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InfoVis: The Impact of Information Overload on Decision Making Outcome in High Complexity Settings

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ABSTRACT

Dealing with an ever increasing amount of information is a major challenge in decision making. This especially pertains to information overload in managers, which is associated with impeding cognition and thus impairs objective decision making. Using visualizations to mitigate this effect has been widely discussed as a potential countermeasure. The theory of cognitive fit is far from being consistent or holistic when it comes to explaining information overload and leaves ample room for data driven advancements. In this paper we thus report the results of an experiment utilizing eye tracking that investigates how information overload alters the relationship between task complexity and decision making outcome. It is shown that information overload acts as a mediating variable between task complexity and decision making outcome and that it occurs less often when graphs instead of tables are being used. This also improves decision making outcome.

Keywords

Information Visualization, Information Overload, Task Complexity, Data Density, Structural Equation Model

INTRODUCTION

Technology allows the collection of data from hitherto untapped sources in a much more efficient way, and, as a consequence, the amount of available data has increased tremendously, bringing with it issues of complexity and ambiguity (Lemieux et al., 2014). Former research shows that decision making quality is enhanced by an increase of information (Schroder et al., 1967). However, a turning point exists where adding further information deteriorates decision making quality because the amount information surpasses the cognitive abilities of decision makers (Tortaso-Edo et al., 2014). The benefits of a high volume of information are often outweighed by the occurrence of information overload (Lurie and Mason, 2007).

A widely accepted method to assist managers in understanding high volumes of data is the use of tables and graphs. They provide cognitive support by representing information visually and transforming laborious cognitive processes into few simple perceptual operations (Huang et al., 2009). Extensive research has been conducted on the applicability of tables and graphs but no empirical evidence can be found on whether one outperforms the other, a quest which the theory of cognitive fit is trying to answer (Vessey, 1991).

Cognitive fit theory investigates how information needs to be presented in order to reduce cognitive load and thus enhance efficiency and effectiveness of decision making. This theory suggests that a fit between visual representations and tasks needs to be established (Vessey, 1991). If a presentation is congruent with existing schemas (i.e., knowledge structures) stored in long term memory, decision makers can more easily process information (Chandra and Krovi, 1999) and also higher amounts thereof. The theory recommends using tables to achieve better results for symbolic tasks (e.g., the search for a specific value) and graphs for spatial tasks (e.g., identification of trends, patterns or sequences) (Vessey, 1991).

In this study we investigate high levels of data density and high levels of task complexity and their implications on mental models. Especially such models are rather unexplored as the theory of cognitive fit does not account for such subtleties in the theoretical model (Speier, 2006). We propose that using graphs instead of tables in cases of high data density and high task complexity better supports decision makers irrespective of the task type. We assume that (1) visual representations of data (i.e., graphs) trigger processing with the human visual system, which operates faster and with less constraints in comparison to plain text or plain numbers, (2) the increasing use of graphs presuppose the better applicability of graphs (Falschlunger et al., 2015) and (3) using graphs enhances human processing capabilities irrespective of the data presented because it reduces the demand on working memory (Huang et al., 2009).

HYPOTHESIS DEVELOPMENT

In this part of the paper we use the two variables task complexity and information overload, and put them in a new perspective when applying cognitive fit theory:

Task complexity is used as an independent variable, (instead of a moderator or mediator) representing a combined measure for visualization type, data density and task type. To understand the complexity and applicability of certain information presentation modes which support decision making these three influential factors need to be considered and aligned (Speier, 2006; Wood, 1986). The most useful concept for task complexity with respect to these requirements was introduced by Wood (1986), who presented a formula to objectively calculate task complexity ($TC = \alpha TC_1 + \beta TC_2 + \gamma TC_3$). It is defined as "(1) a function of the number of distinct information cues that must be processed (TC_1); (2) the number of distinct processes that must be executed (TC_2); and (3) the relationship (i.e., interdependence and change over time) between the cues and processes (TC_3)" (Speier et al., 2003; p. 1117).

Only when task complexity is low, the probability of achieving cognitive fit and a high-quality decision-making outcome is high (Falschlunger et al., 2016; Chandra and Krovi, 1999). This formula accounts for information cues (dependent on data density levels) and behavioral acts necessary to fulfill a task dependent on the task type and the type of information presentation mode. For instance, behavioral acts change when comparing tables to graphs, when comparing different graph types, and also when comparing various task types. In our research, therefore the focus shifts away from matching task types and visualization types, to receiving the best possible outcome on the objective task complexity measure.

H1: High task complexity reduces decision making outcome.

The second variable of interest is information overload. Hwang and Lin (1999, p. 213-218) describe information overload as an inverted u-curve function based on the original work of Schroder et al. (1967): "... in response to increases in information load, decision makers will increase their information processing initially. However, if the information load keeps increasing and finally exceeds the capacity of decision makers, information processing will cease being increased. Instead, decision makers will decrease information processing as they experience a phenomenon termed 'information overload'." As soon as the amount of information exceeds working memory capacity limits, biased or even irrational decisions can be the consequence (Tortaso-Edo et al., 2014). Each individual has a different working memory capacity which depends on experience, knowledge and the respective topic. Information overload occurs if working memory capacity is outreached. A high task complexity, caused by performing highly complex tasks and/or using huge amounts of data, increases the likelihood of information overload (Mostyn, 2012). This indicates a mediating effect of information overload on the relationship of task complexity and decision making outcomes. We therefore conclude:

H2: Information Overload mediates the relationship between task complexity and decision making outcome.

H3: Information Overload is moderated by working memory capacity of the decision maker.

By using these two variables and by introducing high task complexity levels we focus our attention on the applicability of graphs. Tables and graphs are often seen as competing modes of presenting information (Chan, 2001). However, recent studies focus on graphs rather than tables because visual representations are supposed to further reduce the demand on working memory because the visual system operates in a highly automated manner (Mostyn, 2012). "Our senses, particularly the visual sense, are able to handle a huge amount of input, and to identify significant patterns within it" (Bawden and Robinson, 2009, p. 180-191). Visualizations allow patterns to materialize and focus the attention on specific aspects of the data depending on the visualization type being used (Lemieux et al., 2014). They boost information processing by relying on the human perceptual system which is highly developed and allows multiple processes to be executed at the same time (Mostyn, 2012). Visual representations are therefore often said to be an "external memory to reduce demand on human memory" (Huang et al., 2009, p. 139). We hypothesize:

H4: The information presentation mode moderates the effects of the relationships between task complexity, information overload, and decision making outcome.

RESEARCH METHODOLOGY

We used a laboratory experiment with a 4x3x3 within-subjects and between-subjects design. Within-subject effects were tested with 4 different visualization types (two graphical designs as well as two tabular designs) and 3 different task types with various complexity levels (accumulation, recognition, estimation/projection). Between-subjects effects were tested with 3 different levels of data density (dashboard with 3 key performance indicators (KPIs); dashboard with 2 KPIs; dashboard with 1 KPI). In total, 2,184 individual observations were gathered using validated questionnaires and an eye tracking study.

Subjects and Design Setup

91 international students participated in this experiment, who either received credit points or a small financial compensation. Participants were randomly assigned into two out of three sessions. Only two levels of data were tested with the same participant due to time constraints. The 91 students were recruited from a university with a focus on business and economics thus representing the future target audience of financial reports.

For measuring working memory capacity a computer-based test using E-Prime 2.0 was conducted (Foster et al., 2015). Data was collected at two different points in time. First, we measured working memory capacity and gathered demographical information. Second, the actual eye tracking experiment was carried out. Data collection was done on an individual basis (eye-tracking sample rate 120 Hz, experimental software: SMI Experiment Center 3.6; analysis software: SMI BeGaze 3.6). The participants were not allowed to use external devices for solving the tasks and no feedback on the accuracy of the task or their performance efficiency was given during the session. For the experimental tasks participants slipped into the role of the CEO of a fictitious company. The tasks the participants had to perform and the decisions they had to make were common in business. In total, the participants had to answer 48 questions. One individual session took from 15 to 30 minutes.

Experimental Design

Figure 1 shows our final research model and in the following paragraphs we briefly describe the manipulations used to change task complexity levels. Due to space constraints the test material is not provided in this paper, but can be downloaded on the main author's web site.

Visualization Type Manipulation: The most frequently used graphs in business communication are bar, line, and pie charts. Although the use of graphical aids is gaining importance, tables are still the preferred mode (Falschlunger et al., 2015). In our study we used a dashboard with two graphical and two tabular layouts for each business line. All four visualization types were used within one session and each business line was presented differently and in random order.

Data Density Manipulation: Three different data density levels were tested: high (3 KPIs within one dashboard; 180 distinct data points), medium (2 KPIs; 120 distinct data points), and low (1 KPI; 60 distinct data points).

Task Complexity Manipulation: Task types were applied in accordance with Hard and Vanecek (1991) resulting in three different complexity levels for each type of dashboard: (1) Recalling, reading, retrieving of one item of information (e.g., How high was the actual throughput-time in August?); (2) Comparing several items of information, recognizing patterns (e.g., Which month had the highest negative deviation between the actual value and the budget?); (3) Retrieving multiple items of information, developing trends (e.g., When you compare the actual customer satisfaction index with its outlook, which statement is true? (multiple choices were given)).

Measurement models

Task Complexity (TC) – reflective construct: Task complexity was operationalized using the formula of Wood (1986) shown above.

Decision Making Outcome (DMO) – formative construct: Decision making outcome was measured in two ways: response accuracy (RA) and response time (RT). RA accuracy pertains to the correct completion of a task. The scores for accumulation, recognition and estimation included two tasks with the same complexity level in each setting. A score of 1 indicates that both answers were correct, 0.5 was given for 1 correct answer and 0 in case both answers were incorrect. RT was measured as the time span between stimuli onset and offset. As a low response time is favorable we reversed the scale for RT.

Information Overload (IO) – formative construct: Pupil size and fixation count are used to measure cognitive load. A high pupil diameter and a high amount of fixations indicate high cognitive load (Granholm et al., 1996). To measure pupil diameter, controlled lighting settings are of utmost importance. Our laboratory did only have artificial light which was positioned in an angle that caused minimal reflections in glasses or contact lenses. When measuring pupil diameter possible confounds exist. The unaffected pupil diameter is different for each person and an initial high or low diameter results in a lower variance than a medium-sized pupil. Furthermore, different levels of screen brightness cause variations that do not relate to differences in cognitive load. To account for these changes in pupil diameter we introduced two control variables, namely pupil diameter difference and color intensity. The tracking ratio per stimulus, which is the time being recorded by the eye tracking system divided by the time of the stimulus, needed to be above 95% to be included in further data analyses. In the case of missing or excluded values mean replacement was used.

Working Memory Capacity (WMC) – formative construct: Working memory capacity is used as a moderator for the relationship between task complexity and information overload. We used the shortened automated operating span and symmetry span tests. Combining blocks of operation and symmetry span is recommended since multiple indicators should be used to draw conclusions about working memory capacity (Foster et al., 2015). These two tests helped us to draw conclusions about spatial and mathematical thinking. The operation span infers the cognitive ability in a test where one has to remember letters and at the same time calculate math problems. The symmetry span tests the ability to recall colored areas on the screen while simultaneously judging the symmetry of figures. These two different procedures allowed us to draw conclusions about the applicability of symbolic and spatial information visualization types from a working memory capacity perspective.

Information Presentation Mode (IPM) – formative construct: Information presentation mode is a dichotomous variable based on the used visualization type manipulation (table or graph) splitting the dataset for evaluation in half (1,092 observations per IPM).

RESULTS

For data analysis we used SmartPLS3 which is based on partial least squares modeling. PLS is able to simultaneously estimate all the proposed relationships while taking the existence of measurement error into account and it allows for a complete representation of the influences (Hair et al., 2012). We chose PLS SEM over

CBS SEM because formative and reflective measurements are used, asking for a composite factor model. Model fit is measured by SRMR (standardized root mean square residual) which is 0.077 for our model and below the recommended upper threshold of 0.08 (Henseler et al., 2014).

Table 1 shows that hypotheses 1-3 are corroborated. Task complexity significantly impacts decision making outcome (H1, $p<0.05$). Additionally, this relationship is mediated by information overload (H2, $p<0.05$) and the dataset shows an indication for information overload to be moderated by working memory capacity (H3, $p<0.1$). The bootstrapping results are shown in Table 1.

	Original Sample	**Standard Error**	**T-Value**	**P-Values**
TC => DMO **(accept H1)**	-0.200	0.018	11.303	0.000
TC=>IO IO=>DMO **(accept H2)**	0.622 -0.726	0.019 0.029	32.228 25.431	0.000 0.000
WMC=> IO Moderating Effect **(accept H3)**	-0.086 -0.057	0.030 0.031	2.836 1.814	0.005 0.070

Table 1: Bootstrapping Results

Decision making outcome has an R^2 of 0.726 (R^2 adjusted: 0.726) indicating that task complexity and information overload are the main drivers of DMO. The model's out of sample predictive power (or the predictive power) was measured using the blindfolding routine (0.391 for DMO). VIF, HTMT as well as AVE were well within the proposed thresholds proving construct reliability and discriminant validity.

Multigroup analysis was used to test H4. Splitting the data into the two fundamental presentation formats graphs and tables makes it possible to test for the moderating role of visualization mode. A multigroup comparison based on the Welch-Satterthwaite test was used and the results are shown in Table 2.

(accept H4)	**Ip(1)-p(2)I**	**T-Statistics**	**P-Values**
TC => DMO	0.058	1.660	0.097
TC=>IO IO=>DMO	0.088 0.000	2.240 0.009	0.025 0.993
WMC=> IO Moderating Effect	0.028 0.034	0.404 0.438	0.686 0.661

Table 2: Multi-Group Analysis (tables vs. graphs)

When task complexity increases the dataset indicates a higher effect when decisions are based on tables. Additionally a significant effect can be identified when it comes to the occurrence of information overload (H4, $p<0.05$). Tables seem to trigger information overload more frequently than graphs. The higher the complexity of a task and the higher the data density, the more important the use of graphs as decision aids is (see Figure 1).

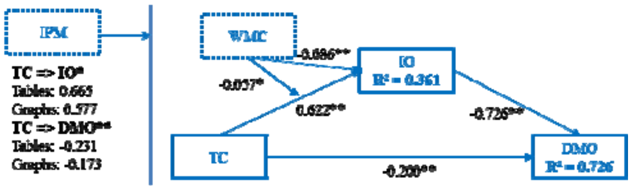

Figure 1: Decision Accuracy Model
(IPM: Information presentation mode; WMC: Working memory capacity; IO: Information Overload; TC: Task Complexity; DMO: Decision Making Outcome)

DISCUSSION

This paper shows that individual differences result in varying information overload levels, which have to be considered when testing for cognitive fit. Our findings add to the ongoing discussion of information visualization as well as to the decision making literature which focusses on information processing of high amounts of data. Our model predicts information overload and decision making outcome independently while it acknowledges and considers their interrelatedness. Combining various eye tracking measures such as pupil dilation and fixation count, standardized span tests as well as questionnaire based research, our model has considerable power in explaining and predicting decision making outcome (R^2: 0.709). This paper shows shortcomings of the theory of cognitive fit which suggests using spatial modes for spatial tasks and symbolic modes for symbolic tasks respectively. It presents an alternative method using the task complexity formula introduced by Wood (1986) and accounting for individual differences by taking working memory capacity into account. We show that information overload mediates the relationship between task complexity and decision making outcome.

In line with previous research this experimental study highlights visualizations as a presentation mode that supports the comprehension of large amounts of information, and that enhances the ability of humans to detect patterns, trends, and sequences (Gettinger et al., 2012). Therefore, an effective and efficient visualization of information can be seen as a precondition and a possible first step in reducing cognitive load and enhancing decision making quality (Dilla et al., 2010).

Limitations

Limitations of this study include a potential sample bias due to a population solely based on students. However, this population includes extra-occupational as well as full time students of various age groups, varying work experience and different cultural backgrounds. Additionally, the amount of information and data cues in our study might not have induced a state of information overload in all participants. Looking at the nature of these limitations it is possible that actual effect sizes might be even higher if more data sets or a higher task complexity were used. Furthermore, some limitations stem from using eye tracking data: First, while eye tracking provides a good approximation for cognition, it is not ensured that the perceived information is actually being processed ("eye-mind hypothesis" - Just and Carpenter, 1980); and, second, eye tracking cannot capture every occurring peripheral vision (Kim et al., 2012).

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