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Examining the Components of Trust in Map-Based Visualizations

C. Xiong[1] L. Padilla[1] K.Grayson[2] and S. Franconeri[1]

[1]Northwestern University, Department of Psychology
[2]Northwestern University, Kellogg School of Management

Abstract

Prior research suggests that perceived transparency is often associated with perceived trust. For some data types, greater transparency in data visualization is also associated with an increase in the amount of information depicted. Based on prior work in economics and political science that has identified four dimensions of transparency, we examined the influence of accuracy, clarity, amount of disclosure, and thoroughness on a decision task where participants relied on map-based visualizations with varying complexity to solve a crisis. The results of our preliminary analysis suggest that perceived clarity, amount of disclosure. and thoroughness significantly predicted individuals' selection of a Google Maps-like application with either less information or more information. Trust and perceived accuracy did not significantly predict which navigation application visualization participants decided to use (i.e., one with more information or less information). Further, our preliminary results suggest that an individual's ratings of accuracy and disclosure of a visualization predicted their ratings of the trustworthiness of that visualization. We discuss the implications of a possible dissociation between trust and decision tasks on visualization evaluation. In future work, we aim to examine the influence of the amount of information shown in a visualization on ratings of trust and determine the generalizability of our preliminary findings to different task types and visualization approaches.

CCS Concepts

• ***Human-centered computing*** → ***Laboratory experiments; HCI theory, concepts and models; Empirical studies in HCI;***

1. Introduction

In 2014, 668 cases of measles were reported in the US, which was the largest annual total number of measles cases since the introduction of the measles vaccine. A substantial proportion of these cases were the result of parents choosing to not vaccinate their children [PBSO16]. The rise in measles outbreaks is among the consequences of declining public trust in science [Tsi18, Int17]. Since trust plays a significant role in how people perceive scientific information and make critical decisions with data [SSK*16, DC98], research examining trust in data communication is vital. Further, understanding how the visual communication of data can influence trust in science is an essential step in identifying methods to help viewers reason about the trustworthiness of findings.

Researchers in communications, economics, and policy have examined the nonvisual communication of information and propose that *transparency* is closely associated with increased trust [HH06]. Transparency is the perceived quality and quantity of intentionally shared information [ST16]. It helps citizens become more familiar with government, brings people closer, and sometimes can help solve market crises [GW02, NZK97, CJK10]. Some visualization research parallels this finding, suggesting that increasing transparency by showing more information, specifically representing the uncertainty in data, can improve trust [KMK*13, JSGS15, JL13].

In some cases, however, having too much transparency may negatively influence trust [HK16]. For example, too much transparency may lead to political scandals or harm market efficiency [Hea06, SS91, NP92]. In a visualization, plotting too much information could lead to confusion or influence the accuracy of its interpretation [Leo19, PWR04]. Motivated by prior work on trust and transparency, we speculate that there could be a curvilinear relationship between trust and transparency. Two possible instantiations of the curvilinear relationships between trust and transparency are illustrated in Figure 1.

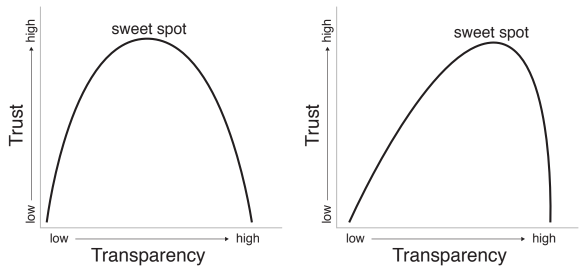

Figure 1: *Possible trade-offs between trust and transparency.*

Since people make decisions using information visualizations, it

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is important that the visualizations are trustworthy [SSK*16]. We examine the relationship between data visualization transparency and trust to identify components of a visualization that could impact its trustworthiness, aiming to optimize design to increase the probability that people make data-driven decisions.

2. Dimensions of Transparency

In an extensive review on trust and transparency, Schnackenberg and Tomlinson synthesized prior research and proposed three dimensions of transparency – accuracy, clarity, and disclosure [ST16].

Accuracy measures the extent to which the information is correct. Information is not accurate if it is purposefully biased or contrived [WLAO11]. For example, in a map visualization, visualizing the farthest route as the closest route can be considered to be inaccurate.

Clarity is defined as the perceived level of comprehensibility of information [Win00, ST16]. The readability and interpretability of a visualization both contribute to its clarity.

Disclosure is about the perceived completeness of relevant information [BO99, ST16]. Disclosure can be interpreted as "information quantity" in visualizations [Ave97], or the amount of information visualized.

However, with regard to the amount of information, it is not enough to consider the breadth of the information when making decisions. The thoroughness of the information presented should also be considered [HI13, Pau13].

Thoroughness of information can be shown through the extent to which a procedure generates, evaluates, and exhausts all possible states and alternatives [MWTAT06, Gre02]. Thoroughness should also be considered in evaluating the transparency of a visualization. In map-based visualizations, for example, thoroughness can be thought of as how many alternative routes the algorithm appears to have considered [MWTAT06]. An algorithm that computes only one possible route from is less thorough than one that computes and compares numeral possible routes.

3. Design Motivation

To examine the influence of trust and transparency on visualizations of data, we selected a map-based driving application as the first type of visualization we examined. This visualization type was selected for our pilot exploratory study because it is representative of visualizations that many people are familiar with, and, therefore, participants do not have to learn the conventions underlying the visualization. Further, when examining trust, we sought to use a context where people did not have preconceived notions that would override the presented information. Different displays of driving instructions are not likely to evoke differential emotional responses.

Additionally, many people have first-hand experiences with the uncertainty associated with predicted routes from driving applications. Anecdotally, we found that people may even compare the driving route predictions between applications such as Google Maps, Waze, and Apple Maps. We propose that many people are aware of the uncertainty associated with driving route predictions, and, therefore, we sought to test if perceived trust influences the driving application individuals decide to use. In this context, we can also manipulate the amount of information shown by increasing or decreasing the number of routes each application shows.

The importance of trust becomes more apparent in high-risk situations [RL91]. Therefore, we created a firefighting dispatch task using driving route visualizations to elicit trust judgments from participants. In future work, we seek to examine different contexts and visualization types. The presented study is our first step in our examination of trust, transparency, and visualizations of data.

4. Hypothesis

The present experiment examines the effect of transparency by manipulating the amount of information in a visualization (by including more or fewer possible routes). However, transparency can also be subjective. People may perceive the quality of shared information to vary in the degree of accuracy, clarity, disclosure, and thoroughness [ST16, PB11]. The present experiment also measures individuals' perceived accuracy, clarity, disclosure, and thoroughness of competing driving applications by collecting self-report ratings of these components.

Broadly, we hypothesize the following:

1. As an extension of prior work [ST16], we predict that perceived accuracy, clarity, amount of disclosure, and thoroughness can predict reported trust in a visualization.
2. We predict that trust, perceived accuracy, clarity, amount of disclosure, and thoroughness can influence decision tasks and predict the likelihood an individual would prefer visualizations containing varying amounts of information.

5. Experiment

In the current study, we investigated how the amount of information presented in a driving route application can impact trust. A power analysis, based on pilot data ($Cohen'sf$ = 0.29), suggested that a target sample of 77 participants would yield sufficient power to detect an overall difference between visualization designs. In the current study, 77 participants were recruited from Amazon's Mechanical Turk (N_{male} = 54, N_{female} = 23, M_{age} = 33.34, SD_{age} = 9.26).

5.1. Procedure and Design

Participants were given a crisis-solving scenario in which they were asked to assume the role of a fire department dispatcher. The participants were shown a screenshot of a cropped portion of Google Map's depiction of downtown Vancouver, Canada as a base map (see Figure 2). Either three or six blue icons were superimposed on the base maps to denote fire stations in the area. Additionally, the maps indicated the location of a fire emergency with a red dot.

For each trial, participants were shown two maps and were told that each map was a screenshot from a different driving application created by competing companies. Each company used its own algorithm to generate highlighted recommended fastest route(s) to

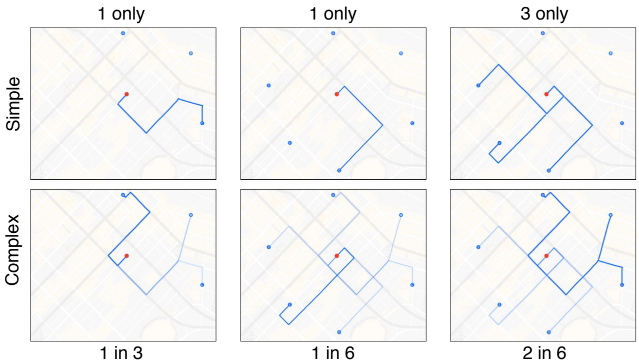

Figure 2: ***Left**: a trial comparing an interface showing only 1 route with an interface highlighting 1 route and showing 2 alternative routes. **Middle**: a trial comparing an interface showing only 1 route with an interface highlighting 1 route and showing 5 alternative routes. **Right**: a trial comparing an interface showing 3 routes with an interface highlighting 3 routes and showing 3 alternative routes. The top row includes simple interfaces with relatively less information, whereas bottom row includes complex interfaces with more information.*

the fire location (shown in dark blue) along with other possible routes (shown in light blue). In each trial, the recommended fastest route(s) in the two screenshots did not agree. Participants were tasked with deciding 1) which application to use and 2) from which fire stations to dispatch firefighters. At the end of the experiment, participants also rated the trustworthiness, accuracy, clarity, disclosure, and thoroughness of all the stimuli they were shown using a five-point scale, with lower numbers indicating less and higher numbers indicating more (trustworthiness, accuracy, etc.).

The stimuli varied in three dimensions: the number of fire stations shown (3 or 6), the number of total routes shown (1, 3, or 6), and the number of recommended fastest routes shown (1 or 3). Three pairs of combinations were tested in this preliminary work, as shown in the columns of Figure 2. Each participant was shown all three pairings of stimuli in a randomized order. We recorded whether the participants chose the simple interface with less information (top row in Figure 2) or the complex interface with more information (bottom row in Figure 2).

To examine the relationship between visualizations and trust, we conducted two analyses. The first tested the effects of users' subjective interpretations of accuracy, clarity, disclosure, thoroughness, and trust on their decision to select a simple or complex driving application (Section 5.3). The second analysis used accuracy, clarity, disclosure, and thoroughness to predict the perceived trustworthiness of the visualizations (Section 5.4).

5.2. Multicollinearity Diagnostics

By varying the amount of information visualized, we unavoidably increased the amount of disclosure and thoroughness, while decreasing clarity in this manipulation. To ensure the regression models were not influenced by potential multicollinearity, we conducted collinearity diagnostics on our predictors. As shown in Table 1, the variance inflation factors among the four dimensions of transparency - accuracy, clarity, disclosure, and thoroughness were all close to one. This result suggests that none of the four factors were significantly impacted by correlations with each other.

variable	VIF
accuracy	1.25
clarity	1.11
disclosure	1.68
thoroughness	1.79

Table 1: *Variance inflation factors (VIF) of the four dimensions of transparency.*

5.3. Analysis of Decision Task

Overall, the simpler interfaces were chosen (n = 111) a roughly equal number of times compared to complex interfaces (n = 120), suggesting that participants may rely on different characteristics of the interface to make their decisions.

A logistic general linear model predicting whether participants chose the simple interface or the complex interface suggested that perceived clarity, amount of disclosure, and thoroughness were significant predictors of interface selection over and beyond the effects of the other predictors (as shown in Table 2 and Figure 3) [BSBM07]. Trust and perceived accuracy did not account for a significant proportion of variance in interface selection.

variable	estimates	SE	p-value	odds ratio
accuracy	-0.156	0.177	0.378	0.856
clarity	-0.482	0.155	0.002**	0.618
disclosure	0.483	0.195	0.013*	1.621
thoroughness	0.590	0.187	0.002**	1.804
trust	-0.1919	0.172	0.265	0.825

Table 2: *Logistic regression statistics model predicting odds of selecting the more complex visualization in the decision task. The odds ratio is interpreted as the likelihood of choosing the more complex visualization given a unit change in the predictor. For example, for each unit increase in disclosure, we expect to see the odds of the participants choosing the complex interface to increase by 62.1% [NWK89].*

The preliminary findings of this analysis suggest users consider how clear and thorough a system is when comparing multiple systems. Further, users also consider how effectively the system discloses information.

5.4. Analysis of Trust

We also used a linear regression model to test if the four dimensions of perceived transparency – perceived accuracy, clarity, disclosure, and thoroughness – significantly predicted trust, as shown in Figure 4. The results of the regression indicated the four predictors explained 12.02% of the variance ($R^2 = 0.12$, $F_{(4,380)} = 14.12$, $p < 0.001$). Among the four predictors, perceived accuracy ($Est = 0.21$,

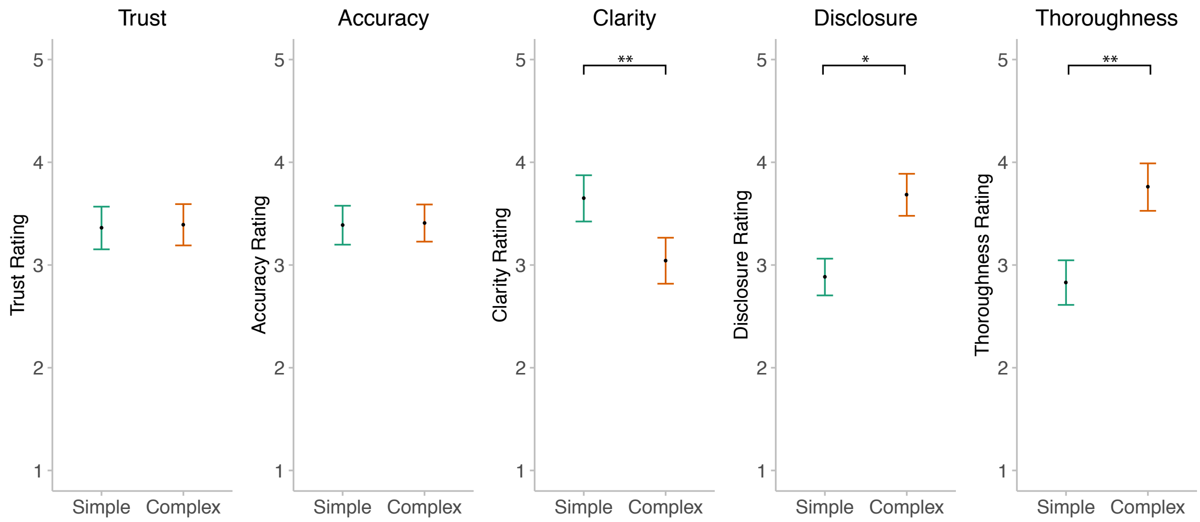

Figure 3: *Figure showing the influence of trust, accuracy, clarity, disclosure, and thoroughness on participants' selection of the simple or complex driving route application. Error bars represent 95% confidence intervals. * indicates p < .05, ** indicates < .005.*

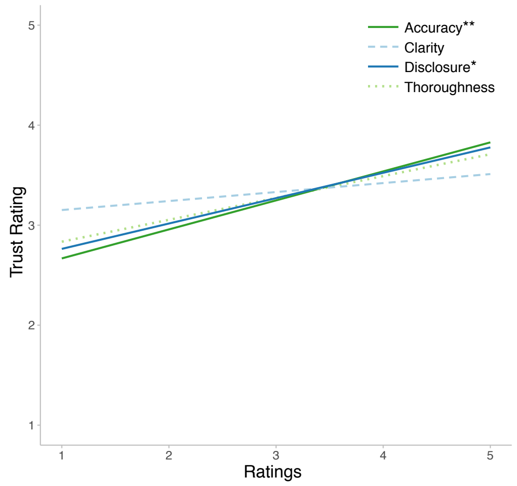

Figure 4: *Regression lines predicting trust with perceived accuracy, clarity, disclosure, and thoroughness. Solid lines are significant predictors. * indicates p < .05, ** indicates < .005.*

$SE = 0.053$, $p < 0.001$) and disclosure ($Est = 0.16$, $SE = 0.059$, $p = 0.0055$) significantly predicted trust. Perceived clarity ($Est = 0.39$, $SE = 0.045$, $p = 0.38$) and thoroughness ($Est = 0.060$, $SE = 0.057$, $p = 0.29$) were not significant predictors of trust.

6. Discussion and Conclusion

Although we found that perceived accuracy and the amount of disclosure in visualized data significantly predicted trust in a visualization, the results of our preliminary analysis suggest that participants were more likely to select visualizations that appeared clear and thorough and disclosed a greater amount of information. Trust and perceived accuracy did not have a significant influence on what visualization the participants selected in our decision task, which suggests that trust might not predict what visualization people select. A dissociation between trust and selection in decision-making tasks suggests that an existing evaluation of visualization trustworthiness, such as directly asking participants how much they trust the visualized information, might not be the most informative evaluation of how likely participants would be to use the visualization to make decisions.

7. Limitations and Future Directions

The present analysis did not analyze whether the amount of information shown in a visualization predicts which visualization participants would choose in this decision task. The amount of information visualized can be more finely divided beyond "simple" and "complex", such as by the number of recommended or alternative routes shown. Additional analyses and experiments are required to examine the effect of varying amounts of information visualized.

The present analysis also did not consider from which fire station the participants ultimately chose to dispatch firefighters *after* they selected the application interface in each trial. We anticipate further analysis to reveal the relationship among trust, perceived accuracy, clarity, disclosure, thoroughness, and decision-making.

Finally, we observed that some participants selected the visualization that appeared less thorough but more clear, whereas others selected visualizations that appeared more thorough and less clear. We suspect that participants could vary in which factors they prioritized to make decisions with visualizations. Future experimentation and analysis are required to investigate this hypothesis and isolate the effect of prioritization.

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