**OSF Pre-registration**

**Title:** The effect of conceptual metaphors on the interpretation of graphs (Experiment 2)

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**Research questions:** Will (1) axis inversion, (2) quantity mapping, or (3) emotional valence affect participants’ understanding of line graphs?

**Study rationale:**

In our first experiment, we sought to conceptually replicate a study conducted by Pandey et al. (2015) by demonstrating the effect of axis inversion on the interpretation of graphs. We also sought to replicate the work of Fischer et al. (2005), who showed that bar charts mapping quantity on the y-axis were easier to interpret than those mapping quantity onto the x-axis. Additionally, as prior work has emphasised the influence of emotional valence on spatial conceptualisations of information (e.g., Meier & Robinson, 2004), we also manipulated whether our graphs aligned with valence associations and investigated the effect that this manipulation had on responses. We hypothesised that:

1. normal, non-inverted graphs would elicit more accurate responses than graphs with inverted axes,
2. graphs mapping quantity onto the y-axis would elicit more accurate responses than graphs mapping quantity onto the x-axis, and
3. graphs aligning with vertical valence associations would elicit more accurate responses than graphs not aligning with these associations.

We found strong support for hypotheses 1 and 3. However, we found a significant trend in the opposite direction of hypothesis 2; namely, participants were more accurate when responding to graphs that mapped quantity onto the x-axis. An exploration of response latencies suggested that participants were more accurate when responding to x-axis graphs because they took longer to verify their answers, perhaps because they recognised that these graphs were more difficult to interpret. Exploratorily, we also found that participants were more accurate when answering questions about graphs depicting positive quantities (vacation days) compared to negative ones (murders). We speculate that easier processing of positively-valenced stimuli may be due to humans assuming positive outcomes by default, due to positive outcomes generally being more likely than negative ones (e.g., Peeters, 1971).

In our second experiment, we aim to replicate our results from Experiment 1, and to conduct a confirmatory analysis of the influence of valence (positive vs. negative) on graph interpretation. We also introduce a test of Casasanto’s (2009) body-specificity hypothesis, which suggests that people tend to associate the dominant side of their body (and therefore that side of space) with more positive valence, and vice versa. To do so, we collect handedness information from participants, allowing our valence alignment measure to be applied to graphs where quantity is mapped onto the x-axis. We test horizontal and vertical valence metaphors separately for direct comparison with the results from our first experiment, where we tested vertical valence metaphors only. Horizontal and vertical metaphors are also posited to have different experiential origins, which may affect the extent to which they matter for the interpretation of graphs. For instance, most people are right-handed (an estimated 90% of the world’s population; Kassin, 2007: 72), meaning that a good is right association has become instantiated in cultural practices (e.g., raising one’s right hand when taking an oath) and language (e.g., the ‘correct’ answer is the ‘right’ one). This may result in a good is right association even for left-handers (Casasanto & Bottini, 2014; Casasanto, 2017). For this reason, we will also test valence alignment for horizontal valence metaphors, irrespective of participants’ handedness.

To access a large group of people with equal numbers of left- and right-handers, we will utilise Amazon’s Mechanical Turk, which allows for the qualification criterion of handedness. We will collect but not analyse response times (although some exploration of these response times will be conducted), as it is unclear how to control for variation in browser loading speeds. In addition, conducting experiments online inevitably introduces noise to one’s dataset in other ways that makes it difficult to detect small differences in response latencies.

**References**

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**Hypotheses:**

1. Directional: normal, non-inverted graphs will elicit more accurate responses than graphs with inverted axes
2. Non-directional: graphs mapping quantity onto the y-axis will elicit more/fewer accurate responses than graphs mapping quantity onto the x-axis
3. Directional: graphs aligning with vertical valence associations will elicit more accurate responses than graphs not aligning with these associations
4. Directional: graphs aligning with horizontal valence associations (relative to handedness) will elicit more accurate responses than graphs not aligning with these associations
5. Directional: graphs aligning with horizontal valence associations (where good is right, irrespective of handedness) will elicit more accurate responses than graphs not aligning with these associations
6. Directional: graphs depicting positively-valenced quantities will elicit more accurate responses than graphs depicting negatively-valenced quantities

**Existing** **data:** Pre-registering prior to collecting new data

**Explanation of existing data:** NA

**Data** **collection procedures:** Study will be advertised on Amazon Mechanical Turk and users of the platform will volunteer to participate. Participation will be restricted to US users of the platform. Payment will be $1.00 per participant based on US minimum wage laws. Participants have to be 18 years or older to use MTurk. Data from participants who quit partway through study will be excluded, as will data from participants who self-report not being a native speaker of English, or speaking a language with a different reading/writing directionality (e.g., right to left) to English, even if not a native language. Data from duplicate MTurk response IDs will be excluded. 50% (*N* = 150)of participants will have self-identified as left-handed and 50% (*N* = 150)as right-handed.

**Sample size:** 300 participants.

**Sample size rationale:** Same number as in previous experiment, which detected significant effects.

**Stopping rule:** 300 participants.

**Manipulated variables and the different levels of each variable:**

1. Axis Inversion
   * No inversion
   * Either x-axis inverted or y-axis inverted
2. Orientation
   * Quantity on y-axis, time on x-axis
   * Quantity on x-axis, time on y-axis
3. Valence
   * Positive
   * Negative
4. Trend
   * Rising
   * Falling

Trend included as control.

**Indices:** N/A

**Study type:** Experiment

**Blinding:** All dependent variables will be measured automatically and fed into statistical models. Because no coding is necessary for this study, no blinding is necessary, either.

**Study design:** Axis inversion and graph orientation varied between subjects, because varying these two factors from task to task would be misleading and thus confusing to participants. Valence and trend varied within subjects to assess effect of valence on responses, to control for the possible confounding influence of trend, and to ensure that participants cannot use the same strategy to interpret each graph.

**Randomisation:** Participants will be randomly allocated into one of the following between-participants conditions:

G1. Normal graph with quantity on y-axis and time on x-axis

G2. Normal graph with quantity on x-axis and time on y-axis

G3. Y-axis inverted with quantity on y-axis and time on x-axis

G4. Y-axis inverted with quantity on x-axis and time on y-axis

G5. X-axis inverted with quantity on y-axis and time on x-axis

G6. X-axis inverted with quantity on x-axis and time on y-axis

Participants will then complete the following four trial types in a randomised order:

V1. Positive valence, rising trend

V2. Positive valence, falling trend

V3. Negative valence, rising trend

V4. Negative valence, falling trend

**Measured variables:**

DV: Accuracy (right vs. wrong)

IV: Axis Inversion, Orientation, Valence, Valence Alignment (Vertical), Valence Alignment (Horizontal - Handedness), Valence Alignment (Horizontal - Absolute)

**Statistical models:** Logistic regression (categorical dependent variable):

Accuracy ~ AxisInversion + Orientation + Valence + (1 + Trial | Subject)

A significant effect of AxisInversion in our predicted direction will provide support for hypothesis 1. A significant effect of Orientation will provide support for hypothesis 2. A significant effect of Orientation in our predicted direction will provide support for hypothesis 3.

Accuracy ~ ValAlVert + (1 + Trial | Subject)

ValAlVertapplies to only those graphs where quantity is mapped onto the y-axis (half the graphs), so this is modelled separately. A significant effect of ValAlVert in our predicted direction will provide support for hypothesis 4.

Accuracy ~ ValAlHorHand + ValAlHorAb + (1 + Trial | Subject)

ValAlHorHand and ValAlHorAb apply only to those graphs where quantity is mapped on the x-axis, so these are modelled separately. A significant effect of ValAlHorHand in our predicted direction will provide support for hypothesis 5. A significant effect of ValAlHorAb in our predicted direction will provide support for hypothesis 6.

If these models do not converge, in the following order we will (1) sum-code predictors, and (2) use all\_fit from the R package ‘afex’ to find a suitable optimiser, and 3) simplify random effects structure.

**Transformations:** None

**Follow-up analyses:** We will perform likelihood ratio tests on the above models to test the likelihood of the full models (given the data) against models with each predictor left out individually.

**Inference criteria:** In line with mainstream Null Hypothesis Significance Testing, we will use *p* = 0.05 as a hard cut-off for statistical significance.

**Data exclusion:** Response latencies that are greater than 2 standard deviations above the mean response will be excluded.

**Missing data**: Data partially missing because participant quit study halfway through, or because they failed an attention check question, will be excluded.

**Exploratory analyses**: For inverted graphs, look at which condition (x-axis inversion vs. y-axis inversion) yields the most incorrect or correct responses. Look at response times for graphs with quantity mapped onto the y-axis versus the x-axis. Look at cumulative effects of quantity, time and valence metaphors and their subversion.