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### **Representation Matters: The Effect of Graph Selection on Data Interpretation**

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#### Introduction

Most psychological studies of graph comprehension focus on how people extract information from graphs. However, in the real world, graphs are used as a reasoning tool to interpret data rather than to read off single data points. This paper investigates the effects of the graphical representation on the quality of that interpretation. Because of the importance of representation in general to successful problem-solving (e.g., Kotovsky et al, 1988) we expected that participants who chose better graphs would have a better understanding of the data.

#### Method

40 university undergraduates participated. They were shown 2 datasets from the U.S. Census Bureau (www.census.gov/). Data showed annual income by age group and education (age dataset) and projected lifetime earnings by education and gender (gender dataset). Participants worked in pairs, so that we could record their on-line conversation. They were shown Excel's graph functions and told to use the data table to make a graph, to use the graph to interpret the data, and to summarize their interpretation (up to 3 bullet points.)

Each dataset contained 2 main effects and an interaction. We assigned each graph a score of 0 to 10 (10 was best), based on its appropriateness to the data and its interpretability (as outlined in Gillan et al., 1998). The best display for each dataset was a line graph, because it allowed ready interpretation of all the trends as well as the interaction (see Fig. 1). We also graded the summaries, with one point awarded for each main effect identified, and one point for the interaction (ie. 0-3).



Figure 1: Line graph of age dataset (score: 10)

#### **Results and Discussion**

Most of the graphs chosen were some type of vertical bar graph (63%). Only 18% were the optimal line graphs. Other choices were horizontal bar (15%) and pie (5%).

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We expected that the quality of participants' graphs would affect the quality of their interpretation. Based on the graph scores, we divided the graphs into 2 groups, "bad" (score 0-5, N = 21) and "good" (score 6-10, N = 19). A single factor ANOVA, with graph type as the independent variable and summary score as the dependent variable, was significant, F (1,38) = 12.29, MSE = 6.32, p < .01. The mean summary score for the good graphs (1.6) was twice that for the bad graphs (0.8). This result shows that the quality of the graph was directly related to the quality of the data interpretation. Possibly, some participants were simply better with graphs and data than others; if so, they should produce good graphs for both datasets. However, participants' scores across the datasets were uncorrelated, r = .21, p > .35, suggesting that it was the graph itself and not an underlying variable that led to better or worse interpretations.

We also analyzed participants' interpretations, by coding each utterance made when the graph was on screen as readoff (single data point extraction), partial integration (integration of a subset of data, e.g. 2 levels of a multiplelevel variable), or full integration (taking into account all data) (see Trickett et al, under review). We counted the number of full integrations: 0, 1, 2, or more than 2. Differences were notable at the ends of the scale: more good graph users made 2 or more full integrations than bad graph users and more bad graph users made no full integrations (all good graph users made at least one full integration). This difference was significant,  $\chi^2$  (3) = 10.2, p < .05.

Our results cast light on the processes by which participants reasoned about data: they were influenced by the surface features of the graph, which shaped the information they were able to extract. If they were lucky and picked a good representation, they were able to perform much better than those who chose poorly, who came—at best—to a marginal understanding of the data.

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