

accuracy and RT across three variables: density, chart type, and question difficulty.

By Density:

Response Time: For charts of density 7, there is evidence that mean times were faster for visual artists compared to MCS by 3.8s (CI(0.9, 6), $p < 0.001$). For charts of density 14, visual artists were 4.4s (CI(2, 7), $p < 0.001$) faster than MCS.

Accuracy: There is no evidence of mean accuracy differences across densities between visual artists and MCS.

By Chart Type (Fig. 6):

Response Time: There is evidence that mean times were 2.9s faster (CI(0.2, 6),$p < 0.05$) for visual artists than MCS for Vertical charts. Looking at Radial charts, visual artists were 5.9s faster (CI(3, 9),$p < 0.001$) than MCS. Last, for Circular Bar Plots, visual artists were 5.1s faster (CI(2, 9),$p < 0.001$) than MCS.

Further, within domains, there was an increase in time between Cartesian and polar coordinate charts, with visual artists incrementing by a smaller amount than MCS: visual artists increased by 2.8s (CI(0.3, 4), $p < 0.05$) and MCS increased by 6.0s (CI(4, 8), $p < 0.001$).

Accuracy: There is no evidence of mean accuracy differences across chart types between visual artists and MCS. Within domains accuracy means were lower for polar coordinate plots when compared to Cartesian coordinate charts: visual artists accuracy dropped by 10.4% (CI(5, 16), $p < 0.001$) and MCS accuracy dropped by 7.5% (CI(3, 12), $p < 0.01$).

By Question Difficulty:

Response Time: Interestingly, for Hard questions alone, there is strong evidence that visual artists were faster than MCS by 6.6s (CI(4, 10), $p < 0.001$).

Accuracy: There is no evidence of mean accuracy differences across question difficulty between visual artists and MCS.

⇒ Our results partially confirm **H3**. We did find differences in task performance between visual artists and MCS, but not what was hypothesized. We found that visual artists were faster than MCS while remaining equally accurate. According to Tandon et al. [74], MCS is generally faster than business professionals and more accurate than law professionals – from our results, it follows that visual artists might also be faster and more accurate than those domains as well. As spatial visualization is similar between MCS and artists, similar performance is expected, however the decreased response times for artists indicates cognitive abilities do interact with domain experiences to affect performance.

4 PHASE 2: EXPERT ARTIST INTERVIEWS

The results from Phase 1 indicated visual artists may have increased performance compared to MCS despite lower motivations surrounding data visualization. In this phase, we move beyond previous methods analogous to [74] to explore how expert visual artists might account for this difference and their perspectives on visual artists' relationship to data visualization.

4.1 Participants

To understand the dichotomy between motivations and performance, we conducted expert interviews with 5 full-time visual artists to gain perspective and feedback on our outcomes. The artists came from the extended network of the first author – their backgrounds included a range of art experience with education and established careers in art and design.

4.2 Procedure

The relevant ethics approvals were obtained and all participants signed consent forms prior to any data collection. The interview protocol was developed by the first author and the interview guide centred around perceptions and familiarity with data visualization, comparison of visual versus mathematical tasks, and initial thoughts on findings from Phase 1. The interviews had open-ended questions followed by an online survey hosted on Qualtrics to understand familiarity level and preference of common data visualization representations. Interviews were conducted by the first author over Microsoft Teams and in person. Interviews lasted 28 minutes on average, including the online survey.

4.2.1 *Online Survey.*

The online survey had three parts. The first part asked experts to select the most familiar basic visualization sketches from [62] (see Fig. 7). Experts were asked to select 2 out of 4 sets of 10 randomized sketches then rank their selected 8 in order of familiarity. The second part consisted of ranking preference, perception of accuracy, and impact of three examples of data visualization; the three visualizations showed different representations of the same data from a (1) basic black-and-white representation, (2) a design with additional colors and icons, and (3) a hand drawn visual designed by [12]. The last part consisted of five 5-point Likert scale questions about perspective on hand-drawn versus computer generated visualizations and math anxiety. See supplementary material for complete interview material.

4.3 Data Analysis

All interview recordings were transcribed by Microsoft Teams. The interview transcripts and recordings were analyzed using an inductive approach. This process produced three defined themes identified as the most relevant to gain expert perspective on the outcomes of Phase 1: defining data visualization, artists' perception of mathematics, and preference for visual tasks.

4.4 Findings

In this section we discuss the key themes that emerged from our analysis. To protect anonymity, participants are referred to by using 'A' for artist, followed by a participant number. Paraphrasing is indicated by words surrounded by brackets and ellipses. For more quotes by theme see the supplementary material.

4.4.1 *Defining Data Visualization.*

Without prompting on interview content, experts were asked to describe what data visualization means to them. 4 out of 5 of them mentioned *"pie chart"* and *"charts and graphs."* When asked if anything different comes to mind for information visualization, a dichotomy between quantitative data and qualitative information began to arise.

> *"I think there are different ways to visualize information and data. I think it's different for qualitative and quantitative data. Qualitative data can get more into information visualization where you're visualizing a quote or something like that, that's information. But data to me is hard facts rooted in quantitative analysis." [A2]*

Moving forward, experts were given, "the representation of information in the form of a chart, diagram, picture, etc." as a working definition of data visualization. Experts mentioned interacting with data visualization daily to weekly in mediums such as newspapers, social media, financial contexts, and online content. In the online survey, bar charts, across all representations (stacked bar, multi-set bar, histogram, etc.) were by far the most familiar followed by a pie and donut chart.

Experts exhibited a preference for *"intriciate"* visuals and visualizations with *"color and movement"* [A2, A3] rather than hand-drawn or black-and-white data visualizations. In the online portion, the majority indicated preference toward hand-drawn visualizations for impact, but traditional computer-generated visualizations for drawing conclusions.

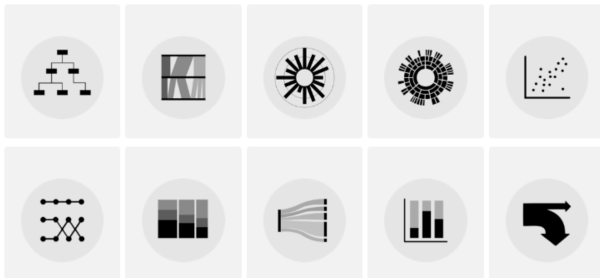
> *"I find the graphics so harsh, but I didn't like the pictograms either. It's great art, but I'm not going to trust the data...the softening of the visual in the circular format was much more appealing to me." [A2]*

This sentiment is reflected in research on human aesthetic preference for circular shapes [10]. Experts additionally affirmed that they associate traditional data visualizations to *"math," "tech,"* and *"complex data"* [A1, A2, A4, A5].

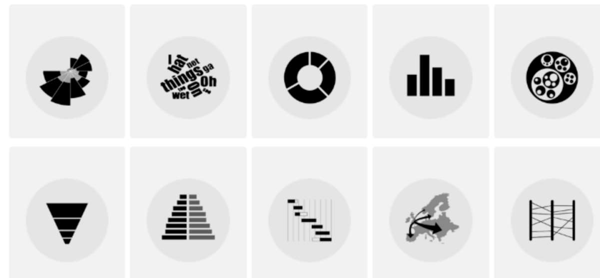
> *"I don't think you can get away from thinking about math with data visualization – but I would much rather see it with shapes and color than with written words." [A3]*

4.4.2 *Perception of Mathematics.*

When asked how they personally feel about mathematical tasks, 4 out of 5 artists presented with a negative physical reaction: leaning away, cringing, shrinking. All experts indicated negative emotions associated with mathematical tasks and their preference for visual tasks.



(a) Set 1



(b) Set 2

(c) Set 3

(d) Set 4

Figure 7: 4 sets of 10 common data visualization charts designed by [62] shown to experts. Kept black on a grey background to reduce confounding variables.

> *"I would say I'm not good at math. I would choose a visual task – definitely." [A2]*
> *"I would choose a visual task for sure, math I would stay away from completely if I can." [A3]*
> *"If there weren't a visual involved, I would create a visual. 100%. Every time." [A4]*

Experts pointed to the causes of math anxiety in themselves and their community likely stem from childhood education, social constructs, and preconceived societal notions regarding artists and math. 3 out of the 5 experts mentioned they enjoyed geometry in school as it was *"rooted in visuals"* or had a *"visual element,"* [A2, A3, A4] while being highly averse to mathematics in general.

> *"I think when I was in school, it was you were 'one or the other'. You're either really good at math or you're the weird art kid. An artist can't be good at math – that's how it was for me." [A2]*
> *"I think we've always had this stigma that we're not good at school or we're not good at math and there's no hope for us." [A1]*
> *"It probably goes back to school – doing math without any charts or graphs or visualization attached to it. If you take that piece away, it brings that anxiety back. It's a historical anxiety attached to math." [A3]*

However, when prompted that visual artists performed with quicker response times and equal accuracy to MCS, including tasks with mathematical computation, experts found it *"surprising"* and *"encouraging"* [A1,A4,A5]. They additionally acknowledged math and visualization play a role in their daily work. They noted that due to the nature of their work, their instinct isn't to approach tasks thinking about math.

> *"I think we have to use maths a lot, but it's presented to us not as a 'maths test,' which is very anxiety inducing. It's presented in a visual way – so you've got measurements that go with your drawings that respond to scale and things like that. The way we're presented with maths is that we need it to achieve a design." [A1]*
> *"Our medium is hands on, or even with graphics let's say, you're still incredibly hands on even if your tool is a mouse or computer or whatever. And you're integrating so many different variables, color, scale, proportion, all those principles and elements of design, so you're in your comfort zone of what you're doing and we're not thinking about it like math." [A4]*

4.4.3 Preference for Visual Tasks. Experts noted that in order to complete a mathematical task, their first instinct would be to manipulate an image or material rather than perform the calculations and that their *"confidence would increase"* if there were a visual involved in a mathematical task [A1,A3].

> *"I'm just used to visualizing everything in my head and thinking of it in different ways, and going through things quite quickly...I would estimate the line lengths rather than the math computation." [A5]*
> *"I think that there's a lot of problem solving that goes into our daily work that's different from a business person or someone in finance that might be constrained by*

> *numbers or words. I think as a designer or artist, there's a multitude of ways in which something can be done. To be able to compare and contrast [two elements] quickly is something we do on a daily basis – which one explains or does the job better? Visually, it's easier for me to be able to compare two things and the mass that it takes up. I might not be able to tell you the mathematical equation or how that came up, but I think it's a little more intuitive to artists and designers – being able to spatially layout things. We do it on a daily basis." [A2]*

Additionally, they spoke to approachability and preference of visuals over text in data and math representations.

> *"if we include visual and physicalization instead of just text that can make math education more approachable for many people" [A4]*
> *"If you have too much copy or text, it's probably not going to get absorbed." [A3]*

Artists problem-solve in unique ways and practice spatial manipulation as part of their daily work – this practice appears to increase their effectiveness in data visualization tasks regardless of their perception of mathematics and data visualization. Our expert's perspectives are substantiated by psychology research demonstrating visual artists have higher levels of creative problem-solving skills (even in scientific fields) and display quick and accurate visual encoding [2, 35].

> *"We just approach things so differently. We see the world differently. What we're comfortable with is taking things and rearranging things in our mind to get to an answer...we can take shapes and change them and move things around in our head. We do it everyday and kind of all the time" [A4]*
> *"In our work, and even if you've gone to art school, you're being asked to think about things upside down or see things differently and physically do it. Your brain is being trained with your eyes and your hand to constantly flex elements." [A3]*

5 PHASE 3: TEXT REPRESENTATION PERFORMANCE

Inspired by findings from interviews with expert artists, we set out to empirically test whether artists perform better using a visual chart versus text representations of data and how they compare to MCS.

5.1 Motivation & Hypothesis

Increased spatial visualization has been connected to increased performance in mathematics [4, 24, 37, 54, 65, 68, 84], however artists present elevated levels of spatial visualization with a preference for visual tasks where mathematics is involved. How then is visual artists' performance affected by text representations of data versus MCS?

Text-representations of data are often studied in information visualization research [40, 48, 49, 72] and are often found helpful for low-level tasks; however, charts and graphs increase understanding, accuracy, and retention while often reducing response times for complex tasks [40, 48, 49]. However, these studies do not focus on performance between educational and professional domains. We aim to evaluate how domain background and spatial visualization level affect performance on text vs graphical representations of data.

To claim differences in performance on text versus visuals, we tested 10 visual artists and 10 MCS out of the original 30 from each domain to facilitate within- and between-subjects analysis. We aim to evaluate if visual artists are more adept to visual representations of data versus text representations and how performance compares to MCS, given similar levels of spatial visualization, by investigating the following hypotheses.

H1: Between groups, performance (accuracy and time) on text representations of data will differ, with MCS outperforming visual artists. Given MCS domain expertise, we expect MCS to have increased performance on text conditions.

H2 (a): Within-groups, visual artists and MCS performance (accuracy and time) will differ on chart versus text conditions. Research has demonstrated that for high task difficulty and data complexity, graphic visualization increases performance, while tables are often faster for 'look up' tasks [49, 80]. Thus, we expect differing performance within domains on charts versus text, especially depending on task difficulty.

H2 (b): Visual artists will have higher levels of increased performance (accuracy and time) utilizing charts when compared to MCS. Following H2 (a), we anticipate visual artists will have higher levels of increased performance on visuals versus text compared to MCS given artists' self-reported preference for visual tasks. Further, MCS may be more adept at text representations than visual artists leading their performance differences to be smaller.

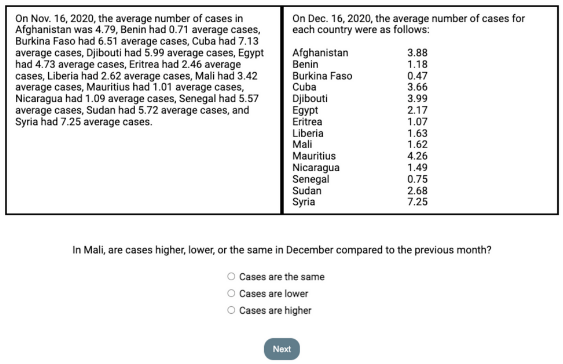
5.2 Methodology

To address the hypotheses, and for direct comparison from text to chart conditions, we extrapolated methods from Phase 1 to create a text version of the original study for Phase 3.

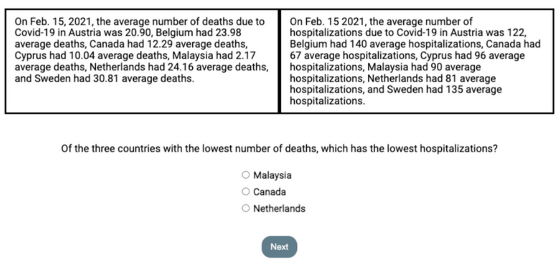
To maintain consistency in fatigue and experience, Part 1 of this study consisted of the same spatial visualization psychometric test from Phase 1. Part 2 consisted of text conditions of a subset of the same data and questions from Phase 1. We discuss study structure and stimuli below.

5.2.1 Recruitment. To ensure balanced, timely, and high-quality data, we opened the text study to 10 visual artists and 10 MCS of the original 30 from each discipline on Prolific. We followed a strict rule of balanced samples across groups to support our between and within subject design. The average response time was 20 minutes and 28s, resulting in an average pay of £2.70 per participant. We collected data 4-6 months after Phase 1 to ensure details of data would not be a confounding factor.

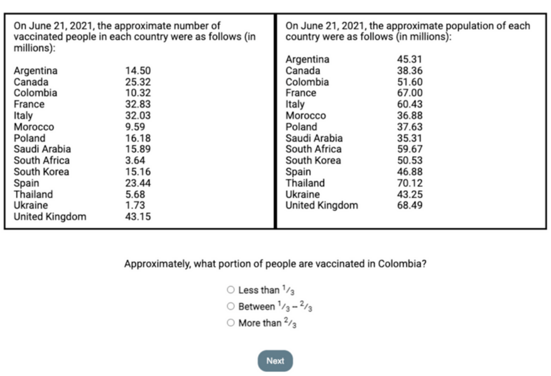
5.2.2 Study Format. The two-part online study was created using the same Flask Web App to ensure consistent environment between Phase 1 and Phase 3. This included consent, training, and the same trigger warning from Phase 1. No identifiable data was collected,



(a) Easy



(b) Medium



(c) Hard

Figure 8: (a) Easy question with a paragraph representation on the left and list on the right of density 14, (b) Medium question with two paragraphs of density 7, and (c) Hard question with two lists of density 14.

and all data was stored and maintained on a private server at the authors' institution.

Part 1 of this study was replicated from Phase 1. Active training for Part 2 consisted of 4 sample questions displaying the various text conditions participants would see throughout the study. Additionally, we decided to integrate a break halfway through Part 2 to remain consistent with Phase 1. The catch question used in the break was not analyzed (other than ensuring all respondents answered correctly for quality assurance) and was not included in response time data analysis.

5.2.3 Screening. As stated, participants consisted of a subset of participants from Phase 1. Thus, their education and professions aligned and had already passed our data standards in Phase 1.

5.2.4 Part 2 Text-Stimuli Design. We mirrored Phase 1 and manipulated the same three elements to analyze performance over: data density, text condition, and task difficulty. The data consisted of the same COVID-19 Pandemic data with the same data points as the graphic charts from Phase 1. Additionally, we varied density between 7 and 14 points as in Phase 1. Across stimuli, the data was ordered alphabetically by country. We varied the two set sizes amongst the two text conditions and three questions detailed in Phase 1 (sec. 3.2.6).

Text Conditions. To mirror conditions from Phase 1, we created two text conditions that draw on representations of data and mathematical word problems. We chose to display data in a list/tabular representation and a written paragraph. We varied the two text conditions amongst the two set sizes and three questions (see Fig. 8) and ensured each appeared on the left and right when presented in conjunction. See supplementary material for complete stimuli set.

5.2.5 Part 2 Tasks. We used the same 3-alternative forced-choice multiple-choice questions that required use of two text conditions across the three levels of difficulty. See Phase 1 methodology (sec. 3.2.6 and Fig. 8 for question examples).

5.2.6 Part 2 Measures. Two possible text conditions, four possible layouts (e.g., list or paragraph together or in combination on either right or left), two levels of data density, with three question types/difficulty levels made for a total of 24 multiple-choice questions. We recorded the same measures as Phase 1 – the selected answer and the response time (RT) of each question. Stimuli were shown randomly to participants to minimize learning effects.

5.3 Results

We analyzed differences in performance using the same methods as in Phase 1, sec 3.3: confidence intervals and hypothesis testing with BCa. We ran analysis between visual artists and MCS on the 20 participants who saw the text conditions. To maintain statistical integrity of balanced samples and direct comparison of performance on charts versus text, we ran analysis of the 20 participants versus themselves over conditions. Below we report on our high-level findings; detailed statistics are reported in supplementary material.

5.3.1 H1: Text Performance Between Groups. We hypothesized that performance (accuracy and time) would differ between disciplines with MCS outperforming visual artists due to domain differences.

We found almost no statistically significant differences in performance between MCS and visual artists. In fact, the only minor difference we detected was that visual artists were faster than MCS

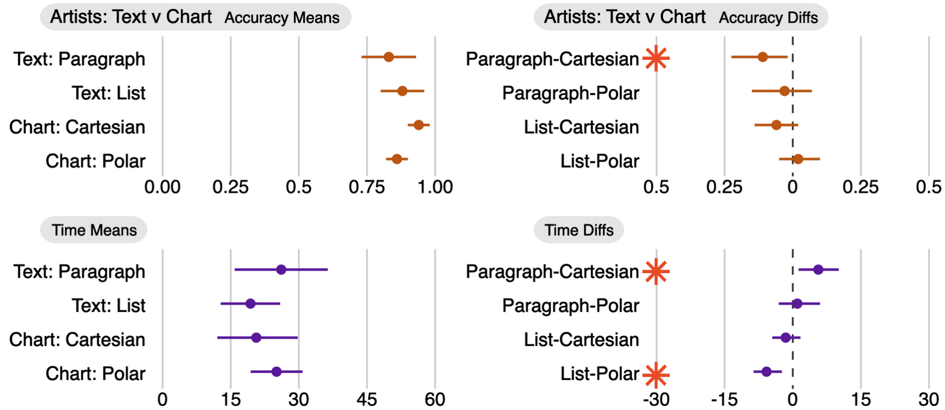


Figure 9: H2(b): Visual artists' performance means (left) and mean differences (right) for text and chart conditions. Time in seconds. Stars indicate evidence of significant differences.

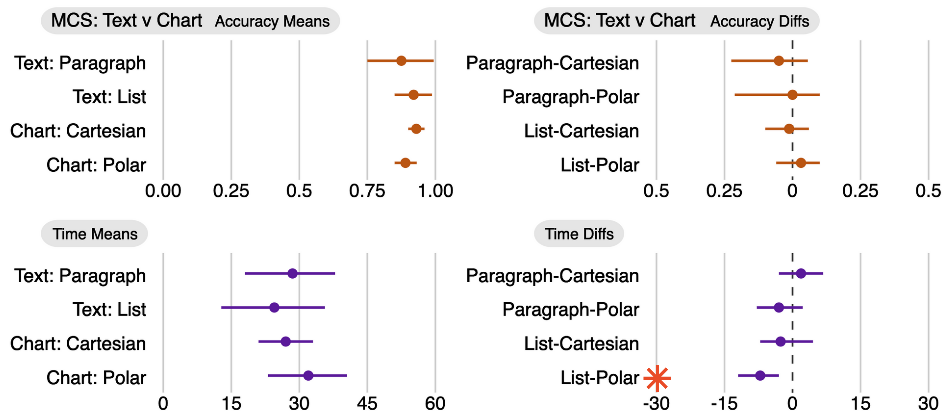


Figure 10: H2(b): MCS performance means (left) and mean differences (right) for text and chart conditions. Time in seconds. Stars indicate evidence of significant differences.

by 5.2s (CI(0, 12), $p < 0.1$) where two lists were displayed side-by-side. We did find that MCS had the longest response time on the Medium task question of density 14 with a paragraph and a list text combination, while visual artists took the longest on the Hard question of density 14 with a paragraph and a list text combination. This is in contrast with the longest response time for the chart representations being the same for both domains: the Medium question with a Radial chart of density 14. Together, this indicates that visual artists might spend more time on tasks involving mathematics compared to MCS in text conditions at some level.

⇒ We did not find sufficient evidence to support **H1** that MCS would outperform visual artists on text conditions. The text versions of Phase 1 did not elicit differences in performance between domains; the tasks in this study may not be to the level of complexity such that MCS would outperform visual artists due to domain expertise. However, we detected a very small difference ($p < 0.1$) in perception of difficulty of Part 2 between visual artists and MCS. Visual artists rated Part 2 (out of 4) 2.2/4 on average, while MCS rated it 1.4/4 (CI(0, 1.1)). This indicates that though visual artists perform just as well as MCS, they function with a higher level of perceived difficulty in text representations of data. Additionally, there may be a time/error trade for MCS as higher domain motivations may lead to a higher value placed on accuracy [32, 74].

5.3.2 H2 (a) and (b): Text vs Chart Performance. We hypothesized that both domains would display different levels of performance (accuracy and time) on chart conditions versus text conditions, especially between question difficulty. Additionally, we expected visual artists to have increased performance differences on chart versus text conditions.

Looking at overall mean differences, we found that MCS was faster in text conditions than charts by 3.7s (CI(1, 7), $p < 0.05$) while visual artists had no difference in response times. We detected no significant differences in overall accuracy between text and chart conditions within each group.

By Density:

Response Time: Within MCS, for stimuli of density 7, there is evidence that mean times were faster for text conditions compared to charts by 4.3s ($CI(1, 8)$, $p < 0.05$). There were no RT differences detected within visual artists.

Accuracy: There is only slight evidence that for stimuli of density 7, visual artists' accuracy dropped in the text conditions by 7.6% ($CI(0, 15)$, $p < 0.1$) compared to charts. There was no evidence of accuracy differences within MCS.

By Chart Type & Text Condition: We tested Cartesian (Vertical and Horizontal) and polar (Radial and Circular Bar Plot) chart conditions versus list and paragraph text conditions. See Figs. 9 and 10 for visual artists and MCS performance on chart versus text conditions.

Response Time: Within MCS, there is evidence that mean times were 7.3s faster ($CI(0, 12)$, $p < 0.05$) for list text versus polar charts. Similarly, within visual artists, mean times were 5.8s faster ($CI(2, 9)$, $p < 0.001$) for list text versus polar charts. However, for visual artists mean times were 5.2s faster ($CI(1, 10)$, $p < 0.05$) using Cartesian charts versus paragraph text.

Accuracy: Within visual artists, there is evidence that accuracy means were higher for Cartesian charts versus paragraph text by 10.6% ($CI(1, 23)$, $p < 0.05$). There is no evidence of accuracy differences within MCS.

By Question Difficulty:

Response Time: Within MCS, for Easy questions, there is strong evidence that text conditions were faster than charts by 8.3s ($CI(6, 12)$, $p < 0.001$). However, there is evidence that chart conditions were faster than text conditions for Medium questions by 4.3s ($CI(0, 10)$, $p < 0.01$) and for Hard questions by 7.0s ($CI(2, 12)$, $p < 0.01$).

Within visual artists there is also strong evidence that text conditions were faster than charts by 4.5s for Easy questions ($CI(3, 6)$, $p < 0.001$). However, there is also strong evidence that chart conditions were faster than text conditions for Medium questions by 7.4s ($CI(4, 10)$, $p < 0.001$).

Accuracy: There is limited evidence that within both MCS and visual artists, accuracy may increase for Medium questions alone using chart conditions versus text; MCS accuracy increased by 10.3% ($CI(0, 24)$, $p < 0.1$) and visual artists accuracy increased by 7.5% ($CI(0, 17)$, $p < 0.1$) using chart conditions.

$\Rightarrow$ Our results partially support **H2 (a) and (b)** that performance (accuracy and time) will differ within groups between chart and text conditions under certain conditions. MCS were generally faster on text conditions overall when compared to chart conditions while maintaining similar levels of accuracy across both (Fig. 10) – specifically in low density and low difficulty questions (**H2(a)**). Both visual artists and MCS were faster using list text representations of data compared to polar charts. However, visual artists had lower accuracy using text conditions across density 7 charts and when comparing paragraph text to Cartesian charts (Fig. 9). Additionally, visual artists took the longest on a Hard question involving math computation under text conditions, while they took the longest on a Medium question under chart conditions. These findings are in line with visualization and perception research [49, 80] demonstrating that tables are often fastest for data look up, but performance increases on chart representations as task difficulty increases. They also demonstrate that under certain conditions, visual artists perform better on charts compared to text than MCS who have slightly reduced speed using text (**H2(b)**). These findings and implications are further discussed below.

6 DISCUSSION

Our results confirm and build upon research in information visualization that both spatial visualization abilities and domain experience influence use of data visualization [32, 74]. Due to similar levels of spatial visualization in visual artists and MCS but disparate levels of mathematics and data interaction, we extended research to run a thorough comparative investigation on statistical data visualization task performance of visual artists versus MCS. We built upon established methodology in Information Visualization, aimed at gender and global diversity, gained perspective from experts on our findings, and directly compared performance of chart versus text representations of data between domains. We found that visual artists perform uniquely well on data visualization tasks using charts versus text, regardless of lower domain motivations, due to expertise and increased cognition around the visual medium.

Visual Artists, MCS, and Data Visualization. We began by comparing visual artists' performance on common data visualization and tasks to MCS using established methods from [74] for increased applications, comparability, and extrapolation to further domains. Our Phase 1 findings demonstrate that even with similar levels of spatial visualization, visual artists are faster at visualization tasks than MCS across data density, chart type, and in Hard tasks while maintaining similar levels of accuracy. While we hypothesized there would be performance differences, we expected MCS to have higher performance on tasks involving mathematical computation given domain expertise and creation/consumption of data visualization [13, 26, 32, 47]. However, our findings demonstrate visual artists are highly proficient at data visualization tasks regardless of low reported experiences with data visualization.

This prompted us to seek perspectives and understanding from expert visual artists on elevated performance of artists on data visualization tasks (Phase 2). These interviews demonstrated that visual artists are uniquely skilled at spatial manipulation and find visual tasks comfortable. Visual manipulation is part of the daily practice of visual artists, proving them deft at data visualization tasks involving spatial visualization abilities regardless of any numeracy or mathematical computation involved. Experts noted this may be due to visual artists' skill and preference of spatial manipulation over rote math computation.

Conversations with experts provoked us to empirically test if visual graphics increase performance of artists compared to text conditions (Phase 3). We tested our same respondents on text versions of the data and questions from Phase 1 for direct comparison. We did not find performance differences between visual artists and MCS on text conditions (likely due to the nature of our tasks) but did detect some variations *within* domains on performance between text and chart conditions. We detected that MCS has slightly higher performance on text conditions compared to chart conditions – this finding comes as no surprise given MCS domain expertise in mathematics. However, we found that chart conditions are helpful as task difficulty increases for both domains. Additionally, visual artists have increased performance utilizing Cartesian charts versus paragraph text representations. These findings shed light on the cognitive similarities and skills utilized by visual artists and MCS [5]; they indicate visual artists are more adept at using visual chart representations of data compared to text and compared to MCS professionals.

Our results imply elevated spatial visualization abilities might mitigate performance differences on visual tasks where domain experiences are low around data visualization. Further, this work demonstrates that exposure and daily practice of spatial manipulation increases abilities and performance on statistical visual tasks, in line with cognitive abilities research [36, 46, 59]. Tandon et al. [74] indicate increased domain motivations around data visualization task performance could make up for spatial visualization deficits. By studying disciplines with similar levels of spatial visualization and varying domain expertise, we found the reciprocal to also be true – increased spatial visualization levels could make up for low motivations: domain experience and cognitive abilities should not be taken separately, but they interact to affect performance of individuals [32, 74].

Implications on Visual Artists and STEM. Our work illustrates where word problems or paragraphs are offered as numerical representations, visual artists, those with high spatial abilities, and/or visual task preferences might benefit in timing and accuracy when basic visual mediums (i.e., graphical charts) are implemented. The fact that visual artists exhibit elevated performance on data visualization tasks with low domain experience and motivations should be compelling to the visualization and education communities. It might be important for visualization to play a significant role in math education as increased graphic visualization and manipulation has potential to decrease anxieties around mathematics and creativity – both having impacts on student participation and performance in visual arts and STEM subjects [5, 18]. Art-science collaborations prove beneficial, empowering, and developmental to both communities [11]; the reach and impact of data and visualization could be expanded as communities and individuals with visual manipulation skills are empowered and included in creating and consuming data visualization [45]. Our research highlights how data visualization can empower not only an entire community but could encourage students toward participation in both STEM and visual arts without preconceived notions of performance in either domain.

6.1 Outlook and Future Work

Though we attempted to mitigate such factors, it is important to note that other variables can influence visualization task performance such as domain knowledge, representational fluency, visual familiarity, emotional bias, or demographic differences [25, 32, 41, 43, 79]; the factors that create whole persons are complex and none alone can explain differences in visual task performance. Additionally, emotional response to COVID-19 data could have an influence task performance, though we attempted to forestall this [43, 66]. Further domains can be empirically tested to gain a robust picture of how domain experience and spatial visualization level come together to affect visualization task performance for design implications. Interventions that increase performance of low spatial individuals might be studied to increase inclusive design practices in Information Visualization. Though outside of our domain, our work could also influence education research in how visualizations affect performance of arts and STEM students.

Our study advances initial work in the visualization community toward cataloguing cognitive differences of domains [32, 74] and furthers understanding of cognitive abilities in visualization performance.

7 CONCLUSION

The aim of our research was to build on work in visualization, tying spatial visualization and domain differences, to empirically investigate data visualization performance between visual artists and MCS. These domains were historically intertwined, one influencing the other for decades. We aimed to evaluate how the cognitive similarities but different domain expertise affected performance on statistical data visualization tasks. Our study exposed the utility of visual artists' expertise and high levels of spatial visualization in performance on statistical visualization tasks despite perceived inexperience around data visualization. Additionally, we corroborated research showing visual charts increase performance versus text representations as task difficulty increases. Our findings have ramifications in visualization and education research – information visualization can empower entire communities toward increased performance on data visualization tasks.

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