Association for Information Systems
AIS Electronic Library (AISeL)

AMCIS 2000 Proceedings

Americas Conference on Information Systems (AMCIS)

2000

Mitigating Information Overload: A Comparison of Perceptual and Textual Query Interfaces in a Decision Support Environment

Cheri Speier
Michigan State University, cspeier@msu.edu

Michael Morris
Air Force Institute of Technology, michael.morris@afit.af.mil

Mitigating Information Overload: A Comparison of Perceptual and Textual Query Interfaces in a Decision Support Environment

Cheri Speier, Michigan State University, Eli Broad College of Business, cspeier@msu.edu
Michael G. Morris, Air Force Institute of Technology, Graduate School of Engineering and Management, michael.morris@afitl.af.mil

Abstract

This paper reports on an empirical investigation of two "maximally different" database query interfaces. The first interface utilized a traditional textual interface similar to those found within common database management systems. The second interface employed a "perceptual" interface that was highly visual in nature and allowed users to directly manipulate query attributes in order to understand how changing those attributes changed the solution set for an individual query. Results indicated that for some tasks--particularly those where a precise answer was required--the textual interface performed better. However, for tasks where an approximate answer was all that was required, the perceptual interface was a better fit. These results have important implications for the design of managerial decision making systems, particularly in an environment where the potential of information overload is significant.

Introduction

In today's business environment, decision makers often have more data available than they are able to process effectively. As anyone who has conducted an Internet or database search has likely experienced, much of this data is irrelevant, or even worse, is not what the decision maker was looking for, resulting in a high potential for information overload (Wurman, 1989). Therefore, when developing information systems, the cognitive limits of human information processing need to be weighed against the information acquisition, processing, and presentation strategies needed to result in effective decision making.

A number of prior studies have examined how different query languages and database structures can differentially support decision makers. While these studies have focused on the effective way to get data out of a database, they have not adequately dealt with the problem of information overload. Even a properly designed query can result in an overwhelming number of alternatives, placing a significant cognitive load on a decision maker. One method for dealing with this load is to facilitate the use of visualization strategies to provide the decision maker information regarding the size of the solution set. Prior research has demonstrated that perceptual processes are an effective mechanism for mitigating the deleterious effects of high cognitive load and thus, will be examined in this study.

Therefore, this research empirically evaluates the effectiveness of textual versus perceptual user interfaces in processing database queries and the outcomes of those queries. Understanding the effectiveness of the user interface enables system developers to construct information systems that can improve decision maker effectiveness and/or efficiency.

Human Information Processing

Research in human information processing has clearly demonstrated that decision makers have limited cognitive ability and therefore, are only able to store and process limited amounts of information (March and Simon, 1958; Miller, 1956). Information overload has been defined as a condition in which the amount of input to a system exceeds its processing capacity (Cook, 1993; Milford and Perry, 1977; Schick, Gordon, and Haka, 1990). More specifically, overload occurs when there is more information available than necessary for processing a task and where this extraneous information has a detrimental effect on decision quality.

In explaining information overload, Streufert (1973) developed the concept of an information saturation point, beyond which, additional information is detrimental. Streufort (1973) suggests that information processing continues to increase as the amount of available information increases. During this phase, all information received has the potential to be used by the decision maker. However, at some point, a saturation point is reached. Beyond the saturation point, information processing actually decreases as decision makers can no longer process all of the information available. Empirical evidence indicates that the saturation point can occur in tasks that have as few as 6 attributes and 6 alternatives (Payne, 1976).

Empirical examination of the information overload phenomena has extended across a number of disciplines including accounting (Chewning and Harrell, 1990; Shields, 1980) and consumer behavior (Jacoby, Speller, and Kohn, 1974a, 1974b; Malhotra, Jain, and Lagakos, 1982). Results from these studies indicate that information overload results in decreased decision quality, increased decision time, and increased confusion.

In addition to influencing decision outcomes, information load also influences decision processing (March and Simon, 1958; Shields, 1980; 1983) resulting in a trade-off between accuracy and choice (Johnson and Payne, 1985; Payne, 1976). For example, decision makers solving tasks with higher information loads are more likely to rely on non-compensatory (e.g., approximate decision quality) decision strategies while tasks that have small information loads are more likely to involve compensatory (e.g., precise decision quality) decision processing (Biggs, et. al., 1985; Einhorn, 1971). Information load leads decision makers to use cognitive simplification processes, such as heuristics, that many lead them to ignore available, relevant information or encourage them to process incorrect information. Alternatively, decision makers may seek to reduce effort (Beach and Mitchell, 1978) by relying on perceptual processes, which consume less time (and are typically less accurate) than analytical processes (Payne, Bettman, and Johnson, 1988).

Information Visualization and Perceptual User Interfaces

Managing the information load and the corresponding accuracy/effort trade-off inherent in data-laden problems is challenging. The reliance on perceptual processes under high load conditions suggests that user interfaces should be designed to facilitate the use of these perceptual processes. Research in geographical information systems (GIS) has begun to examine the role of visualizing information to support more effective decision making. For example, different levels of data aggregation (e.g., how much information is viewed within the GIS) can influence facility location decisions (Taylor and Iwanek, 1980). Empirically, decision quality improved in a given GIS context as more detailed information was made available to the decision maker (Swink and Speier, 1999). It appears that up to a certain (saturation) point, increased data detail provides a visual pattern of activity to the decision maker that facilitates the decision making process. However, after this saturation point, human decision making capabilities degrade radically in performance if too much detail is provided.

Similarly, prior work in human computer interaction research has identified the importance of visual browsing to support perceptual processing of large data spaces (Robertson, Card, & Mackinlay, 1993; Shneiderman, 1998). Visual browsing tools enable the visual filtering of data based on user parameters to reduce the solution set to a reasonable size. User interface design techniques to support visual browsing include dynamic query filters and starfield displays (Shneiderman, 1998). Dynamic query filters make use of "slider bars" and buttons to adjust query parameters (e.g., a home for purchase between the values of $150,000 and $300,000). As the decision maker manipulates these features, he/she can visually see the size of the solution set and the impact of adjusting the parameters on the number of data points remaining in the solution set. This visual, real-time display of data points is provided using a starfield display. The downside of the starfield display is that while decision makers are able to see number of data points and patterns associated with the data points, the specific attributes (e.g., house price, number of bedrooms) can not be assessed and compared for each data point simultaneously.

Given the differences between text-based (e.g., an Access database form that is tied to a query) and perceptual query interfaces, we expect differences in decision effectiveness across decision tasks and decision processing strategies. More specifically, when decision tasks exist such that the required decision task query parameters result in a very small solution set, text-based query interfaces are likely to result in enhanced decision accuracy. Performing the task correctly results in a small number of solutions (e.g., cognitive load is low) and thus the decision maker can manage this load using available cognitive resources. Similarly, because information load is low, decision makers have no need to change from a compensatory to a non-compensatory decision strategy. In other words, because the decision-maker does not reach the saturation point, they are able to effectively process all available information. Thus:

H1: Precise decision accuracy is higher with text-based query interfaces than perceptual when performing tasks with small solution sets.

H2: Approximate decision accuracy is higher with text-based query interfaces than perceptual when performing tasks with small solution sets.

Alternatively, when database queries result in large solution sets, decision makers need some type of mechanism for reducing information overload. Furthermore, decision-making performance can be severely inhibited when information is in abundance as the quantity of available information may encourage decision makers to focus on irrelevant information instead of acquiring information that is essential for effective problem solving (Simon, 1979). One mechanism is to use perceptual query processes to dynamically modify query preferences to obtain a manageable number of solutions. Thus:

H3: Precise decision accuracy is higher with perceptual query interfaces than text-based when performing tasks with large solution sets.

Theory further suggests that as cognitive load increases, decision makers are likely to adjust their decision strategies to non-compensatory strategies in order to help filter the available information. Decision-makers may forgo coming up with an "optimal" decision and settle on a solution that is "good enough." Perceptual query interfaces are likely to better support this "satisficing" strategy as decision makers can visually assess the trade-offs between different parameters leading to a set of "better" solutions. Visual displays enable decision makers to use visual heuristics reducing the number of outcome paths or knowledge states available for examination (i.e., reducing problem complexity) (Smelcer and Carmel, 1997). Additionally, decision makers' abilities in recognizing or establishing patterns in visual data influence performance outcomes for problems which include large solution sets or where the data has many attributes (Kleinmunz & Schkade, 1993; Scriabin and Vergin, 1975; Taylor and Iwanek, 1980). Thus:

H4: Approximate decision accuracy is higher with perceptual query interfaces than text-based when performing tasks with large solution sets.

Because perceptual query interfaces allow complex data to be coded in multiple ways (e.g., utilizing spatial cues, color, intensity, etc.), cognitive load should be reduced across all tasks. Therefore, perceptual query languages have the potential of reducing effort on the part of the decision-maker thereby reducing the time needed to reach a decision. Thus:

H5: Decision time is faster with perceptual query interfaces than text-based interfaces.

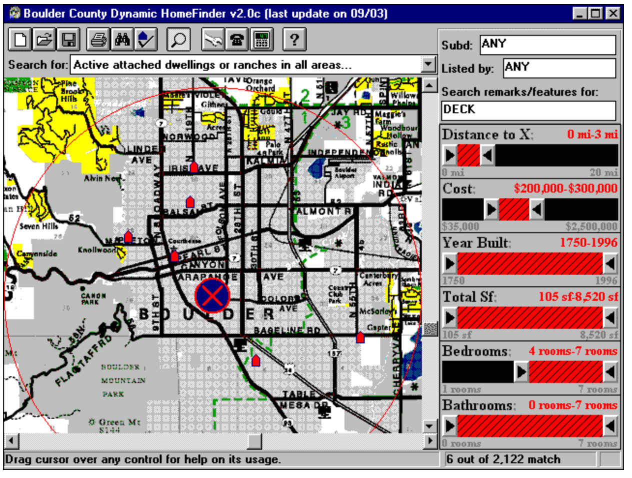
Research Method

An experiment involving a within subjects design was used to test the hypotheses. The two manipulated factors were user interface (perceptual versus text) and size of solution set (small versus large). The sample consisted of 260 undergraduates who had either limited or no prior experience using a text based database user interface. None of the subjects had any experience with the perceptual interface used in this study. Participants completed an initial pretest, completed two tasks using one of the interfaces, completed a post-test, performed two tasks using the second interface, completed a post-test, and finally completed a final post-test comparing the different interfaces. The order of the user interface treatments was counterbalanced across subjects.

All of the tasks involved identifying 5 homes one would like to visit (home purchasing task) out of approximately 1000 based on criteria provided to the decision maker. For the small solution set tasks, the home attributes were defined such that between 3 and 5 homes met the criteria. For large solution set tasks, "must have" and "would like to have" attributes were defined. After implementing the "must have" criteria, there were still approximately 200 homes in the solution set. Decision makers were then asked to identify the homes that provided as many of the preferences as possible yet provided the overall "best value" for the buyer. Thus, decision makers needed to iterate across different attributes (e.g., number of bedrooms, fireplace, cost, location, etc) to obtain better solutions. This task was constructed such that there was a "best 5" as well as identifiable better solutions (approximately 25) across the 200 homes included in the solution subset.

The perceptual interface was the Homefinder (Ahlberg and Shneiderman, 1994). Figure 1 illustrates an example of the Homefinder interface. This interface used visual tools to define or narrow the decision criteria and a starfield display illustrating the number of homes associated with a specific set of criteria. Decision makers could click on a "dot" in the display to obtain all the detailed information associated with a home in their solution set. The data underlying the Homefinder application was imported into an Access database to create the text interface. A form was created enabling the user to enter identical information as was available in the Homefinder. The results were presented in an Access table where each home was a row in the table and all attributes were displayed. Decision makers could create an unlimited number of queries to obtain their final solution.

Figure 1: Dynamic Homefinder Perceptual Interface



Three dependent variables were examined: precise decision accuracy, approximate decision accuracy, and decision time. Precise decision accuracy as the number of matches the subject had to the top five answers. Approximate decision accuracy was measured using a point scale based on the quality of the answer. For small (large) tasks, the top three (ten) solutions were awarded 20 points, the next five (ten) solutions were awarded 10 points, and the next ten (fifteen) solutions were awarded 5 points. Finally, decision time was measured as the number of minutes required to complete each of the tasks using a given user interface.

Results

The hypotheses were testing using ANOVA. In tasks with small solution sets, for precise decision accuracy, the text based (2.51) user interface was significantly better ($F(1, 260) = 162.43$, $p < .001$) than the perceptual (.69) interface, providing support for H1. Similarly, when looking at approximate decision accuracy, the text based (52.52) user interface was significantly better ($F(1, 260) = 246.46$, $p < .001$) than the perceptual (18.17) interface for small solution set problems, consistent with H2.

For problems with large solution sets, the perceptual interface (mean = .23) was significantly better than the text-based interface (mean = .12), as hypothesized in H3. In addition, the perceptual interface (10.53) was significantly better ($F(1, 260) = 3.950$, $p < .05$) than the text-based (5.92) interface in approximate decision accuracy, providing support for H4.

Finally, there was no significant difference in decision time ($F(1, 260)=.007$, $p=.934$) between the text-based (23.95) and perceptual (23.86) interfaces (H5).

Discussion/Conclusion

The results presented above reveal an interesting phenomenon. Specifically, the text-based query interface used here performs better in cases where we would expect cognitive load to be low. When the solution set is small, the text-based interface outperforms the perceptual interface on tasks requiring either precise or approximate accuracy. However, when the solution set is large, those advantages disappear. For large solution sets, the results were exactly opposite those for small solution sets--that is, perceptual interface was significantly better in both precise and approximate decision accuracy.

This result suggests that perceptual interfaces can help ease the cognitive burden on decision makers for many of the tasks they are required to perform. For many problems, there is no "one correct answer" that a manager is expected to pull from a set of data. Examples of these problems include searches from a large data field where multiple attributes must be "traded off" in order to come to an acceptable solution (e.g., "who would be the best candidate to hire?" or "where should a franchise be located?" may be best served with a perceptual interface. Similarly, finding data that is similar to a known data point may be best served by perceptual interfaces (e.g., answering "if I like music by Diana Krall, what other artists might I enjoy?").

Similarly, pereptual interfaces help users "see the whole": an important aspect of information visualization. Because the potential bandwidth is higher in perceptual interfaces (allowing data to be encoded based on type, color, intensity, spatial attributes, etc.), it may better support users in filtering information (i.e., when the potential solution set is large), and in providing managers with an overview of the data set, then allowing them to filter and "drill down" to get additional detail only when needed. Similarly, the increased bandwidth available in perceptual interfaces may help users make sense of multi-attribute data and how potential solution sets change as constraints are relaxed or tradeoffs among competing attributes are adjusted.

In conclusion, the results of this study suggest that dynamics of the task/solution scenario are an important consideration in the design of query interfaces designed to support such tasks. Particularly when there is no "one best answer" and when the potential solution set is large, perceptual interfaces may help users navigate through a sea of potentially misleading information efficiently with great effectiveness. With the explosion of information available through the Internet and/or other push technologies, the potential of such tools to reduce information overload would seem to be a powerful tool for next generation database and information retrieval systems.

References

Ahlberg, C. and B. Shneiderman (1994). Visual information seeking: Tight coupling of dynamic query filters with starfield displays, Proceedings of the *Computer Human Interaction Conference*, New York: ACM.

Beach, L.R., and T.R. Mitchell (1978). “A Contingency Model for the Selection of Decision Strategies,” *Academy of Management Review*, 3, 439-449.

Biggs, S.F., J.C. Bedard, B.G. Gaber, T.J. Linsmeier (1985). “The Effects of Task Size and Similarity on the Decision Behavior of Bank Loan Officers,” *Management Science*, 31(8), 970-987.

Chewning, E.G. Jr. and A.M. Harrell (1990). “The Effect of Information Load on Decision Makers' Cue Utilization Levels and Decision Quality in a Financial Distress Decision Task,” *Accounting, Organizations, and Society,* 15(6), 527-542.

Cook, G.J. (1993). “An Empirical Investigation of Information Search Strategies with Implications for DSS Design,” *Decision Sciences*, 24,(3) 683-698.

Einhorn, H.J. (1971). “Use of Nonlinear, Non compensatory Models as a Function of Task and Amount of Information.” *Organizational Behavior and Human Performance*, 6, 1-27.

Jacoby, J, D.E. Speller, and C.A. Kohn (1974a). “Brand Choice Behavior as a Function of Information Load,” *Journal of Marketing Research*, 15, 532-544.

Jacoby, J. D.E. Speller, and C.A. Kohn (1974b). “Brand Choice as a Function of Information Load: Replication and Extension,” *Journal of Consumer Research*, 1, 33-42.

Johnson, E.J. and J.W. Payne (1985). “Effort and Accuracy in Choice,” *Management Science*, 31(4), 395-414.

Kleinmuntz, D.N. & Schkade, D.A. (1993). “Information displays and decision processes,” *Psychological Science*, 4, 221-227.

Malthotra, N.K, A.K. Jain, and S.W. Lagakos (1982). “The Information Overload Controversy: An Alternate Viewpoint,” *Journal of Marketing*, 46, 27-37.

March, J. and H. Simon (1958). “Cognitive Limits on Rationality,” in J.March and H. Simon (Eds.), *Organizations*, New York: Wiley and Sons.

Milford, J.T. and R.P. Perry, (1977). “A Methodological Study of Overload,” *The Journal of General Psychology*, 97, 131-137.

Miller, G.A. (1956). “The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information,” *Psychological Review*, 81-97.

Payne, J., J.R. Bettman, and E.J. Johnson (1988) “Adaptive Strategy Selection in Decision Making,” *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 15(3), 534-552.

Payne, J.W. (1976). “Task Complexity and Contingent Processing in Decision Making: An Information Search and Protocol Analysis,” *Organizational Behavior and Human Performance*, 16, 366-387.

Robertson, G.G., S.K. Card, & J.D. Mackinlay (1993). “Information visualization using 3-D interactive animation,” *Communications of the ACM*, 36(4), 56-71.

Schick, A.G., L.A. Gordon, and S. Haka (1990). “Information Overload: A Temporal Approach,” *Accounting, Organizations, and Society*, 15(3), 199-220.

Scriabin, M., & Vergin, R.C. (1975). “Comparison of computer algorithms and visual based methods for plant layout.” *Management Science*, 22(2), 172-181.

Smelcer, J. and Carmel, E. (1997). “The effectiveness of different representations for managerial problem solving: comparing maps and tables,” *Decision Sciences*, forthcoming.

Shields, M.D. (1980). “Effects of Information Load on Search Patterns Used to Analyze Performance Reports,” *Accounting, Organizations, and Society*, 5(4), 429-442.

Shields, M.D. (1983). “Effects of Information Supply and Demand on Judgment Accuracy: Evidence from Corporate Managers,” *The Accounting Review*, LVIII(2), 284-303.

Simon, H. A. (1979). “Information Processing Models of Cognition,” *Annual Review of Psychology*, 30, 363-396.

Shneiderman, B. (1998). *Designing the user interface: Strategies for effective human computer interaction*, 3rd Edition. New York: Addison Wesley.

Streufert, S.C. (1973). “Effects of Information Relevance on Decision Making in Complex Environments,” *Journal of Experimental Social Psychology*, 389-403.

Taylor, P.B. and R. Iwanek (1980). “Intuitive Versus Optimal Solutions to Some Problems in Distribution,” *OMEGA*, 8(2), 183-192.

Wurman, R.S. (1989). *Information Anxiety*, New York: Doubleday.