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Effects of Spatial Abilities and Domain on Estimation of Pearson's Correlation Coefficient

Sara Tandon
King's College London, UK
sara.tandon@kcl.ac.uk

Alfie Abdul-Rahman
King's College London, UK
alfie.abdulrahman@kcl.ac.uk

Rita Borgo
King's College London, UK
rita.borgo@kcl.ac.uk

***Abstract*—This study builds on past research bridging spatial visualization, psychology, and information visualization to holistically inform visualization design. We investigate the effects of chosen disciplines in psychology and math & computer science, combined with cognitive abilities and demographic differences, on visual tasks by measuring estimation of Pearson's correlation coefficient in scatterplots. Results reveal mathematicians demonstrate greater accuracy, benefiting from domain expertise. However, psychologists with high spatial skills outperform some mathematicians with lower spatial skills. Spatial visualization, level of education, and age (inversely) correlated with quicker and more accurate responses. Findings prove that domain expertise and spatial cognition affect correlation judgments in scatterplots, supporting that individual differences should inform visualization design. This work introduces psychologists as a new target domain for visualization research and reveals the impact of combined effects of cognitive abilities and domain on the estimation and manipulation of Pearson's correlation coefficient.**

***Index Terms*—Pearson's Correlation Coefficient, Spatial Abilities, Domain Differences, Human Factors, Cognition, Perception**

I. Introduction

Visualization research has begun to tap into the wealth of design implications when evaluating the combined factors of spatial cognitive abilities with domain differences and expertise, which are not easily separated in individuals [17], [45], [55]. By combining these factors, we can discover how an individual's chosen domain and cognition come together to impact interactions with data visualizations. This allows us to extract and pinpoint differences in domain motivations versus cognitive effects on performance.

We focus our study on the disciplines of psychology and math & computer science; the use of visualization is important to these disciplines, from research evaluation to data analysis. In this paper, we present past research on spatial visualization in psychology and visualization design that led us to create hypotheses of how our target domains would perform in estimations of Pearson's correlation coefficient (PCC) in scatterplots. We offer a detailed statistical analysis demonstrating that visualization task performance (accuracy and response times) varies with spatial visualization and discipline across demographic factors. Our results presented correlations between various combinations of demographic factors, spatial abilities, and discipline expertise – this reflects how individual backgrounds, choices, and abilities combine to affect visualization interaction and perception, contributing to the ongoing discussion in visualization research of who our designs & research benefit, and how designs impact perception from diverse audiences [5], [17], [45]. Our sample further allows us to illustrate how discipline expertise in math & computer science could increase performance even when spatial visualization is low. This paper offers insight into psychologists, a new domain of interest for visualization designers. It also novelly evaluates the effects of spatial visualization on a commonly studied visualization task: estimating Pearson's correlation coefficient.

II. Background

A. *Effects of Spatial Visualization and Domain*

Spatial visualization (SV) relates directly to the internal process of manipulation, rotation, 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 is considered a key cognitive factor in interpretation, speed, and accuracy of information visualization (IV) tasks [6], [22], [31]. Education psychology research has thoroughly tied elevated SV to advancement in STEM subjects [2], [14], [19], [32], [39], [41], [54], which is often posed in research both as an indicator of, and/or developed from, STEM subject acumen [3], [43]. Research also suggests that further education in any field and age (inversely) correlate with spatial skills [47], [50]). Shea et al. [41] and Wai et al. [50] conducted comprehensive studies assessing spatial abilities across domains, levels of education, and occupation: both detected social scientists tended to have lower spatial abilities than STEM students.

Research has demonstrated that high SV specifically, can correlate with higher recall, understanding, and increased task performance using various data visualizations (e.g., parallel coordinate plots, Bayesian reasoning, tables, box plots, graphical lineups, bar, radar, and value charts) [22], [34], [48], [51]. Hall et al. [17] and Tandon et al. [45], [46] went on to confirm SV and domain experiences combine to explain performance on IV tasks among Education, Chemistry, Business, Law & Political Science, Visual Artists, and Math & Computer Science disciplines. These findings imply discipline is strongly related to the development of both SV abilities and interaction with data visualization. We build on past research to evaluate a new domain and new visual task in combination: Psychologists and Pearson's correlation coefficient estimation.

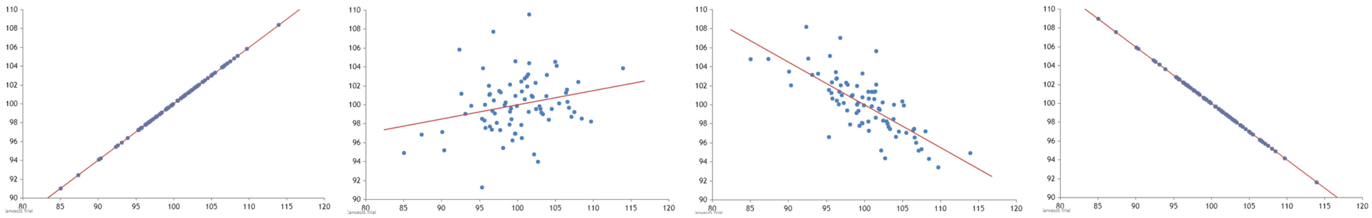

Fig. 1. Four examples of plots with various Pearson's correlation coefficients (r = 1, 0.25, -0.75, -1) displayed to participants in training

B. Pearson's Correlation Coefficient Perception

Perception & estimation of PCC and the effects of various visual variables have been thoroughly studied in IV; this research has demonstrated density, color, personal data bias, scale, dot size, direction, shape, orientation, and dispersion of data affect perception of PCC [4], [24], [26], [28], [30], [36], [38], [42], [52], [53]. Sher et al. noted that human perception of PCC does not consistently correlate with the statistical measure while indicating data distribution, symmetry, and large variations in density can affect perception [42]. Doherty et al. observed that judgment of discriminability increased with higher correlations [7]. Harrison et al. [18] and Kay & Heer [21] thoroughly demonstrate scatterplots are consistently the best visualizations for visual data correlation representation. Yang et al. [52] recently concluded viewers attend to a small number of visual features, like distance to a regression line and data dispersion when judging correlation. Best et al. [4] demonstrate cognitive function increases as correlation decreases while observing changes in PCC. However, none of these studies evaluate the effects of cognitive abilities nor domain experiences. We expand on this past work by offering a novel approach to explaining and understanding the estimation of PCC through the lens of individual differences.

III. Motivation & Hypothesis

Inspired by previous work in domain, cognition, and IV perception, we set out to study how these elements combine to affect judgment of PCC. We chose PCC given it has been thoroughly investigated without cognition or individual differences being accounted for in evaluation. We carefully considered disciplines with familiarity with statistics, but varying expertise that could result in differing development of SV. We recruited those with aligned professions and education in Psychology (Psych) and Math & Computer Scientists (MCS). We treat MCS as benchmark participants as they are often the creators, researchers, and participants in IV studies [5], [17]. MCS display high levels of SV, and often outperform other domains in visual tasks [45], begging if IV designs are accessible and useful to those with differing expertise. We chose Psych professionals as they are an unevaluated domain in IV research while often interacting with data and statistics, especially in social science research [13], [27]. Given psychologists' familiarity with data and trends, alongside research demonstrating social scientists have differing SV skills to MCS [7], [50], there may be measurable differences in how these domains perceive PCC. We present novel research into how specific individual differences might combine to affect the estimation of PCC in a quantitatively significant way by investigating the following hypotheses.

H1: Performance (accuracy and response time) will correlate with SV level overall. Accuracy and timing of visualization tasks vary with SV abilities [22], [34], [48], [49], [51], [55]. High spatial individuals tend to have higher accuracy and reduced response times. We expect to see comparable results, emphasizing the role of SV in performance and use of IV.

H2: SV will differ between domains. Research shows systematic differences in SV abilities between domains that impact visual reasoning in a discriminating way, in turn affecting performance of domains on IV tasks [17], [45]. Past research further demonstrates MCS exhibits heightened SV versus other domains, including social scientists [50].

H3: Performance (accuracy and response time) will correlate with domain and SV combined such that average performance will vary between groups given their background. SV and individual differences are an important underlying source of variations in performance on visual tasks [17], [45]. Given their domain expertise, we anticipate that MCS will outperform Psych in estimations of PCC. As effective visualizations should consider not only the needs of a discipline but also the abilities of the individuals within domains, we hope this finding could prompt future research in design given individual differences.

IV. Study Methodology

A. Recruitment & Apparatus

Participants were recruited through Prolific [35]. Our participants were educated and current professionals in our target domains, 21 years and older, and fluent in English. We recruited balanced samples of 30 participants in each domain with valid data for a total of 60 participants. Participants were paid £9.00/hour according to Prolific's fair pay policy. The online study was created using a Flask Web App with D3.js for interactive chart generation. Participants completed consent and training before each part of the study and could leave at any time, ending their participation. The average response time was 17 minutes and 19 seconds (s).

B. Study Structure

1) Screening & Demographics: Following consent, participants completed 7 demographic questions on gender, age, education history, profession, and countries of origin and influence. Those who self-identified on Prolific as having studied and currently work in Psych or MCS were admitted and reconfirmed their primary field of study and work in our demographic collection. Prolific offers a participant score based on the quality of an individual's past submissions: our participants scored 98% or higher. We excluded the data of 10 participants due to a lack of consistency in their primary field of study or failed attention checks. We collected data until achieving balanced samples across target domains.

2) Spatial Visualization Assessment: Following demographics, participants began the SV assessment from the Kit of Factor Referenced Cognitive Tests [11], a well-established 2D psychometric assessment [1], [31] largely utilized in previous data visualization studies [22], [29], [34], [45]. This assessment has the added benefit of a 3-minute time limit for participants to complete it. We gathered both the selected answer and response time for each question of the assessment. The test consists of training followed by 10 questions in which an image of a paper is folded and punched; participants must then choose from 5 options of what the paper will look like when unfolded. The SV score is calculated as the number of correct answers out of 10. Congruent to [8], [22], [34], [39], [45] the score was centered by its mean so that participants above the mean are classified as having high SV, while participants below are classified as having low SV.

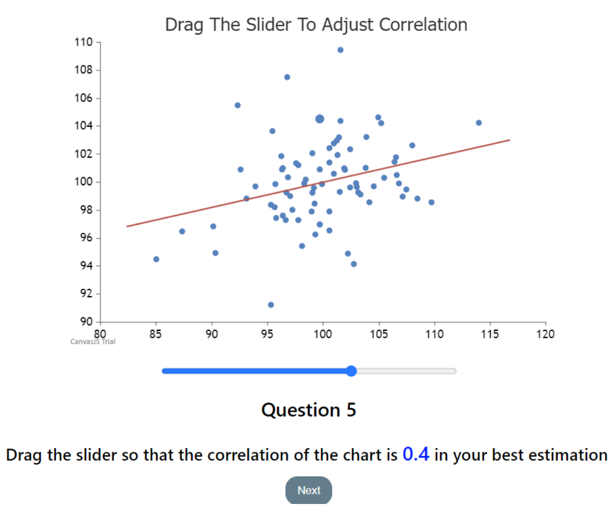

Fig. 2. Example stimuli for PCC estimation

3) Part 2 Stimuli Design (Fig. 2): Human judgment of PCC is inconsistent and dependant on many visual variables [42]. Strain et al. suggest that the mean or standard deviation of geometrical distances between points and the regression line is commonly used to estimate correlation or is a good proxy for what is being attended to [44]. Thus, we chose to allow participants to change the perceived width of a given probability distribution by changing the perceived distance between points and the regression line. The variables are sampled from the standard normal distribution, which are then transformed to have a given correlation by using Cholesky decomposition. We utilized randomized data of 80 data points with a mean of 100 for both the x and y coordinates with standard deviations of 3.0 for the x coordinates and 5.0 for the y coordinates to maintain a consistent data distribution throughout so as not to affect perception adversely [28], [36], [42]. We chose 80 data points as Sher et al. [42] demonstrate that perception of PCC is only affected by large differences in data set size, with no differences detected with data set sizes between 60-120 points. We added a regression line to give participants a visual anchor when assessing correlation without adding any explicit indications of PCC to the chart [52].

4) Part 2 Task Design: Inspired by current methodology in vision science and PCC estimation [12], [25], [26], [38], [44], we began by choosing a direct estimation paradigm as our basic task such that we can assess how close a participant's response is to the true Pearson value at different magnitudes; thus, our results can be used to evaluate, generalize, and predict future estimation performance. We followed a task design inspired by [26], allowing participants to manipulate and adjust the scatter plot themselves towards a given correlation to evoke the cognitive skills involved in SV (i.e., visual working memory and mental manipulation & rotation of points). Participants were offered a scatterplot and slider to manipulate the plot, with the variables moving continuously as the slider was dragged. In training, participants were shown PCC as they moved the slider to familiarize themselves with PCC, understand the chart manipulation, and what the chart looks like at target PCCs (Fig. 1). Participants then manipulated the scatter plot such that it reflected their best estimation of a given Pearson's correlation between -1 and 1 in 0.1 increments: the target value was randomly offered to the participants. The scatterplot and slider position were randomized after each guess, such that participants had to re-adjust the scatterplot to their best estimation of a given PCC for each target. Additionally, the values 0.6 and -0.3 were repeated to confirm participants were paying attention to the target value and offering consistent estimations. This created a total of 23 questions for participants. Responses were recorded continuously between -1 and 1 in 0.01 increments for precision. We recorded the estimated value and response time (RT) for each question to assess performance.

V. Results

We analyzed differences in performance and SV using sample means and hypothesis testing at the $p < 0.05$ level of confidence 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 CIs for the Monte Carlo permutation procedure along with hypothesis testing using Weltch's t-test to obtain a test statistic and p-value for further validation for detecting significance between group responses for our parametric data [20], [33], [37]. We used analysis of covariance (ANCOVA) regression and validated results with a Robust Linear Model (RLM) with Huber-White standard errors to test multiple variables and interaction terms as predictors of accuracy. We use multiple analysis techniques to validate and demonstrate the strength of evidence about the population means [9], [16]. We present high-level findings below; detailed statistics are in supplementary materials.

We successfully gathered 60 participants with reliable data, giving us 30 participants in each domain. Self-identified gender participation overall: 58% men, 42% women. Within Psych: 57% men, 43% women. Within MCS: 73% men, 27% women. These are consistent with known educational domain gender differences across Europe [10]. All participants' average age (±standard deviation) was 30±9, ranging from ages 21-68, with the median at 28. 55% of the total population held an undergraduate degree and 45% held a graduate degree (Masters or Doctorate) in their field.

A. Overall & Demographic Findings

The overall SV score was 4.7/10. The overall mean distance to the PCC target was 0.17 ± 0.06 with a mean RT of $9.9s \pm 3.4$ for each estimation. Participants spent an average of $51.1s \pm 6.7$ on training for PCC estimation questions. This suggests participants had enough time to grasp and interact with the scatterplot distribution across different target values.

ANCOVA and RLM returned significant effects ($p < 0.05$) across most variables and interactions tested. Independently, SV score, domain, gender, age, and level of education all had significant effects on accuracy. Interaction terms between demographic variables, SV, and domain were tested: all interactions except gender were deemed significant across both regressions, meaning the impact of SV or domain on accuracy is influenced at least by age and level of education. Thus, we explore these variables and their interactions in our results. As the average age was 30, we split groups into under-30 and over-30 and found that under-30s were significantly faster (CI$(1.5s, 4.8s)$, $p < 0.001$) and more accurate (CI$(0.08, 0.11)$, $p < 0.001$). This aligns with research into spatial abilities and age, in which young adults under 28.6 display higher spatial skills than older adults [47]. We observed those with a graduate degree had higher SV (CI$(0.11, 2.6)$, $p < 0.05$), quicker RTs (CI$(2.0s, 5.5s)$, $p < 0.001$), and were more accurate in target value estimation (CI$(0.02, 0.08)$, $p < 0.001$) than those with undergraduate degrees. This supports research that further education in any field is correlated with higher spatial skills [50]. See below for interaction results in context with SV and domain of these demographic factors.

B. H1: Overall performance will correlate with SV

We hypothesized that performance (accuracy and RT) would differ between high spatial (HS) and low spatial (LS) participants. LS comprised 12 Psych and 19 MCS participants; HS had 18 Psych and 11 MCS. We detected HS participants had higher accuracy and quicker RTs than LS: HS estimating, on average, 0.16 closer to the target value than LS (CI$(0.14, 0.19)$, $p < 0.001$) and 3.3s faster (CI$(1.8, 5.5)$, $p < 0.001$). Our results demonstrate HS participants were significantly closer at $p < 0.05$ to the target value at every increment of 0.1 between -1 and 1 (save 0.9). LS participants tended to overestimate the steepness of correlation compared to HS ($p < 0.05$), and they flipped the direction of correlation (i.e., estimating a positive correlation when a negative correlation target value was offered) significantly more than HS at $p < 0.001$.

TABLE I
SV (OUT OF 10) AND PERFORMANCE BY DEMOGRAPHICS

	n	Spatial Score	Response Time	Difference
Low Spatial (LS)	31	2.6 ±0.3	11.49 ±6.0	0.25 ±0.1
High Spatial (HS)	29	6.9 ±0.4	8.20 ±3.5	0.08 ±3.5
LS-Undergraduate	20	2.55 ±0.4	12.90 ±8.7	0.27 ±0.12
LS-Graduate	11	2.8 ±0.4	8.93 ±4.3	0.21 ±0.16
HS-Undergraduate	13	6.5 ±0.6	9.19 ±6.7	0.07 ±0.05
HS-Graduate	16	7.3 ±0.6	7.40 ±3.1	0.1 ±0.06
LS under-30s	9	3.2 ±0.6	9.05 ±4.8	0.16 ±0.13
LS over-30s	22	2.4 ±0.3	12.49 ±8.0	0.28 ±0.12
HS under-30s	15	6.7 ±0.5	7.72 ±3.2	0.07 ±0.04
HS over-30s	14	7.3 ±0.7	8.72 ±6.3	0.10 ±0.07

TABLE II
DOMAIN STATISTICS BY SPATIAL VISUALIZATION

	n	Spatial Score	Response Time	Difference
Psych	30	5.6 ±0.8	10.63 ±6.2	0.19 ±0.09
MCS	30	3.8 ±0.6	9.17 ±3.0	0.14 ±0.07
LS-Psych	12	2.8 ±0.5	14.76 ±9.5	0.33 ±0.18
LS-MCS	19	2.6 ±0.4	9.42 ±4.0	0.19 ±0.11
HS-Psych	18	7.6 ±0.5	7.87 ±4.9	0.10 ±0.06
HS-MCS	11	6.0 ±0.6	8.74 ±4.5	0.05 ±0.04

As in Table I, when SV is split by level of education, we see that LS-graduates were quicker (CI$(2.0, 7.2)$, $p < 0.001$) and more accurate (CI$(0.0, 0.1)$, $p < 0.05$) than LS-undergraduates. However, HS-undergraduates display a time/error trade off, taking slightly longer (CI$(0.3, 4.4)$, $p < 0.05$) to be slightly more accurate than HS-graduates (CI$(0.01, 0.05)$, $p < 0.001$). Looking at interaction between age group and SV, LS under-30s had quicker RTs (CI$(6.3, 12.9)$, $p < 0.05$) and closer estimations than LS over-30s (CI$(0.08, 0.17)$, $p < 0.001$). Similarly, HS under-30s were slightly more accurate than HS over-30s (CI$(0.0, 0.05)$, $p < 0.05$).

⇒ We confirmed **H1** and our regression analysis results that SV alone, and combined with age and education level, significantly affected estimation of PCC. We detected that LS respondents have longer RTs and offer less accurate estimations of PCC than HS respondents. Further, we note that age and education, in combination with SV, affect the accuracy of PCC estimation, which may affect domain results depending on the representation of these subgroups. These findings are in line with previous research that SV plays a role in visual task performance [17], [45], [46], [51] and can be affected by education and age [47], [50].

C. H2: Spatial visualization between domains

We hypothesized that SV would differ between domains due to expertise and education experiences. SV score for MCS was

TABLE III
DOMAINS BROKEN DOWN BY DEMOGRAPHICS

	n	Spatial Score	Response Time	Difference
Psych under-30s	11	6.4 ± 0.8	7.97 ± 3.1	0.11 ± 0.07
Psych over-30s	19	5.2 ± 1.1	12.17 ± 9.6	0.24 ± 0.12
MCS under-30s	13	4.5 ± 0.9	8.43 ± 4.3	0.09 ± 0.08
MCS over-30s	17	3.3 ± 0.77	9.74 ± 4.2	0.18 ± 0.11
Psych Undergraduate	12	5.2 ± 1.3	14.2 ± 10.5	0.25 ± 0.16
Psych Graduate	18	5.9 ± 1.0	8.24 ± 3.5	0.16 ± 0.1
MCS Undergraduate	21	3.52 ± 0.7	9.85 ± 4.1	0.16 ± 0.09
MCS Graduate	9	4.6 ± 1.3	7.59 ± 2.9	0.11 ± 0.09

3.83 ± 0.6 (19 LS, 11 HS), while Psych had a mean score of 5.63 ± 0.8 (12 LS, 18 HS) – there is strong statistical evidence of difference between them with CI$(0.6, 3.0)$ and $p < 0.001$.

$\Rightarrow$ We confirmed **H2**, that SV is significantly different between Psych and MCS. However, our finding is inconsistent with previous research into spatial abilities of these domains [41], [50], which report MCS outperforming social scientists. Our use of a research focused crowdsourcing site and representation of low spatial, over-30, undergraduate participants in MCS (37%) might have skewed these results. Past research using the same SV assessment [45] found that MCS has elevated SV (5.33/10) over other domains, while our sample has significantly lower SV than previously detected. This allows us to investigate how domain expertise might affect performance when SV is low in individuals. Conversely, we may understand how SV affects performance where discipline exposure and expertise differ from the task at hand.

D. H3: Performance correlates with domain & SV combined

We hypothesized that performance would differ between disciplines following their SV and expertise. Unexpectedly, we did not detect a difference in RTs for PCC estimation. Still, we did see that MCS was slightly more accurate in estimations than Psych (CI$(0.02, 0.08)$, $p < 0.001$), despite their lower SV scores. Further, we observed Psych tended to underestimate the steepness of correlation compared to MCS at $p < 0.01$. Our sample allows us to explore what happens when spatial abilities differ from the norm of given discipline expertise.

Table II breaks down domains by SV to understand their combined effects. MCS participants took the same time, or were faster, and more accurate than their Psych counterparts with the same level of SV. LS-MCS was 5.3s faster than LS-Psych (CI$(2.7, 10.7)$, $p < 0.001$) while offering closer estimations (CI$(0.09, 0.20)$, $p < 0.001$). HS-MCS had similar times to HS-Psych but were more accurate by 0.05 (CI$(0.03, 0.07)$, $p < 0.001$). This indicates that MCS' domain expertise might increase their performance compared to Psych's when SV is comparable. Consistently, all scores, times, and estimation differences between subgroups of low and high spatial were significant at $p < 0.01$, save for RT of LS-MCS with HS-Psych and HS-MCS. This suggests that domain expertise in mathematics could increase performance where spatial abilities are lacking and supports research that increased SV can increase performance where domain expertise varies [46].

As in Table III, we evaluated domains split by age and education. There were no differences in SV or performance between under-30s Psych and under-30s MCS, while over-30s Psych had higher SV than over-30s MCS (CI$(0.3, 3.5)$, $p < 0.05$). However, over-30s Psych had similar RTs but less accurate estimations than over-30s MCS (CI$(0.02, 0.11)$, $p < 0.01$). Within domains, under-30s were faster and more accurate than over-30s (all $p < 0.05$). This indicates that age group has a strong impact on performance, with under-30s performing similarly regardless of domain, while domain can outweigh SV in over-30s. Graduate Psych participants had similar SV and RTs to graduate MCS but were less accurate in estimations (CI$(0.0, 0.09)$, $p < 0.05$). Similarly, undergraduate Psych had similar spatial scores but slower RTs (CI$(1.4, 9.9)$, $p < 0.05$) and lower accuracy (CI$(0.05, 0.14)$, $p < 0.001$) than undergraduate MCS, indicating discipline increases performance within level of education. Graduate participants were faster and more accurate than undergraduate participants within their same discipline (all $p < 0.01$).

$\Rightarrow$ We confirmed **H3**, that performance correlates with domain and SV. We further confirmed our regression analysis that domain affects performance on PCC estimation alone and combined with age and education. When splitting domain into SV groups, it becomes clear that MCS domain expertise contributes to increasing the accuracy of PCC estimation. Our sample allows us to demonstrate that high SV affects performance, given HS-Psych was faster and more accurate than LS-MCS. Breaking down domain by demographics further supports that discipline has a strong effect on performance regardless of education level, but that age can outweigh domain expertise in under-30s. As expected, performance increases when SV increases within domains and demographics.

VI. DISCUSSION

A. Spatial visualization performance

Consistent with research into SV and data visualization task performance [22], [48], [51], we found that increased SV correlates with significantly higher accuracy and quicker RT in estimations of PCC (**H1**). High spatial respondents had significantly closer estimations of every individual target value than LS respondents. This emphasizes the increased ability of chart manipulation and visual working memory of HS individuals. We observed that demographic factors, in combination with SV, also impacted accuracy. Under-30s were more accurate within SV groups than over-30s, which indicates that age might affect performance when SV is equal. Education interaction varies – within LS participants, Graduates had increased performance (an expected outcome [50]). However, within HS participants, Undergraduates took slightly longer to have better estimations than Graduates. This is a common finding in IV studies, extra time spent can increase accuracy [17], [45]. These findings imply that age and education interact with SV to modify performance in visual tasks. This contributes to the open question of who benefits from data communication and design; the cognitive abilities of audiences should be considered when creating and evaluating visual designs.

B. Domain Performance

We confirmed that SV varies with domain (**H2**); however not overall in the way we anticipated based on past research [50]. Our sample indicated we had more LS-MCS and more HS-Psych participants than expected. Cognition research establishes individuals who studied STEM subjects have increased spatial abilities compared to those in social sciences [41], [50]; IV research also demonstrates increased performance & SV by MCS [17], [45], [46]. As we used the same SV assessment as past research, our sample allowed us insight into how performance might vary when abilities do not line up with the expectation of the domain – what is the effect of discipline versus SV in domains with differing expertise?

Overall, we saw no differences in RT between domains; however, we detected MCS were more accurate than Psych in PCC estimations despite having lower SV as a group. To give context to this finding, we split the domains by SV level (Table II) and other demographic variables that affected outcomes (Table III). We found behavior consistent with SV level, such that performance increased with SV within MCS and Psych participants. Further, low and high spatial MCS were significantly more accurate than their Psych counterparts at the same level of SV, while taking the same amount of time or were even faster (**H3**). This indicates that domain expertise in MCS might contribute to increased performance in PCC judgments. Graduate participants outperformed Undergraduates in the same domain, and MCS outperformed Psych at the same education level. Psych Graduates had higher SV and faster RTs than Undergraduate MCS, but similar accuracy. From this, we can infer that SV and higher education combine to increase performance comparative to domain experts, who perform well regardless of SV level. However, we detected age was a strong indicator of performance alongside domain. While under-30s perform better than over-30s within their domains, under-30s Psych is the only subgroup to perform similarly to their same demographic group in MCS, meaning under-30 is the only demographic factor that might mitigate differences in domain expertise. This has implications for how participant demographics affect research outcomes in IV.

C. Implications

As scatterplots are a commonly used and recognized visualization, they have been a canonical player in perceptual evaluations [4], [38], [40], [42]. Additionally, research has demonstrated scatterplots are the best chart for human detection of data correlation [18], [21], a task common to MCS and research psychology fields. Our results demonstrate that domain expertise in MCS highly influences accuracy and RTs in estimation of PCC across demographics, even with low levels of SV. Further, we found that when SV is elevated in psychologists, their performance increases to meet that of low spatial MCS. We found that further education increases performance, while SV and performance are inversely correlated with age within domains. Age is the only demographic factor that could mitigate performance between domains: our participants under-30 performed similarly, regardless of their domain expertise. PCC estimation is best done by young audiences with high SV and/or domain expertise in MCS. This research may have implications on design study and participant recruitment in general, given IV studies are often conducted on individuals in their 20s and/or students relating to STEM subjects [5]. Some studies may be able to extend applications beyond STEM-subject participants, given that under-30s in other domains display similar performance. However, this leaves a glaring gap in evaluating broader audiences with varying expertise and cognition.

D. Limitations & Future Work

The scope of this study did not include the causal origins of SV differences amongst disciplines and why they affect PCC estimation – these are open questions. We did not evaluate multiple data distributions, visual strategies, or daily interaction/preferences of charts by our participants, which could shed light on how designs could be tailored for domains. Additionally, many factors combine to affect visual task performance (e.g., representational fluency, visual familiarity, domain interactions/values, and further demographic/personal differences [15], [17], [23]) – none alone can explain differences. However, our study demonstrates that individual differences can contribute to visual task performance and where interventions or visual cues/features could be investigated to mitigate domain performance differences. Our study sheds light on the fact that MCS expertise and/or elevated cognitive abilities increase the performance of visual tasks. While much of data visualization is created by MCS experts, it is worth evaluating if those visualizations are effective for other domains with differing visual task/cognitive expertise.

VII. Conclusion

Our research built on work in information visualization exploring spatial visualization differences amongst domains to increase the impact of visualization design and evaluation for specific communities. Our study expanded research to evaluate psychologists and math & computer scientists in estimations of Pearson's correlation coefficient. This work contributes to evidence that the interplay between cognitive and demographic factors should be considered in the holistic evaluation of visual designs. Our research illustrates how visual task performance is affected by domain expertise in mathematicians with low spatial skills, and the effect of high spatial skills in social science experts. This allowed us to make conclusions about the influence of domain versus spatial visualization, in combination with demographic factors, on visual task performance. We hope studies like this can demonstrate how individual differences affect visual task performance and where there is room for improvement, effectiveness, and inclusivity in data visualization research and design.

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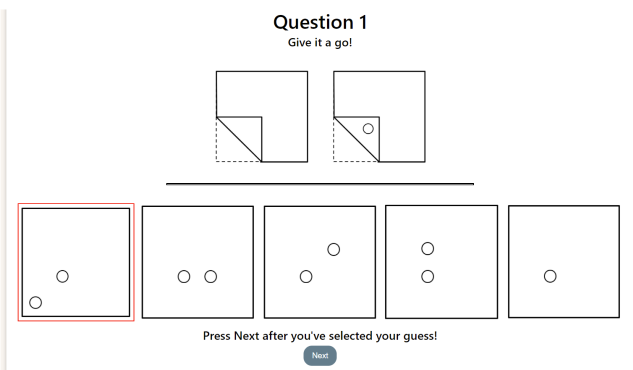
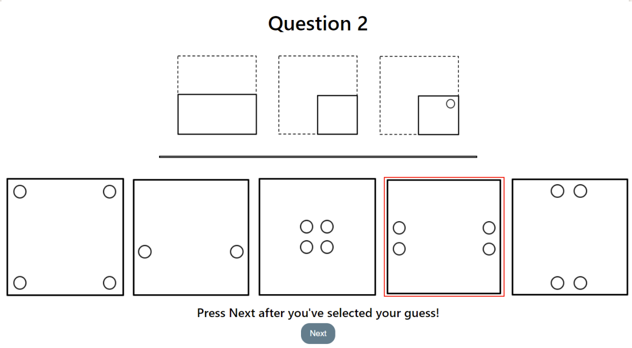
Effects of Spatial Abilities and Domain on Estimation of Pearson's Correlation Coefficient
Supplementary Material

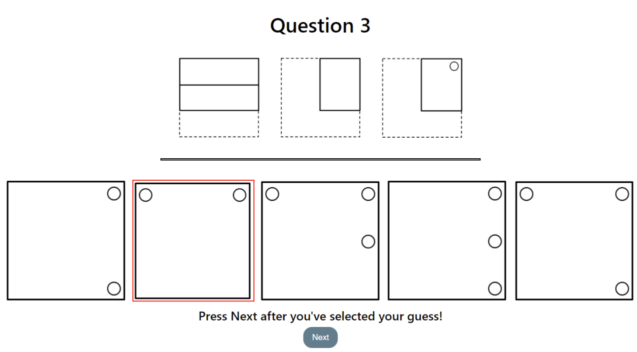
Sara Tandon* Alfie Abdul-Rahman* Rita Borgo*

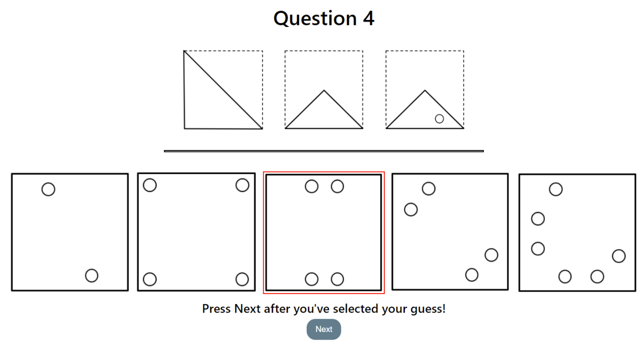
King's College London, UK

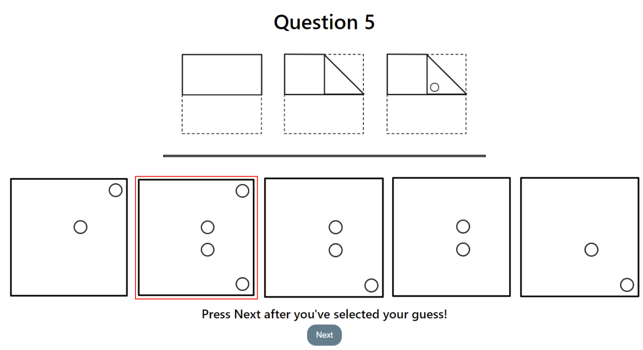
1 Supp Material - Part 1 Paper Folding Task

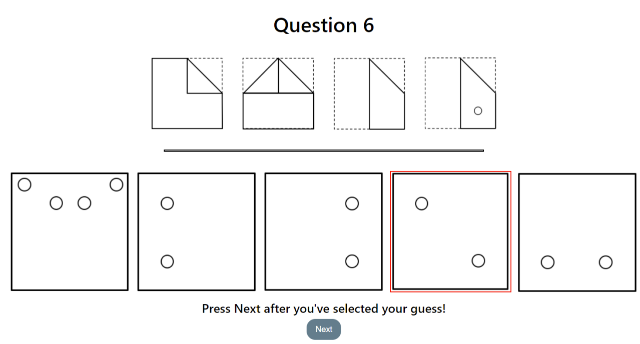






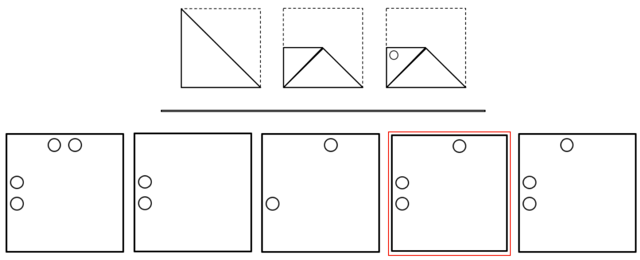






*e-mail: {sara.tandon | alfie.abdulrahman | rita.borgo}@kcl.ac.uk

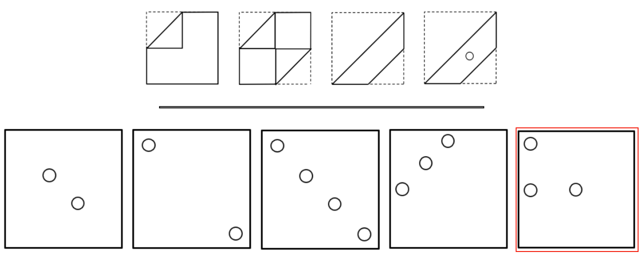
Question 7



Press Next after you've selected your guess!

Next

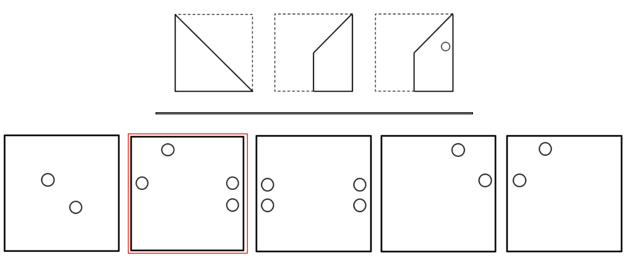
Question 8



Press Next after you've selected your guess!

Next

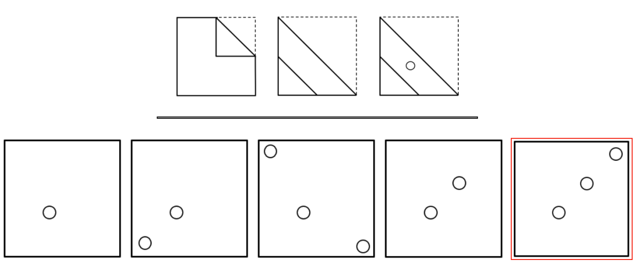
Question 9



Press Next after you've selected your guess!

Next

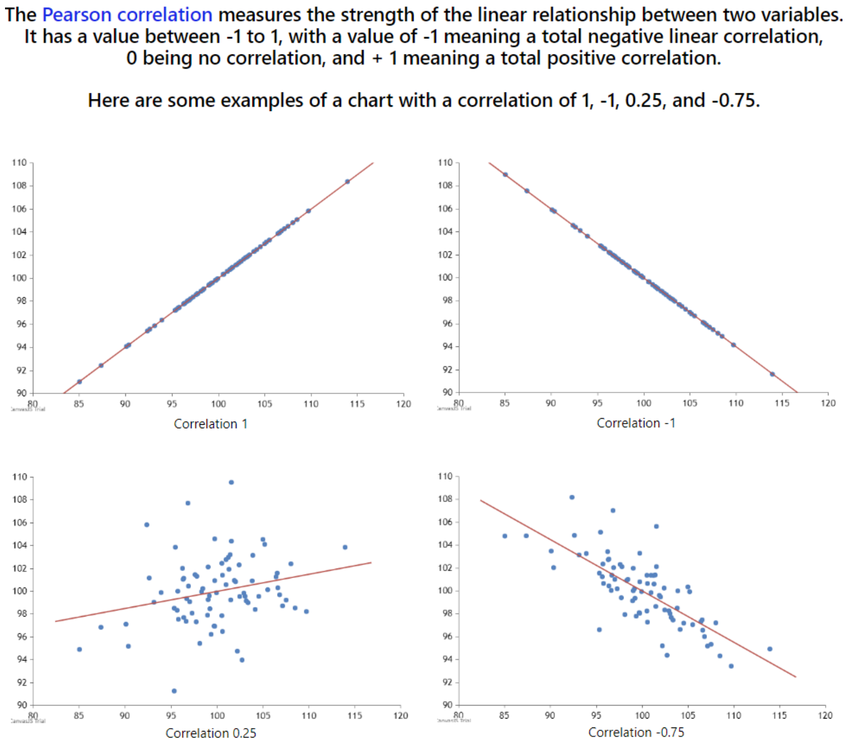
Question 10



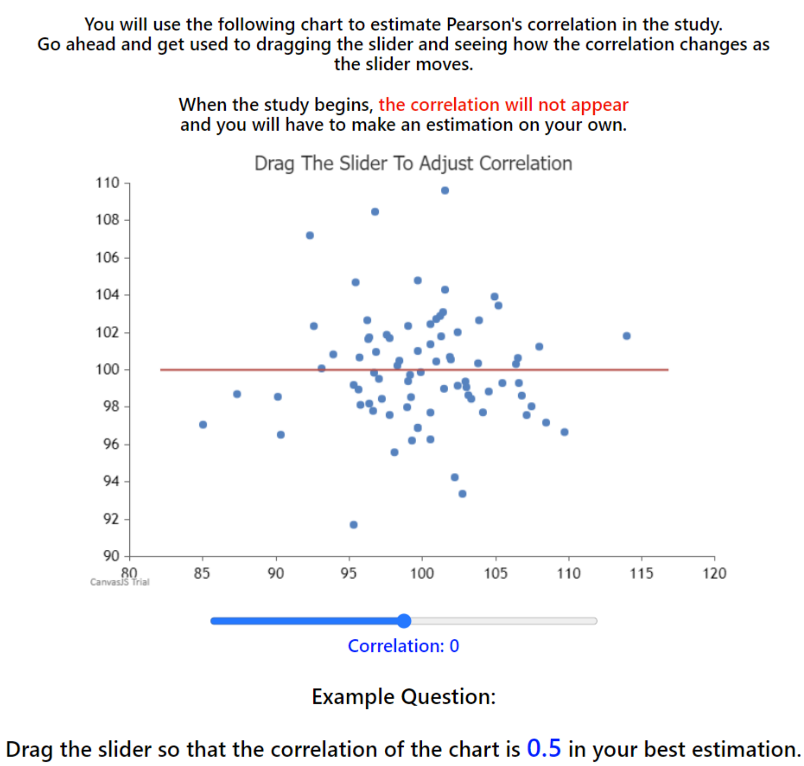
Press Next after you've selected your guess!

Next

2 Supp Material - Training for Part 2 - screenshots

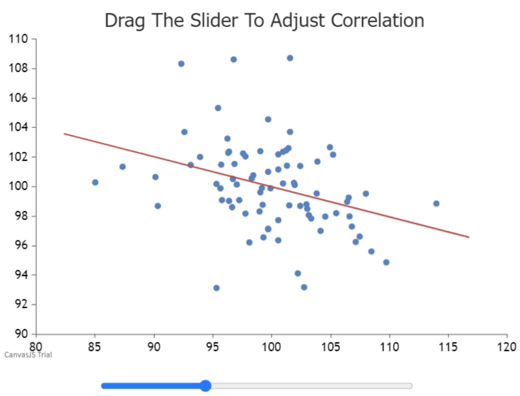


Training - Basic instructions of PCC



Training - slider introduction to participants

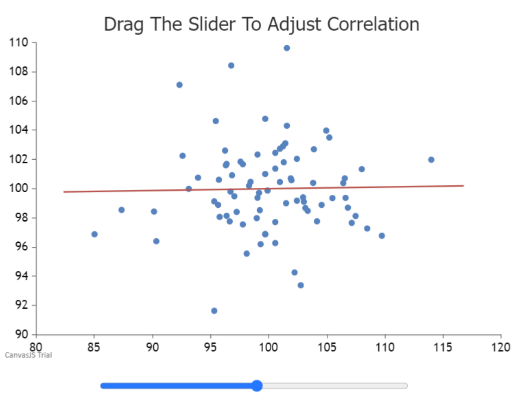
3 Supp Material - Main Question examples (participants must move slider to click next 23 targets offered between -1,1)



Question 1

Drag the slider so that the correlation of the chart is -0.7 in your best estimation

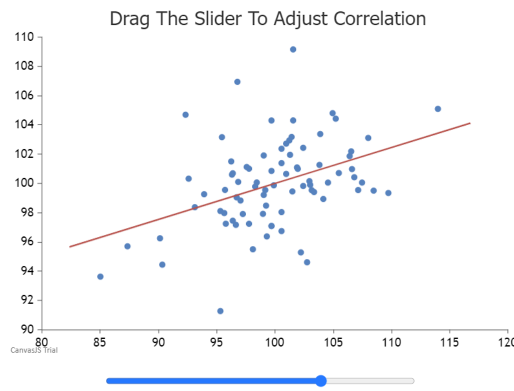
Next



Question 2

Drag the slider so that the correlation of the chart is -0.3 in your best estimation.

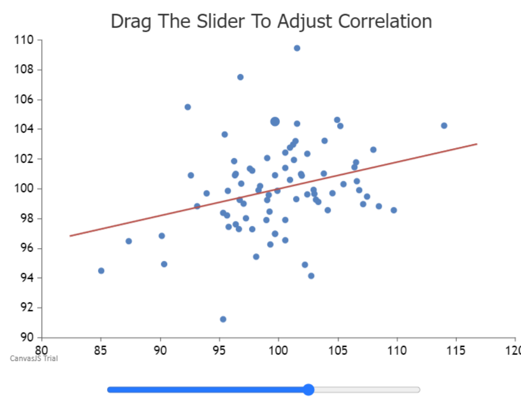
Next



Question 4

Drag the slider so that the correlation of the chart is -0.9 in your best estimation

Next

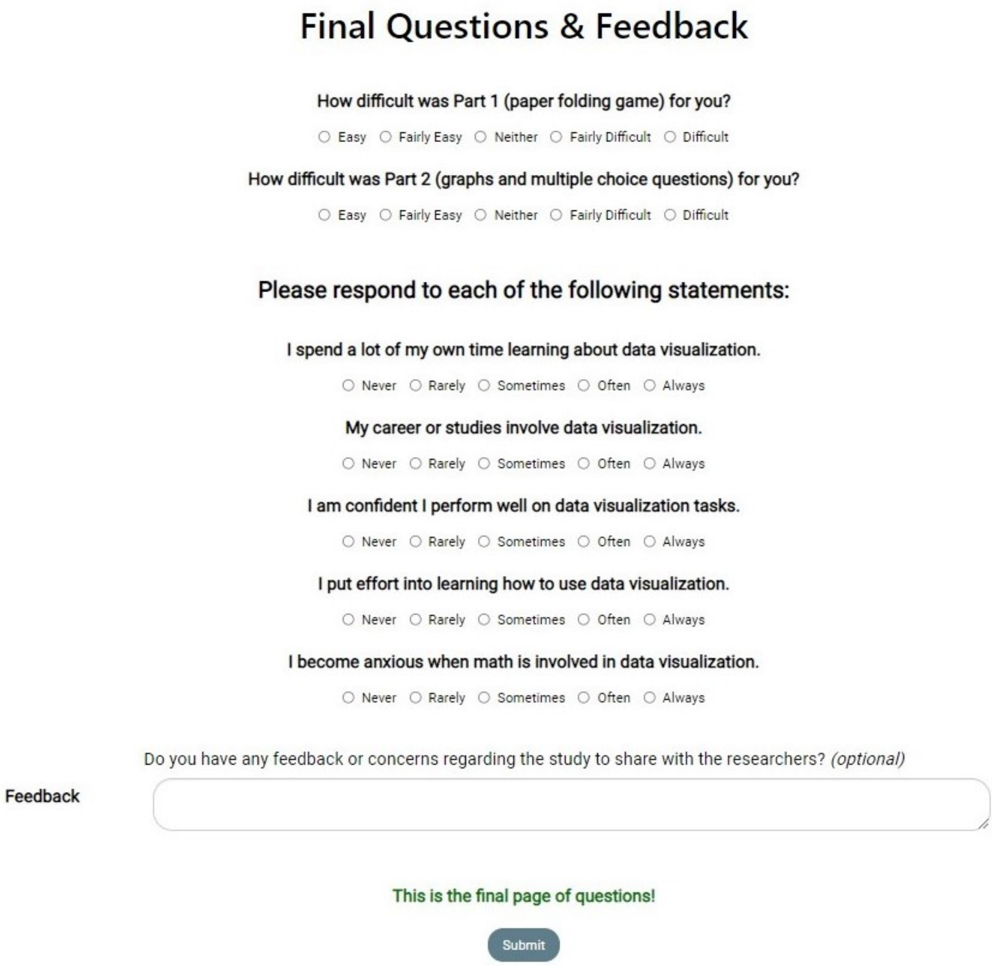


Question 5

Drag the slider so that the correlation of the chart is 0.4 in your best estimation

Next

4 Supp Material - Final Questions (Difficulty and Motivation)



Final Questions & Feedback

How difficult was Part 1 (paper folding game) for you?

○ Easy ○ Fairly Easy ○ Neither ○ Fairly Difficult ○ Difficult

How difficult was Part 2 (graphs and multiple choice questions) for you?

○ Easy ○ Fairly Easy ○ Neither ○ Fairly Difficult ○ Difficult

Please respond to each of the following statements:

I spend a lot of my own time learning about data visualization.

○ Never ○ Rarely ○ Sometimes ○ Often ○ Always

My career or studies involve data visualization.

○ Never ○ Rarely ○ Sometimes ○ Often ○ Always

I am confident I perform well on data visualization tasks.

○ Never ○ Rarely ○ Sometimes ○ Often ○ Always

I put effort into learning how to use data visualization.

○ Never ○ Rarely ○ Sometimes ○ Often ○ Always

I become anxious when math is involved in data visualization.

○ Never ○ Rarely ○ Sometimes ○ Often ○ Always

Do you have any feedback or concerns regarding the study to share with the researchers? *(optional)*

Feedback

This is the final page of questions!

Submit

Final questions assessing difficulty and motivation. First two questions assess difficulty of each part.
Intrinsic Motivation: I spend a lot of my own time learning about data visualization
Extrinsic Motivation: My career or studies involve data visualization
Self-Efficacy: I am confident I perform well on data visualization tasks
Self-Determination: I put effort into learning how to use data visualization
Math Anxiety: I become anxious when math is involved in data visualization

Data Tables

Descriptive Statistics

Gender (n)

Men	35
Women	25

Highest Education Completed (n)

Bachelor's/Undergraduate	33
Masters or PhD	27

Mean Age

30 $\pm$9

Overall Spatial Visualization Score ($\pm$ 95% CI)	Motivation Score	Spatial Ability Difficulty	PCC estimation Difficulty
4.7 $\pm$ 0.53	11.3 / 20	2.03 / 4	1.80 / 4

Overall Stimuli ($\pm$ 95% CI)

Mean Response Time (s) Per Question	9.90 $\pm$ 3.4
Mean Difference	0.17 $\pm$ 0.06

How to read the table:

The table below displays (from the left) the means ($\pm$ 95% CI) of the two groups being compared over the variable displayed in each row.
It then shows the statistical difference between the means followed by the lower and upper bounds of the 95% CI of the difference.
If the interval does not overlap 0 the difference is significant at $p < 0.05$. The farther from 0 and the tighter it is, the stronger the evidence.
Last, the table shows the p-value and test statistic of Welch's t test.
Note: the mean difference and intervals were generated using bias-corrected and accelerated bootstrapping with 5000 iterations.
Rows alternate between response time (RT) in seconds and mean differences (closer to 0 the more accurate).
Highlighted rows denote significance at $p \leq 0.05$.
The following tables are read in a similar fashion.

Gender Performances Overall

	Female Mean	Male Mean	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Spatial Ability Score	5.36 $\pm$ 0.75	4.29 $\pm$ 0.72	1.07	0.0	2.23	0.009	-1.69
Overall RT (s)	8.69 $\pm$ 2.43	10.76 $\pm$ 5.67	-2.07	-4.04	-0.75	0.01	2.53
Overall Mean Diffs	0.13 $\pm$ 0.07	0.19 $\pm$ 0.08	-0.06	-0.09	-0.03	0.00003	4.19

Education Level Performances Overall

	Grad Mean	Undergrad Mean	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Spatial Ability Score	5.48 $\pm$ 0.81	4.12 $\pm$ 0.67	1.36	0.11	2.60	0.03	-2.13
Overall RT (s)	8.02 $\pm$ 2.54	11.44 $\pm$ 5.91	-3.31	-5.55	-2.01	0.00007	4.0
Overall Mean Diffs	0.14 $\pm$ 0.08	0.19 $\pm$ 0.08	-0.05	-0.08	-0.02	0.001	3.22

Age Group Performances Overall

	Over-30 Mean	Under-30 Mean	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Spatial Ability Score	4.31 $\pm$ 0.75	5.38 $\pm$ 0.68	1.07	-0.19	2.22	0.08	-1.74
Overall RT (s)	11.02 $\pm$ 5.46	8.22 $\pm$ 2.72	-2.80	-4.83	-1.49	0.0005	3.46
Overall Mean Diffs	0.21 $\pm$ 0.08	0.10 $\pm$ 0.06	-0.11	-0.14	-0.08	3.4E-15	7.80

ANCOVA Analysis

	Coef	Std Err	t	$P > \|t\|$	[0.025	0.975]
Intercept	0.31	0.05	6.27	0.000	0.216	0.412
Spatial Ability (SA)	-0.049	0.009	-5.214	0.000	-0.067	-0.031
Domain	0.2226	0.041	5.433	0.000	0.142	0.303
Gender	0.1118	0.036	3.113	0.002	0.041	0.182
Age Group	-0.1070	0.036	-2.984	0.003	-0.177	-0.037
Education Level	-0.0763	0.036	-2.135	0.033	-0.146	-0.006
Motivation	-0.0025	0.002	-1.227	0.220	-0.006	0.001
SA * Gender	-0.0177	0.007	-2.658	0.008	-0.031	-0.005
SA * Age Group	0.0226	0.008	2.957	0.003	0.008	0.038
SA * Education	0.0252	0.006	3.889	0.000	0.012	0.038
Domain * SA	-0.0034	0.007	-0.498	0.006	-0.017	-0.010
Domain * Gender	0.0503	0.033	1.518	0.129	-0.015	0.115
Domain * Age	-0.0978	0.033	-2.926	0.003	-0.163	-0.032
Domain * Education	-0.1219	0.032	-3.838	0.000	-0.184	-0.060

Regression Linear Model (Huber)

	Coef	Std Err	z	$P > \|z\|$	[0.025	0.975]
Intercept	0.1986	0.024	8.409	0.000	0.152	0.245
Spatial Ability (SA)	-0.0292	0.004	-6.576	0.000	-0.038	-0.020
Domain	0.2129	0.019	11.024	0.000	0.175	0.251
Gender	0.0700	0.017	4.137	0.000	0.037	0.103
Age Group	-0.0710	0.017	-4.197	0.000	-0.104	-0.038
Education Level	-0.0740	0.017	-4.397	0.000	-0.107	-0.041
Motivation	-0.0022	0.001	-2.310	0.021	-0.004	-0.000
SA * Gender	-0.0107	0.003	-3.410	0.001	-0.017	-0.005
SA * Age Group	0.0156	0.004	4.339	0.000	0.009	0.023
SA * Education	0.0208	0.003	6.838	0.000	0.015	0.027
Domain * SA	-0.0113	0.003	-3.565	0.000	-0.018	-0.005
Domain * Gender	0.0439	0.016	2.807	0.005	0.013	0.075
Domain * Age	-0.0682	0.016	-4.328	0.000	-0.099	-0.037
Domain * Education	-0.0921	0.015	-6.152	0.000	-0.121	-0.063

Performance by Spatial Visualization Level

Low Spatial Participants

Domain (n)	
Psych	12
MCS	19

Gender (n)	
Men	22
Women	9

Highest Education Completed (n)	
Bachelor's/Undergraduate	20
Masters or PhD	11

Age Group (n)	
Under-30	9
Over-30	22

High Spatial Participants

Domain (n)	
Psych	18
MCS	11

Gender (n)	
Men	16
Women	13

Highest Education Completed (n)	
Bachelor's/Undergraduate	13
Masters or PhD	16

Age Group (n)	
Under-30	15
Over-30	14

Mean Differences of Low v High Spatial Visualization

	Low SV	High SV	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score	2.65 ± 0.31	6.97 ± 0.44	-4.32	-4.96	-3.72	5.89E-18	13.13
Overall RT(s)	11.49 ± 6.04	8.20 ± 3.46	3.29	1.79	5.46	0.0003	-3.65
Overall Diffs	0.25 ± 0.10	0.08 ± 0.04	0.16	0.138	0.192	1.07E-29	-11.76
Motivation	12.1 ± 1.09	10.44 ± 1.09	1.65	-0.14	3.41	0.084	-1.756
Sp Vis Difficulty	1.94 ± 0.32	2.14 ± 0.34	-0.20	-0.75	0.35	0.48	0.71
PCC Difficulty	2.26 ± 0.34	1.31 ± 0.30	0.95	0.40	1.46	0.001	-3.456
Training Time	55.17 ± 9.68	46.69 ± 9.08	8.49	-8.18	2.33	0.297	-1.05

		Low Spatial	High Spatial	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
-1.0	**RT (s)**	6.62 ± 1.34	5.40 ± 0.94	1.22	-0.578	3.25	0.223	-1.23
	Diffs	0.31 ± 0.14	0.09 ± 0.08	0.22	0.034	0.41	0.033	-2.20
-0.9	**RT (s)**	22.65 ± 18.78	8.05 ± 2.55	14.59	1.13	62.65	0.21	-1.27
	Diffs	0.35	0.07	0.28	0.13	0.51	0.006	-2.903761
-0.8	**RT (s)**	11.65 ± 3.19	6.62 ± 1.76	5.03	1.15	9.80	0.02	-2.27
	Diffs	0.31 ± 0.10	0.11 ± 0.06	0.20	0.07	0.357	0.008	-2.76
-0.7	**RT (s)**	15.62 ± 5.06	9.97 ± 2.11	5.65	0.543	14.29	0.098	-1.69
	Diffs	0.25 ± 0.09	0.09 ± 0.03	0.16	0.069	0.33	0.01	-2.57
-0.6	**RT (s)**	10.34 ± 2.95	8.43 ± 2.18	1.91	-2.27	6.38	0.39	-0.86
	Diffs	0.24 ± 0.07	0.10 ± 0.03	0.13	0.05	0.23	0.006	-2.88
-0.5	**RT (s)**	15.81 ± 10.83	7.39 ± 1.40	8.42	0.927	35.44	0.21	-1.27
	Diffs	0.29 ± 0.10	0.09 ± 0.03	0.20	0.095	0.36	0.004	-3.10

		Low Spatial	High Spatial	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
-0.4	**RT (s)**	9.62 ± 2.7	14.84 ± 11.46	-5.22	-32.36	3.07	0.41	0.73
	Diffs	0.23 ± 0.08	0.07 ± 0.02	0.16	0.06	0.28	0.004	-3.07
-0.3	**RT (s)**	8.67 ± 1.9	7.22 ± 1.93	1.46	-2.16	4.21	0.38	-0.89
	Diffs	0.22 ± 0.08	0.10 ± 0.03	0.12	0.03	0.23	0.02	-2.34
-0.2	**RT (s)**	8.27 ± 1.56	9.63 ± 4.38	-1.36	-11.46	2.16	0.63	0.48
	Diffs	0.21 ± 0.07	0.08 ± 0.02	0.14	0.06	0.23	0.003	-3.15
-0.1	**RT (s)**	9.83 ± 2.5	6.64 ± 1.05	3.19	0.57	7.07	0.06	-1.93
	Diffs	0.22 ± 0.08	0.05 ± 0.01	0.18	0.09	0.30	0.001	-3.43
0.0	**RT (s)**	8.51 ± 1.14	9.55 ± 2.15	-1.04	-4.52	1.40	0.49	0.70
	Diffs	0.11 ± 0.07	0.007 ± 0.002	0.10	0.04	0.21	0.02	-2.45
0.1	**RT (s)**	13.55 ± 4.23	7.16 ± 1.42	6.39	2.70	14.14	0.02	-2.35
	Diffs	0.20 ± 0.09	0.06 ± 0.02	0.13	0.05	0.26	0.01	-2.49
0.2	**RT (s)**	13.58 ± 6.75	7.56 ± 1.49	6.01	0.52	19.10	0.16	-1.43
	Diffs	0.25 ± 0.08	0.06 ± 0.01	0.19	0.11	0.31	0.0004	-3.89
0.3	**RT (s)**	9.16 ± 2.02	7.53 ± 1.16	1.63	-0.74	4.73	0.26	-1.15
	Diffs	0.20 ± 0.05	0.10 ± 0.04	0.10	0.01	0.17	0.02	-2.46
0.4	**RT (s)**	14.15 ± 4.77	7.05 ± 1.63	7.10	2.23	14.76	0.03	-2.32
	Diffs	0.21 ± 0.07	0.11 ± 0.04	0.10	0.01	0.20	0.06	-1.96
0.5	**RT (s)**	9.98 ± 2.40	13.81 ± 6.48	-3.82	-15.76	2.18	0.37	0.91
	Diffs	0.22 ± 0.08	0.11 ± 0.05	0.11	0.01	0.24	0.05	-1.88
0.6	**RT (s)**	11.76 ± 4.20	7.92 ± 1.98	3.84	-0.36	11.14	0.18	-1.36
	Diffs	0.22 ± 0.07	0.09 ± 0.03	0.13	0.05	0.23	0.008	-2.81
0.7	**RT (s)**	13.51 ± 4.79	8.83 ± 2.61	4.68	-0.88	12.69	0.17	-1.41
	Diffs	0.35 ± 0.12	0.08 ± 0.03	0.26	0.13	0.44	0.001	-3.42
0.8	**RT (s)**	11.14 ± 5.55	5.68 ± 0.87	5.46	1.35	18.90	0.12	-1.60
	Diffs	0.25 ± 0.10	0.11 ± 0.04	0.13	0.03	0.28	0.04	-2.07
0.9	**RT (s)**	8.08 ± 2.27	6.58 ± 1.33	1.50	-1.13	5.15	0.35	-0.94
	Diffs	0.22 ± 0.08	0.11 ± 0.07	0.10	-0.03	0.23	0.11	-1.60
1.0	**RT (s)**	8.79 ± 2.19	6.40 ± 2.16	2.39	-1.63	5.60	0.21	-1.28
	Diffs	0.35 ± 0.16	0.04 ± 0.05	0.30	0.13	0.55	0.006	-2.91

Spatial Visualization Level Split by Demographics

	n
Low Spatial Men	22
Low Spatial Women	9

	n
High Spatial Men	13
High Spatial Women	16

	LS: Women	LS: Men	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score	2.78 ± 0.53	2.59 ± 0.39	0.19	-0.62	0.86	0.65	-0.47
Overall RT (s)	10.07 ± 4.00	12.07 ± 8.06	-1.99	-4.899	-0.026	0.09	1.67
Overall Diffs	0.19 ± 0.14	0.27 ± 0.12	-0.08	-0.13	-0.03	0.001	3.30

	HS: Men	LS: Men	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score	7.15 ± 0.76	2.59 ± 0.39	4.56	3.64	5.56	5.94E-08	-8.77
Overall RT (s)	8.56 ± 6.78	12.07 ± 8.06	-3.51	-6.35	-0.78	0.01	2.53
Overall Diffs	0.06 ± 0.03	0.27 ± 0.12	-0.21	-0.25	-0.18	2.27E-31	12.45

	HS: Women	LS: Men	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score	6.81 ± 0.53	2.59 ± 0.39	4.22	3.47	4.97	1.27E-11	-10.67
Overall RT (s)	7.92 ± 3.02	12.07 ± 8.06	-4.15	-6.94	-2.38	0.0003	3.64
Overall Diffs	0.10 ± 0.07	0.27 ± 0.12	-0.17	-0.21	-0.13	7.03E-19	9.14

	HS: Women	HS: Men	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score	6.81 ± 0.53	7.15 ± 0.76	-0.34	-1.39	0.72	0.55	0.61
Overall RT (s)	7.92 ± 3.02	8.56 ± 6.78	-0.638	-3.29	0.82	0.52	0.65
Overall Diffs	0.10 ± 0.07	0.06 ± 0.03	0.04	0.02	0.06	0.00002	-4.26

	LS: Women	HS: Men	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score	2.78 ± 0.53	7.15 ± 0.76	4.38	3.34	5.48	2.31E-07	-7.72
Overall RT (s)	10.07 ± 4.00	8.56 ± 6.78	-1.52	-3.28	0.93	0.15	1.45
Overall Diffs	0.19 ± 0.14	0.06 ± 0.03	-0.13	-0.17	-0.09	3.40E-10	6.60

	LS: Women	HS: Women	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score	2.78 ± 0.53	6.81 ± 0.52	-4.03	-4.92	-3.23	1.72E-08	-8.87
Overall RT (s)	10.07 ± 4.00	7.92 ± 3.02	2.16	0.89	3.46	0.001	3.24
Overall Diffs	0.19 ± 0.14	0.10 ± 0.07	0.09	0.05	0.13	0.000044	4.16

	n
Low Spatial Under-30	9
Low Spatial Over-30	22

	n
High Spatial Under-30	15
High Spatial Over-30	14

	LS: Over-30	**LS: Under-30**	**Difference**	**95CI - Low**	**95CI - High**	**Welch's p-value**	**Welch's Statistic**
Sp. Vis. Score	2.41 ± 0.34	3.22 ± 0.60	-0.81	-1.44	0.17	0.073	1.95
Overall RT (s)	12.49 ± 7.96	9.05 ± 4.84	3.43	1.29	6.27	0.006	-2.78
Overall Diffs	0.28 ± 0.12	0.16 ± 0.13	0.13	0.08	0.17	1.10E-07	-5.39

	HS: Under-30	**LS: Under-30**	**Difference**	**95CI - Low**	**95CI - High**	**Welch's p-value**	**Welch's Statistic**
Sp. Vis. Score	6.67 ± 0.50	3.22 ± 0.60	3.44	2.64	4.44	9.40E-07	-7.27
Overall RT (s)	7.72 ± 3.23	9.05 ± 4.84	-1.33	-3.03	0.11	0.09	1.73
Overall Diffs	0.07 ± 0.04	0.16 ± 0.13	-0.08	-0.13	-0.05	0.000012	4.48

	HS: Over-30	**LS: Under-30**	**Difference**	**95CI - Low**	**95CI - High**	**Welch's p-value**	**Welch's Statistic**
Sp. Vis. Score	7.29 ± 0.74	3.22 ± 0.60	4.06	3.06	5.26	6.32E-07	-7.02
Overall RT (s)	8.72 ± 6.28	9.05 ± 4.84	-0.33	-2.35	1.81	0.75	0.32
Overall Diffs	0.10 ± 0.07	0.16 ± 0.13	-0.06	-0.10	-0.03	0.003	3.01

	HS: Over-30	**HS: Under-30**	**Difference**	**95CI - Low**	**95CI - High**	**Welch's p-value**	**Welch's Statistic**
Sp. Vis. Score	7.29 ± 0.74	6.67 ± 0.50	0.62	-0.42	1.67	0.27	-1.14
Overall RT (s)	8.72 ± 6.28	7.72 ± 3.23	1.00	-0.39	3.50	0.29	-1.07
Overall Diffs	0.10 ± 0.07	0.07 ± 0.04	0.02	0.004	0.05	0.03	-2.19

	LS: Over-30	**HS: Under-30**	**Difference**	**95CI - Low**	**95CI - High**	**Welch's p-value**	**Welch's Statistic**
Sp. Vis. Score	2.41 ± 0.34	6.67 ± 0.50	-4.26	-4.93	-3.55	8.16E-12	11.64
Overall RT (s)	12.49 ± 7.96	7.72 ± 3.23	4.77	3.00	7.83	0.00003	-4.18
Overall Diffs	0.28 ± 0.12	0.07 ± 0.04	0.21	0.18	0.25	7.09E-31	-12.27

	LS: Over-30	**HS: Over-30**	**Difference**	**95CI - Low**	**95CI - High**	**Welch's p-value**	**Welch's Statistic**
Sp. Vis. Score	2.41 ± 0.34	7.29 ± 0.74	-4.88	-5.80	-3.91	8.74E-09	-9.87
Overall RT (s)	12.49 ± 7.96	8.72 ± 6.28	3.77	1.23	6.63	0.005	2.80
Overall Diffs	0.28 ± 0.12	0.10 ± 0.07	0.19	0.15	0.23	1.40E-22	10.13

	n
Low Spatial Undergraduates	20
Low Spatial Graduates	11

	n
High Spatial Undergraduates	13
High Spatial Graduates	16

	LS: Grad	LS: Undergrad	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score	2.82 ± 0.37	2.55 ± 0.44	0.27	-0.40	0.93	0.45	-0.77
Overall RT (s)	8.93 ± 4.34	12.90 ± 8.69	-3.97	-7.16	-2.02	0.002	3.08
Overall Diffs	0.21 ± 0.16	0.27 ± 0.12	-0.06	-0.11	-0.002	0.03	2.18

	HS: Undergrad	LS: Undergrad	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score	6.54 ± 0.63	2.55 ± 0.44	3.99	3.15	4.88	1.54E-08	-8.51
Overall RT (s)	9.19 ± 6.72	12.90 ± 8.69	-3.71	-6.76	-1.10	0.01	2.55
Overall Diffs	0.07 ± 0.05	0.27 ± 0.12	-0.20	-0.24	-0.17	4.59E-27	11.40

	HS: Grad	LS: Undergrad	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score	7.31 ± 0.60	2.55 ± 0.44	4.76	3.89	5.63	1.78E-11	-10.60
Overall RT (s)	7.40 ± 3.07	12.90 ± 8.69	-5.50	-8.72	-3.68	0.000009	4.50
Overall Diffs	0.10 ± 0.06	0.27 ± 0.12	-0.17	-0.21	-0.14	5.97E-20	9.47

	HS: Undergrad	HS: Grad	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score	6.54 ± 0.63	7.31 ± 0.60	-0.77	-1.74	0.25	0.15	1.46
Overall RT (s)	9.19 ± 6.72	7.40 ± 3.07	1.79	0.34	4.43	0.05	-1.82
Overall Diffs	0.07 ± 0.05	0.10 ± 0.06	-0.03	-0.05	-0.006	0.009	2.59

	HS: Undergrad	LS: Grad	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score	6.54 ± 0.63	2.82 ± 0.37	3.72	2.90	4.57	9.46E-08	-8.32
Overall RT (s)	9.19 ± 6.72	8.93 ± 4.34	0.26	-1.38	2.98	0.81	-0.25
Overall Diffs	0.07 ± 0.05	0.21 ± 0.16	-0.14	-0.19	-0.10	4.01E-10	6.49

	HS: Grad	LS: Grad	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score	7.31 ± 0.60	2.82 ± 0.37	4.49	3.67	5.27	2.14E-10	-10.53
Overall RT (s)	7.40 ± 3.07	8.93 ± 4.34	-1.53	-3.01	-0.24	0.03	2.17
Overall Diffs	0.10 ± 0.06	0.21 ± 0.16	-0.11	-0.16	-0.07	5.08E-07	5.14

Spatial Visualization between Domains

Totals (n)	
Psych	30
MCS	30

Spatial Visualization Scores	
Psych	5.63 ± 0.80
MCS	3.83 ± 0.61

Differences of Spatial Visualization Scores

	Mean	Mean	Difference	95CI - Low	95CI - High	MW p-value	MW Statistic
Psych v MCS	5.63 ± 0.80	3.83 ± 0.61	1.80	0.6	2.97	0.004	-2.95

Performance by Domain

Psych Participants

Spatial Ability (n)	
Low Spatial	12
High Spatial	19

Gender (n)	
Men	17
Women	13

Highest Education Completed (n)	
Bachelor's/Undergraduate	12
Masters or PhD	18

Age Group (n)	
Under-30	11
Over-30	19

MCS Participants

Spatial Ability (n)	
Low Spatial	19
High Spatial	11

Gender (n)	
Men	22
Women	8

Highest Education Completed (n)	
Bachelor's/Undergraduate	21
Masters or PhD	9

Age Group (n)	
Under-30	13
Over-30	17

Mean Differences of Psych vs MCS

	Psych	MCS	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score	5.63 ± 0.80	3.83 ± 0.61	1.80	0.60	2.97	0.004	-2.95
Overall RT (s)	50.98 ± 9.18	51.17 ± 9.81	-0.19	-16.19	15.39	0.98	0.98
Overall Diffs	0.19 ± 0.09	0.14 ± 0.07	0.05	0.02	0.08	0.0004	-3.54
Motivation	11.3 ± 1.23	11.3 ± 1.00	0.0	-1.93	1.87	1.0	0.0
Sp. Vis. Difficulty	2.07 ± 0.34	2.0 ± 0.33	0.07	-0.5	0.6	0.82	-0.23
PCC Difficulty	2.07 ± 0.34	1.53 ± 0.34	0.53	-0.07	1.07	0.08	-1.81
Training Time	17.07 ± 3.46	22.53 ± 5.12	-5.46	-8.61	-2.82	0.0001	3.81

		Low Spatial	High Spatial	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
-1.0	**RT (s)**	6.48 ± 1.01	5.58 ± 1.32	0.90	-1.37	2.65	0.38	-0.89
	Diffs	0.25 ± 0.14	0.15 ± 0.09	0.10	-0.08	0.32	0.36	-0.93
-0.9	**RT (s)**	18.73 ± 18.78	12.46 ± 6.16	6.27	-7.91	48.06	0.60	-0.52
	Diffs	0.26 ± 0.13	0.17 ± 0.11	0.09	-0.11	0.29	0.41	-0.82
-0.8	**RT (s)**	9.52 ± 3.17	8.93 ± 2.22	0.59	-3.40	5.57	0.80	-0.25
	Diffs	0.22 ± 0.08	0.20 ± 0.98	0.03	-0.14	0.16	0.73	-0.35

		Low Spatial	High Spatial	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
-0.4	**RT (s)**	9.62 ± 2.7	14.84 ± 11.46	-5.22	-32.36	3.07	0.41	0.73
	Diffs	0.23 ± 0.08	0.07 ± 0.02	0.16	0.06	0.28	0.004	-3.07
-0.3	**RT (s)**	8.67 ± 1.9	7.22 ± 1.93	1.46	-2.16	4.21	0.38	-0.89
	Diffs	0.22 ± 0.08	0.10 ± 0.03	0.12	0.03	0.23	0.02	-2.34
-0.2	**RT (s)**	8.27 ± 1.56	9.63 ± 4.38	-1.36	-11.46	2.16	0.63	0.48
	Diffs	0.21 ± 0.07	0.08 ± 0.02	0.14	0.06	0.23	0.003	-3.15
-0.1	**RT (s)**	9.83 ± 2.5	6.64 ± 1.05	3.19	0.57	7.07	0.06	-1.93
	Diffs	0.22 ± 0.08	0.05 ± 0.01	0.18	0.09	0.30	0.001	-3.43
0.0	**RT (s)**	8.51 ± 1.14	9.55 ± 2.15	-1.04	-4.52	1.40	0.49	0.70
	Diffs	0.11 ± 0.07	0.007 ± 0.002	0.10	0.04	0.21	0.02	-2.45
0.1	**RT (s)**	13.55 ± 4.23	7.16 ± 1.42	6.39	2.70	14.14	0.02	-2.35
	Diffs	0.20 ± 0.09	0.06 ± 0.02	0.13	0.05	0.26	0.01	-2.49
0.2	**RT (s)**	13.58 ± 6.75	7.56 ± 1.49	6.01	0.52	19.10	0.16	-1.43
	Diffs	0.25 ± 0.08	0.06 ± 0.01	0.19	0.11	0.31	0.0004	-3.89
0.3	**RT (s)**	9.16 ± 2.02	7.53 ± 1.16	1.63	-0.74	4.73	0.26	-1.15
	Diffs	0.20 ± 0.05	0.10 ± 0.04	0.10	0.01	0.17	0.02	-2.46
0.4	**RT (s)**	14.15 ± 4.77	7.05 ± 1.63	7.10	2.23	14.76	0.03	-2.32
	Diffs	0.21 ± 0.07	0.11 ± 0.04	0.10	0.01	0.20	0.06	-1.96
0.5	**RT (s)**	9.98 ± 2.40	13.81 ± 6.48	-3.82	-15.76	2.18	0.37	0.91
	Diffs	0.22 ± 0.08	0.11 ± 0.05	0.11	0.01	0.24	0.05	-1.88
0.6	**RT (s)**	11.76 ± 4.20	7.92 ± 1.98	3.84	-0.36	11.14	0.18	-1.36
	Diffs	0.22 ± 0.07	0.09 ± 0.03	0.13	0.05	0.23	0.008	-2.81
0.7	**RT (s)**	13.51 ± 4.79	8.83 ± 2.61	4.68	-0.88	12.69	0.17	-1.41
	Diffs	0.35 ± 0.12	0.08 ± 0.03	0.26	0.13	0.44	0.001	-3.42
0.8	**RT (s)**	11.14 ± 5.55	5.68 ± 0.87	5.46	1.35	18.90	0.12	-1.60
	Diffs	0.25 ± 0.10	0.11 ± 0.04	0.13	0.03	0.28	0.04	-2.07
0.9	**RT (s)**	8.08 ± 2.27	6.58 ± 1.33	1.50	-1.13	5.15	0.35	-0.94
	Diffs	0.22 ± 0.08	0.11 ± 0.07	0.10	-0.03	0.23	0.11	-1.60
1.0	**RT (s)**	8.79 ± 2.19	6.40 ± 2.16	2.39	-1.63	5.60	0.21	-1.28
	Diffs	0.35 ± 0.16	0.04 ± 0.05	0.30	0.13	0.55	0.006	-2.91

Domain split by Spatial Visualization

	n
Low Spatial Psych	12
Low Spatial MCS	19

	n
High Spatial Psych	18
High Spatial MCS	11

		LS: MCS	LS: Psych	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		2.58 ± 0.42	2.75 ± 0.46	-0.17	-0.86	0.56	0.66	0.45
Overall	**RT (s)**	9.42 ± 4.02	14.76 ± 9.5	-5.34	-10.68	-2.68	0.004	2.85
Overall	**Diffs**	0.19 ± 0.11	0.33 ± 0.18	-0.14	-0.20	-0.09	3.76E-07	5.16

		HS: Psych	LS: Psych	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		7.56 ± 0.50	2.75 ± 0.46	4.81	4.03	5.56	3.83E-12	-11.63
Overall	**RT (s)**	7.87 ± 4.9	14.76 ± 9.5	-6.89	-12.35	-4.11	0.0003	3.61
Overall	**Diffs**	0.10 ± 0.06	0.33 ± 0.18	-0.23	-0.28	-0.19	9.68E-19	9.44

		HS: MCS	LS: Psych	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		6.0 ± 0.59	2.75 ± 0.46	3.25	2.47	4.20	7.18E-07	-7.18
Overall	**RT (s)**	8.74 ± 4.5	14.76 ± 9.5	-6.02	-11.30	-3.19	0.002	3.18
Overall	**Diffs**	0.05 ± 0.04	0.33 ± 0.18	-0.28	-0.33	-0.24	5.42E-26	11.72

		HS: MCS	HS: Psych	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		6.0 ± 0.59	7.56 ± 0.50	-1.56	-2.38	-0.63	0.003	3.31
Overall	**RT (s)**	8.74 ± 4.5	7.87 ± 4.9	0.87	-0.80	2.56	0.32	-0.99
Overall	**Diffs**	0.05 ± 0.04	0.10 ± 0.06	-0.05	-0.06	-0.03	3.56E-07	5.15

		LS: MCS	HS: Psych	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		2.58 ± 0.42	7.56 ± 0.50	-4.98	-5.73	-4.22	3.51E-14	12.48
Overall	**RT (s)**	9.42 ± 4.02	7.87 ± 4.9	1.55	-0.44	2.98	0.06	-1.85
Overall	**Diffs**	0.19 ± 0.11	0.10 ± 0.06	0.09	0.06	0.12	3.88E-08	-5.57

		HS: MCS	LS: MCS	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		6.0 ± 0.59	2.58 ± 0.42	3.42	2.63	4.30	1.74E-07	-7.78
Overall	**RT (s)**	8.74 ± 4.5	9.42 ± 4.02	-0.68	-2.13	1.08	0.40	0.85
Overall	**Diffs**	0.05 ± 0.04	0.19 ± 0.11	-0.14	-0.17	-0.11	2.12E-18	9.11

Domain split by Demographics

	n
Psych Men	13
Psych Women	17

	n
MCS Men	22
MCS Women	8

		MCS Men	Psych Men	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		3.73 ± 0.69	5.23 ± 1.50	-1.50	-3.53	0.28	0.15	1.50
Overall	**RT (s)**	9.43 ± 3.9	13.02 ± 10	-3.59	-8.80	-0.80	0.05	1.90
Overall	**Diffs**	0.16 ± 0.09	0.26 ± 0.16	-0.10	-0.15	-0.05	0.000065	4.03

		Psych Women	Psych Men	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		5.94 ± 0.84	5.23 ± 1.50	0.71	-1.41	2.61	0.51	-0.68
Overall	**RT (s)**	8.80 ± 3.15	13.02 ± 10	-4.22	-9.55	-1.52	0.02	2.26
Overall	**Diffs**	0.15 ± 0.08	0.26 ± 0.16	-0.11	-0.16	-0.06	0.000011	4.45

		MCS Women	Psych Men	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		4.13 ± 1.33	5.23 ± 1.50	-1.11	-3.35	1.13	0.38	0.90
Overall	**RT (s)**	8.46 ± 3.6	13.02 ± 10	-4.55	-10.02	-1.93	0.01	2.42
Overall	**Diffs**	0.10 ± 0.12	0.26 ± 0.16	-0.15	-0.20	-0.09	3.19E-08	5.63

		MCS Men	Psych Women	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		3.73 ± 0.69	5.94 ± 0.84	-2.21	-3.43	-0.93	0.001	3.36
Overall	**RT (s)**	9.43 ± 3.9	8.80 ± 3.15	0.63	-0.64	1.97	0.34	-0.95
Overall	**Diffs**	0.16 ± 0.09	0.15 ± 0.08	0.008	-0.023	0.038	0.61	-0.51

		MCS Women	Psych Women	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		4.13 ± 1.33	5.94 ± 0.84	-1.82	-3.44	0.09	0.08	1.89
Overall	**RT (s)**	8.46 ± 3.6	8.80 ± 3.15	-0.34	-1.49	0.98	0.60	0.53
Overall	**Diffs**	0.10 ± 0.12	0.15 ± 0.08	-0.05	-0.08	0.001	0.02	2.33

		MCS Women	MCS Men	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		4.13 ± 1.33	3.73 ± 0.69	0.40	-1.26	2.07	0.67	-0.44
Overall	**RT (s)**	8.46 ± 3.6	9.43 ± 3.9	-0.97	-2.33	0.45	0.17	1.37
Overall	**Diffs**	0.10 ± 0.12	0.16 ± 0.09	-0.05	-0.09	-0.005	0.007	2.67

	n
Psych Under-30	11
Psych Over-30	19

	n
MCS Under-30	19
MCS Over-30	17

		Under-30 MCS	Under-30 Psych	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		4.54 ± 0.91	6.36 ± 0.84	-1.83	-3.21	0.38	0.06	2.43
Overall	**RT (s)**	8.43 ± 4.29	7.97 ± 3.10	0.46	-0.82	1.96	0.52	-0.65
Overall	**Diffs**	0.09 ± 0.08	0.11 ± 0.07	-0.02	-0.05	0.01	0.23	1.20

		Over-30 Psych	Under-30 Psych	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		5.21 ± 1.15	6.36 ± 0.84	-1.15	-2.77	0.59	0.19	1.33
Overall	**RT (s)**	12.17 ± 9.62	7.97 ± 3.10	4.19	2.15	7.85	0.001	-3.13
Overall	**Diffs**	0.24 ± 0.12	0.11 ± 0.07	0.13	0.09	0.17	6.31E-11	-6.66

		Over-30 MCS	Under-30 Psych	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		3.29 ± 0.77	6.36 ± 0.84	-3.07	-4.25	-1.67	0.0001	4.44
Overall	**RT (s)**	9.74 ± 4.22	7.97 ± 3.10	1.77	0.47	3.16	0.01	-2.55
Overall	**Diffs**	0.18 ± 0.11	0.11 ± 0.07	0.06	0.03	0.09	0.0002	-3.71

		Under-30 MCS	Over-30 Psych	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		4.54 ± 0.91	5.21 ± 1.15	-0.67	-2.39	1.05	0.46	0.76
Overall	**RT (s)**	8.43 ± 4.29	12.17 ± 9.62	-3.74	-7.35	-1.54	0.007	2.67
Overall	**Diffs**	0.09 ± 0.08	0.24 ± 0.12	-0.15	-0.19	-0.11	1.25E-12	7.24

		Over-30 MCS	Over-30 Psych	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		3.29 ± 0.77	5.21 ± 1.15	-1.92	-3.52	-0.31	0.03	2.28
Overall	**RT (s)**	9.74 ± 4.22	12.17 ± 9.62	-2.42	-5.96	-0.25	0.08	1.74
Overall	**Diffs**	0.18 ± 0.11	0.24 ± 0.12	-0.06	-0.11	-0.02	0.003	2.93

		Over-30 MCS	Under-30 MCS	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		3.29 ± 0.77	4.54 ± 0.91	-1.24	-2.57	0.10	0.097	1.72
Overall	**RT (s)**	9.74 ± 4.22	8.43 ± 4.29	1.31	-0.21	2.84	0.10	-1.65
Overall	**Diffs**	0.18 ± 0.11	0.09 ± 0.08	0.08	0.04	0.12	0.000009	-4.48

	n
Psych Undergraduates	12
Psych Graduates	18

	n
MCS Undergraduates	21
MCS Graduates	9

		MCS Grad	Psych Grad	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		4.55 ± 1.34	5.94 ± 1.0	-1.39	-3.28	0.5	0.18	1.40
Overall	**RT (s)**	7.59 ± 2.88	8.24 ± 3.53	-0.65	-1.83	0.51	0.28	1.08
Overall	**Diffs**	0.11 ± 0.09	0.16 ± 0.10	-0.05	-0.08	-0.006	0.01	2.50

		Psych Undergrad	Psych Grad	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		5.17 ± 1.34	5.94 ± 1.0	-0.78	-2.75	1.08	0.45	0.76
Overall	**RT (s)**	14.21 ± 10.5	8.24 ± 3.53	5.96	3.09	11.69	0.002	-3.01
Overall	**Diffs**	0.25 ± 0.16	0.16 ± 0.10	0.09	0.04	0.14	0.0003	-3.65

		MCS Undergrad	Psych Grad	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		3.52 ± 0.66	5.94 ± 1.0	-2.42	-3.78	-1.01	0.002	3.33
Overall	**RT (s)**	9.85 ± 4.13	8.24 ± 3.53	1.61	0.25	3.05	0.02	-2.23
Overall	**Diffs**	0.16 ± 0.09	0.16 ± 0.10	-0.003	-0.04	0.03	0.87	0.17

		MCS Grad	Psych Undergrad	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		4.55 ± 1.34	5.17 ± 1.34	-0.61	-2.56	1.67	0.60	0.54
Overall	**RT (s)**	7.59 ± 2.88	14.21 ± 10.5	-6.62	-12.35	-3.79	0.0008	3.38
Overall	**Diffs**	0.11 ± 0.09	0.25 ± 0.16	-0.14	-0.19	-0.09	1.66E-07	5.32

		MCS Undergrad	Psych Undergrad	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		3.52 ± 0.66	5.17 ± 1.34	-1.64	-3.36	0.08	0.09	1.81
Overall	**RT (s)**	9.85 ± 4.13	14.21 ± 10.5	-4.35	-9.86	-1.44	0.03	2.18
Overall	**Diffs**	0.16 ± 0.09	0.25 ± 0.16	-0.09	-0.14	-0.05	0.0001	3.83

		MCS Grad	MCS Undergrad	Difference	95CI - Low	95CI - High	Welch's p-value	Welch's Statistic
Sp. Vis. Score		4.55 ± 1.34	3.52 ± 0.66	-1.03	-2.76	0.52	0.26	1.17
Overall	**RT (s)**	7.59 ± 2.88	9.85 ± 4.13	2.27	0.97	3.55	0.0007	-3.39
Overall	**Diffs**	0.11 ± 0.09	0.16 ± 0.09	0.05	0.002	0.08	0.01	-2.41