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정 원 진*

The Effects of Different Information Visualizations on Decision Quality in a Web Environment

Wonjin Jung*

■ Abstract ■

Depending on the ways of information visualization, information can be interpretable, easy to understand, and represented concisely and consistently. This study explores the effects of different information visualizations on decision quality in a Web environment by conducting a laboratory experiment. The results demonstrated that the effects of information visualizations on decision quality were significant. The findings suggest that information users in a Web environment can expect to improve their decision quality by enhancing information visualizations. This research extends a body of research examining not only the effects of factors that can be tied to human decision-making, but also the predictions of various information visualization usages in a Web environment.

Keyword : Information Visualizations, Decision Quality

1. INTRODUCTION

Information visualization research is of interest to many disciplines, such as Statistics, Psychology, Education, Engineering, Management, and Information Systems [47]. The widely accepted view in the literature is that information in the form of pictures, graphs, or tables is generally regarded as superior in terms of the meaning of information (e.g., the ease of understanding and interpretability) to that in a thousand words [6, 18, 32, 33, 52]. Hence, tra-

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* 단국대학교 상경대학 경영학부

ditionally, decision makers have relied on graphical or tabular representations in improving decision quality [44]. However, when the focus of research is taken on the comparison between graphical and tabular visualizations, then there have been largely equivocal results in the prior research. While some research found that graphical presentations are superior to tabular presentations [10, 35] for decision-making, some research found the opposite [24]. Addo [1] considered the lack of theoretical basis and differences in measurements between studies as two primary reasons for the conflicting results. Specifically, prior studies used different definition and measurement of task type or complexities. Frownfelter-Lohrke [23] provided a comprehensive literature review of additional reasons for the conflicting results, such as use of poor graphical formats, content differences between graphical and tabular formats, uncontrolled task effects, omitted correlated variables, uncontrolled learning effects, differing or unobjective measures of decision quality, and univariate tests of related dependent variables [28, 8, 18].

To make high quality decisions, many organizations use various information visualizations supported by information technologies and systems. High quality decisions are expected to lead to more productive actions, quicker problem-solving, and better organizational performance. However, decision-making with various information visualizations may not be an easy task, particularly where the underlying problem is complex and ill-structured, or people experience information visualization problems. To make high quality decisions, it seems crucial to have access to information that is as interpretable, easy to understand, and represented concisely and consistently as possible, rather than just having an enormous volume of information. In practice, however, information may have visualization problems. That means, information may not be interpretable, easy to understand, and represented concisely and consistently due to a variety of reasons such as poor data formats, missing (incomplete) data, irrelevant data, or inadequately defined or measured data. Thus, it is difficult to get high quality information pertinent to the decision at hand.

Furthermore, because of a huge amount of information in an organization, people may experience information overload. In such a case, information may vary in visualizations, which makes decision tasks more difficult for decision-makers. Accordingly, people in an organization may find themselves bogged down by information systems or database management systems such as data warehouses presenting information in various visualizations. Consequently, organizations where people experience information visualization and/or overload problems may end up taking unnecessary risks by accepting impractical ideas and making errors in interpretation, or ignoring important ideas. Based on a recent industry report, the economic and social damage from poor-quality information costs billions of dollars [40].

The investigation of factors that can be tied to decision-making is important, since the factors will be useful as a basis for improving decision quality. Todd and Benbasat [50] provide a comprehensive literature review of the impact of IT on decision-making. Based on their literature review, the relationship between IT and decision-making is not well understood [9, 21, 42].

To further clarify the role of various moderating and mediating variables that influence decision-making, researchers investigated decision-maker capability in the context of DSS [5] and in the context of experts or knowledge-based systems [19, 27, 37], and the key mediating processes related to decision strategy in the context of DSS [43]. Despite many decision studies that examined these factors, the relationship between the factors and decision-making is still not well understood [50].

Since the relationship between these factors and decision-making is not well understood, rather than studying the direct effects of information technology and/or systems on decision quality [9, 21, 42], or the effects of moderating and mediating variables, such as decision-maker capability [5, 19, 27, 37] and decision strategy [43], on decision-making, this study examined the effects of information visualizations on decision quality.

In fact, the effects of various information characteristics and the importance of information visualizations have been studied in IS literature. However, little empirical evidence and understanding of the interaction effects of information visualizations and other factors that can be tied to decision-making has been documented. Specifically, much of the information visualization research did not manipulate task complexity, nor did it show performance differences between individuals based on the levels of task complexity. Hence, it would be worth investigating the interaction effects of different information visualizations and task complexity on decision quality. Thus, the goal of this research is to examine empirically the interaction effects of different information visualizations and task complexity on decision quality. This research provides a basis for deciding whether different information visualizations with task complexity influences decision quality simultaneously. This area of study is focused on extending a body of research examining not only the effects of factors that can be tied to human decision-making performance, but also the predictions of information visualization usages.

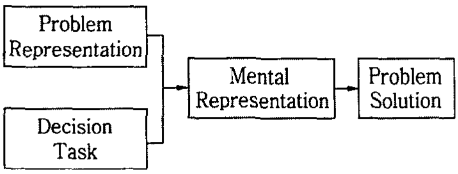
The remainder of this study is organized as follows. In Section 2, literature review and hypotheses are presented in detail. Section 3 describes the research methodology adopted for this study. In section 4, the results and findings are discussed. Finally, section 5 and 6 discusses and concludes the study.

2. LITERATURE REVIEW AND HYPOTHESES

2.1 Information Visualization

Tan and Benbasat [47, p. 417] state : "There is now common agreement in the Information Systems (IS) graphics research literature that the quality of a given information representation depends on the characteristics of the task to which it is to be applied [6, 7, 18, 32, 33]." Vessey [52] also suggests that a decision-maker's task processing would be more efficient and effective when there is a cognitive fit (match) between the information emphasized in the representation type and that required by the task type. That is, the theory of cognitive fit focuses on the effect of a match between problem representation and task on decision-making performance : spatial tasks need spatial information symbolic tasks need symbolic information.

More specifically, while tables emphasize symbolic information and lead to better performance for the task of reading specific data values, graphs emphasize spatial information and lead to better performance for most elementary spatial tasks, including summarizing data, showing trends, comparing points and patterns, and showing deviations [33, 52]. The theory of cognitive fit (see [Figure 1]) is a useful perspective to understand how and when different information visualizations are useful in supporting task strategies (methods or processes) required to perform a task. The three fundamental aspects addressed in the theory are : (1) the problem representation (graphs and tables), (2) the decision-making task (spatial and symbolic), and (3) the processes or strategies decision makers use (perceptual and analytical).



[Figure 1] The Theory of Cognitive Fit[52]

Vessey [52] aptly summarized the relationship between the problem representation and the task type.

Spatial representations therefore best support the solution of spatial tasks ; similarly, symbolic representations best support the solution of symbolic tasks. For example, determining a trend in a set of data values requires making associations among a number of data points : that is, it requires spatial information ; it is therefore a spatial task. A graph is a spatial representation since it also emphasizes spatial information…. Similarly, the task of extracting individual data values (a symbolic task) matches the way in which data are stored in a table of values (a symbolic representation) [52, p. 227].

According to the theory, when there is a complete fit of representation, processes, and task type, each representation (e.g., graphs or tables) will lead to both quicker and more accurate decision-making by formulating a mental representation. That means, while perceptual processes view data values in context ; that is, they enable a set of data points to be examined simultaneously, analytical processes are those used to both extract and act on discrete data values. Since symbolic tasks need precise data values, they are best accomplished using analytical processes.

Chandra and Krovi [12] extended the theory of cognitive fit to account for the congruence between external representation (e.g., information organization) and internal representation, and tested their extended model in an experimental setting with the two models of external representation (prepositional networks model from the cognition literature and object-oriented model from the systems literature). Chandra and Krovi state [12, p. 273] : "While the cognitive fit is an excellent framework for understanding the relationship between problem representation and decision-making task, it does not explicitly account for specific internal representations and their effect on the efficiency and effectiveness of information retrieval." The logic in their model is that if an already existing knowledge structure (internal representation) is congruent with information organization, the decision maker is better able to match the latter to the internal knowledge, thereby leading to the better efficiency and effectiveness of information retrieval performance. Overall findings of their study provide some evidence that the retrieval process benefits when information organization is congruent with internal representation.

Similarly, research in cognition and human information processing suggests that designing for comprehension is an effective way to reduce a reader's mental efforts to understand the contents of a document [49]. The nature of the information retrieval process is likely to differ from managerial decision-making. However, if the system presents information necessary to make decisions in such a way that they are organized, interpretable, easy to understand, and represented concisely and consistently, it would create a congruence between external (information organization) and internal representation. As such, it could be possible to infer that decision quality can be improved due to the congruence leading to the better efficiency and effectiveness of retrieval process for the information necessary to make decisions.

Based on the discussion above, the following hypotheses are proposed.

H1 : Regardless of the levels of task complexity, tabular visualization has more significant effect on decision time than graphical visualization for symbolic decision task.

H1a : Tabular visualization has more significant effect on decision time than graphical visualization for simple symbolic task.

H1b : Tabular visualization has more significant effect on decision time than graphical visualization for complex symbolic task.

H2 : Regardless of the levels of task complexity, tabular visualization has more significant effect on decision accuracy than graphical visualization for symbolic decision task.

H2a : Tabular visualization has more significant effect on decision accuracy than graphical visualization for simple symbolic task.

H2b : Tabular visualization has more significant effect on decision accuracy than graphical visualization for complex symbolic task.

2.2 Task Complexity

Task complexity is defined as the degree of cognitive load or mental effort required to identify and/or solve a problem [39]. Wood [56]suggests that complexity is a function of the number of acts that must be executed and the number of information cues that must be processed when performing a task. Thus, tasks are considered more complex as the number of acts and information cues increases. In an information retrieval context, task complexity increases as the number of potential solutions increases because decision makers must evaluate each potential solution if they want to get the most effective or accurate result [11, 38]. Rossano and Moak [41] also suggest that when task complexity is high, mental workload increases as more information are evaluated and retained in working memory.

Multi-criteria tasks have a set of alternatives and a set of criteria. As the number of alternatives and criteria increases, decision makers must process more information. As mentioned above, task complexity increases where there are more information cues to process [56]. That is, the heightened task complexity for multi-criteria tasks is attributable to increased information processing. Previous research on task complexity has shown that as task complexity increases, task difficulty increases. As a result, decision makers take more time and produce less accurate outcomes [11, 13, 45]. Therefore, multi-criteria tasks are considered more complex and difficult than elementary tasks [13, 30]. Based on the discussion above, the following hypotheses are proposed.

H3 : Regardless of the types of information visualization, complex symbolic task has more significant effect on decision time than simple symbolic task.

- H3a : Complex symbolic task has more significant effect on decision time than simple symbolic task for tabular visualization.
- H3b : Complex symbolic task has more significant effect on decision time than simple symbolic task for graphical visualization.

H4 : Regardless of the types of information visualization, complex symbolic task has more significant effect on decision accuracy than simple symbolic task.

- H4a : Complex symbolic task has more significant effect on decision accuracy than simple symbolic task for tabular visualization.
- H4b : Complex symbolic task has more significant effect on decision accuracy than simple symbolic task for graphical visualization.

3. RESEARCH METHODOLOGY

3.1 Experimental Design and Procedures

Since a laboratory environment provides the control necessary to understand the causal relationship between different information visualizations and decision-making, a laboratory experiment was conducted. For the experiment, two types of information visualization (e.g., tabular vs. graphical) for both simple and complex symbolic tasks were given to subjects. That is, based on the two factors, information visualization types (tabular vs. graphical), and task complexity (simple vs. complex), a 2 x 2 factorial design was implemented to test the hypotheses.

Because different groups of subjects used information in the different combinations of information visualization types and task complexity, decision-making was expected to vary depending on the combinations of information visualization types and task complexity. Each subject's decision-making was assessed based on predetermined measurement, and decision quality referred to decision time and the accuracy of decision-making that most accomplished the objective for the decision task. Thus, the purpose of the experiment to identify the effects of different information visualization types and task complexity on decision quality could be achieved.

A Web-based system to deliver a set of information in different visualizations to the subjects was developed using the latest version of Web programming languages, Hyper Text Markup Language (HTML) and Practical Extraction and Report Language (PERL). The system developed for this experiment can be viewed as a surrogate of the database management systems such as data warehouses that are being used in various functional areas in industry because the subjects accessed information through this system.

Subjects participating in the experiment were undergraduate students. The experimental task for this study asked subjects to solve a decision problem. The information set given to the subjects was fit for the decision task and delivered to them by the system. The subjects were assigned randomly to one of the four treatments. In order to help subjects understand the decision-making rules for the task, an example to simulate the decision-making rules was provided. After that, the subjects were provided with an answer sheet to record their solutions as they performed the task. Next, with the information set and the task, the subjects made decisions. Finally, this study observed the effects of the various treatments on decision quality.

3.2 Independent Variables

The first independent variable is two different types of information visualization, referred to as tabular and graphical visualizations. Previous information visualization research developed a sound taxonomy for classifying tasks : elementary tasks or decision activities [38]. The decision tasks used here, with known solutions, were close to decision activities rather than elementary tasks or spatial tasks in terms of difficulty, requiring higher mental processes and managerial analysis such as judgment, integration of information, and inference. The experiment used two different types of information visualization. That is, two attributes of information visualization (e.g., tabular and graphical) were used to map to the main information types. While a table presents information as a series of discrete numbers, a graph presents information as a series of colors or patterns [52]. This study carefully constructed the tabular and graphical visualizations to contain the same information. In other words, the two types of information visualization provided equivalent values, except in the information visualization formats. Since the experimental decision-making tasks for this study were close to decision activities rather than elementary or spatial tasks, based on the theory of cognitive fit [52], it was believed that there was a cognitive fit between information in the form of tabular visualization and the experimental decision-making tasks. Thus, tabular visualization was expected to facilitate the tasks' solution and to produce superior performance than graphical visualization. That means, tabular visualization was considered to provide more high-quality information than graphical visualization for the symbolic tasks. As such, the types of information visualization weremanipulated by the table and graph representations.

The decision task created by Jarvenpaa [31] was used for this experiment, with some minor adjustments. It asks subjects to select a site for the construction of a restaurant. While the complex task asked subjects to select a site from among five alternative sites in which to locate a restaurant, the simple task asked subjects to select a site from among three alternative sites. The complex task had five factors for each site, while the simple task had three factors for each site. The factors played an important role in deciding where the restaurant should be located. The scores for the factors were predetermined.

The second independent variable was task complexity at two levels (high and low). The degree of task complexity was manipulated by the number of problems in the task. The task required simple arithmetic calculations based on the decision criteria (factors) and decision choices (alternative sites for the restaurant). Specifically, the simple task with 24 problems required subjects to sum scores over three years for each factor. After averaging the summed scores for each factor, subjects were asked to sum the average scores for each site. Finally, they were asked to select a site that overall performs the best from among three alternative sites.

The complex task with 80 problems required subjects to average scores over three years for each factor. In addition, subjects were asked to assign a weight for each factor. After that, they were asked to evaluate the sites by pair-wise comparison (always comparing two sites at a time) with the weighted scores and select the site that wins the last comparison by having the largest number of factors of higher weighted value. That is, subjects were requested to rank the sites according to the predefined decision rules and the weighted scores of each factor.

3.3 Dependent Variables

The dependent variable of this study is decision quality. Decision quality was operationalized as the accuracy of decision-making and decision time. Decision-making accuracy was measured by the number of correct answers from the correct solutions. That is, decision-making accuracy was measured by dividing the number of correct answers by the number of total problems and expressing the result as a percent of the correct solution.

This study measured decision time as the total time in seconds the subjects required to select the best site from the candidates. That is, decision time was measured from the time when the subjects began working on the task until they recorded their solutions on their answer sheet and logged out of the system. Fisher et al. [22] distinguished between time constraints and time pressure. According to them, a time constraint is a specific allotment of time for making a decision, while time pressure is a subjective reaction to the amount of time allotted. Researchers found some mixed results with respect to the effects of time pressure on decision-making. Time pressure decreases decision accuracy [57]and can impair the performance of some decision makers more than others [3]. On the other hand, Austin [4] found that increasing time pressure may increase quality in software development projects. According to Dukerich and Nichols [20], time constraints may have more impact on decision-making for novices than for sophisticated decision-makers. Because time factors, pressure or constraints, affect decision-making, subjects were not informed of any time expectation for this experiment.

3.4 Pilot Study

To test the experimental procedure and task complexity manipulations, two rounds of a pilot testing were conducted. The results of the pilot study indicated that there were ambiguities in the decision-making rules for thecomplex task. The examinations of the results led to make two adjustments. First, subjects were instructed with a revised example to help them understand the decision rules easily. Second, to reduce the degree of task complexity for the complex task, the numbers of factors and alternative sites in the complex task were reduced from 7 and 6 to 5 and 5, respectively.

4. RESEARCH FINDINGS

A total of 40 undergraduate students participated in the experiment. Decision accuracy and time were each analyzed with two-way ANOVAs. The tests were carried out at a 95% confidence level. The descriptive statistics for the dependent variables are summarized in <Table 1>.

The results of the two-way ANOVA for time showed that the main effects of information visualization ($p = .003$) and task complexity ($p = .000$) were significant (see <Table 2>). The results indicated that subjects using tabular visualization took less time than subjects using graphical visualization. That means, decision time with tabular visualization was significantly shorter than with graphical visualization. Therefore, H1 was supported. Also consistent with expectations, the simple task was solved more quickly than the complex task. Therefore, H3 was supported.

〈Table 1〉 Descriptive Statistics for Decision Quality

Measures	Treatment Conditions			
	Simple Task		Complex Task	
	Tabular Visualization	Graphical Visualization	Tabular Visualization	Graphical Visualization
Decision Accuracy : (a higher score implies greater accuracy)				
Mean	96.2	39.59	95.0	46.5
Std. Dev.	4.14	18.66	9.35	17.80
N	10	10	10	10
Decision Time : (minutes : seconds)				
Mean	8 : 24	13 : 07	23 : 58	27 : 13
Std. Dev.	2 : 32	03 : 46	04 : 57	04 : 21
n	10	10	10	10

〈Table 2〉 ANOVA Table for Two-Way Analysis of Decision Time : Information Visualization by Task Complexity

Source	Type III Sum of Squares	Mean Square	F	Sig.
Corrected Model	8513903.672(a)	2837967.891	49.188	.000
Intercept	47552213.386	47552213.386	824.177	.000
Complex Task	7923652.422	7923652.422	137.333	.000
Information Visualization	570493.225	570493.225	9.888	.003
COMP * VISUAL	19758.025	19758.025	.342	.562
Error	2077077.242	57696.590		
Total	58143194.301			
Corrected Total	10590980.915			

주) : (a) R Squared = .804(Adjusted R Squared = .788).

The ANOVA on decision accuracy found a significant main effect for information visualization (p = .000, see <Table 3>). Subjects using tabular visualization made more accurate decisions than subjects using graphical visualization. Therefore, H2 was supported. Surprisingly, the results of ANOVA for decision accuracy showed that there was no significant main effect of task complexity for decision accuracy (p = .522, see <Table 3>). Subjects completing the complex task had comparable decision accuracy to those completing the simple task. That means, the subjects assigned to the complex task were evidently able to handle additional task complexity without significant detriment to decision accuracy. Thus, H4 was rejected. However, it is interesting to note that the main effect of task complexity was significant for decision time. These confounding results suggest that because there was no time constraint, that is, there was no specific allotment of time for making a decision, subjects used as much time as they needed to complete the complex task while keeping decision accuracy as high as possible. Therefore, these unexpected results may imply the existence of accuracy-time trade-offs only in the effect of task complexity.

For decision time, the interaction between information visualization and task complexity was not significant (p = .562, see <Table 2>), indicating these two variables do not jointly affect decision time. <Table 1> shows that a comparison involving tabular and graphical visualization in the effect of the complex task showed no significant mean difference on decision time. Therefore, H1b was rejected. This suggests that tabular visualization did not provide benefits to decision time in the effect of the complex task. That is, subjects using the graphical visualization for the complex task apparently did not take additional time to translate the information in graph format into the precise numeric information it represents. Based on these results, it could be possible to infer that when a complex task was given with graphical visualization, problem solvers spent most time primarily on understanding and solving the decision task, rather than on translating the information presented in the graph into the precise numeric information.

On the other hand, the effect of information

〈Table 3〉 ANOVA Table for Two-Way Analysis of Decision Accuracy : Information Visualization by Task Complexity

Source	Type III Sum of Squares	Mean Square	F	Sig.
Corrected Model	27889.040(b)	9296.347	48.301	.000
Intercept	192296.000	192296.000	999.119	.000
Complex Task	80.325	80.325	.417	.522
Information Visualization	27642.183	27642.183	143.621	.000
COMP * VISUAL	166.532	166.532	.865	.358
Error	6928.762	192.466		
Total	227113.802			
Corrected Total	34817.802			

주) : (a) R Squared = .801 (Adjusted R Squared = .784) visualization on problem-solving time was significant in the effect of the simple task. Subjects using the graphical visualization for the simple task took more time than subjects using the tabular visualization for the simple task. This is likely due to the fact that at a lower level of task complexity, subjects using the graphical visualization might take more effort (as measured by time) to translate the graph information into the precise numeric information it represents to generate good decisions, instead of taking effort to understand the task. In summary, it appears that the insignificant interaction effect between information visualization and task complexity resulted from the insignificant mean difference between tabular and graphical visualization in the effect of the complex task, indicating these two variables do not jointly affect decision time.

For decision accuracy, the interaction between information visualization and task complexity was not significant ($p = .358$, see <Table 3>), indicating these two variables do not jointly affect decision accuracy. This is likely due to the insignificant main effect of task complexity on decision accuracy. There was a significant mean difference between tabular and graphical visualization in the effect of the simple task (see <Table 1>). There was also a significant mean difference between tabular and graphical visualization in the effect of the complex task. It appears that these significant differences resulted from the significant main effect of information visualization on decision accuracy. However, the difference between the information visualization effect in the simple task effect and the information visualization effect in the complex task effect was not significant. It means that this insignificant mean difference resulted from the insignificant main effect of task complexity. Thus, even though the main effect of information visualization was significant on decision accuracy, it was not significant enough to outweigh the insignificant main effect of task complexity on decision accuracy, resulting in the insignificant interaction effect between information visualization and task complexity. <Table 4> presents the results of testing the hypotheses of this study.

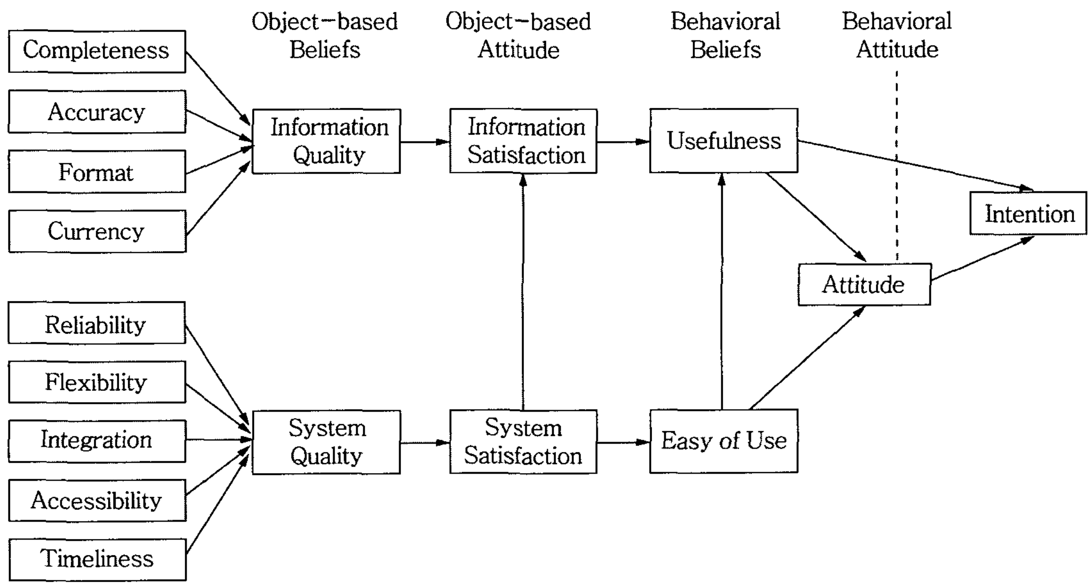
<Table 4> Summary of Hypotheses Testing

Hypotheses	Statistics		Evaluation
H1	F = 9.888	P = .003	Supported
H1a	F = 10.818	P = .004	Supported
H1b	F = 2.413	P = .138	Rejected
H2	F = 143.621	P = .000	Supported
H2a	F = 87.843	P = .000	Supported
H2b	F = 58.148	P = .000	Supported
H3	F = 137.333	P = .000	Supported
H3a	F = 78.300	P = .000	Supported
H3b	F = 59.985	P = .000	Supported
H4	F = .417	P = .522	Rejected
H4a	F = .149	P = .704	Rejected
H4b	F = .719	P = .408	Rejected

5. DISCUSSION

There was a significant main effect of information visualization on decision accuracy and time. In addition, there was a significant main effect of task complexity on decision time. These results, especially the information visualization effect, are consistent with the theory of cognitive fit [52] that was built upon a considerable amount of graphs versus tables representations studies. The task used in this study can be viewed as a symbolic task since it is best accomplished using precise information values. That is, subjects need discrete precise information values for carrying out accurate computations. The task used in this study does not involve the aspects of spatial task facilitated by the spatial properties of graphs, such as detecting trends over time or comparing patterns of variables. Therefore, it is hard to see the task used in this study as a spatial task. When tabular visualization was used in this experiment (e.g., symbolic task), decision-making with cognitive fit resulted in increased decision-making efficiency and effectiveness. However, when graphical visualization was used for the task, a mismatch occurred between the problem representation and the task, which required subjects to transform the information values derived from the problem representation (e.g., graphs) into the mental representation suitable for task solution, which in turn had a negative impact on decision-making effectiveness and efficiency. Therefore, it seems clear that the results of this study, especially the main effect of information visualization on decision accuracy and time, are compatible with the cognitive fit theory.

Wixom and Todd [55] developed a single unified research model by integrating two primary research streams－the user satisfaction literature and the technology acceptance literature (see [Figure 2]). A vast body of technology acceptance studies has focused on the predictions of information technology acceptance and usage by linking an individual's attitudes and beliefs (ease of use and usefulness) with the behavior of interest (system usage) [14, 46, 51]. On the other hand, within the user satisfaction literature, various subsets of beliefs about system and information characteristics have been used to measure user satisfaction [16, 17]. Wixom and Todd [55] addressed the fact that user satisfaction with the systems and its information output is a weak predictor of system usage [15, 25, 29, 36], while the technology acceptance mod-



[Figure 2] The integrated model of user satisfaction and technology acceptance[55] el (TAM) offers only limited guidance about how to influence usage through the systems and its information output [48, 51]. Thus, they distinguished beliefs and attitudes about the system and information characteristics from beliefs and attitudes about using the system. Specifically, in their model they described not only how a set of system and information characteristics influences beliefs and attitudes with the system and the information it produces, but also how these attitudes toward the system and information influence the behavioral beliefs of usefulness, ease of use, and, ultimately, system usage.

The findings of this study can be applicable to Wixom and Todd's integrated model of user satisfaction and technology acceptance. A system user may develop an attitude toward the use of a particular information systems. That attitude can be shaped by beliefs about the information characteristics including information visualization types. That is, the system user may form an attitude toward use of the information systems, which can be influenced by information usefulness and satisfaction, which are affected by beliefs about the information characteristics. The information characteristics includes information visualization types and/or formats as one of its four aspects. Since this study did not explore the relationship between information quality and information satisfaction, the relationship between information satisfaction and usefulness, and the relationship between usefulness and intention in the Wixon and Todd's model, the assertion mentioned above may not occur as predicted. In order to support the assertion, future research should investigate the relationships in the Wixom and Todd's model as well as the relationship between intention and decision performance.

The results of this study may have a practical implication for organizations to justify their attempt of improving information quality and/or their investments in a certain information technology. A data warehouse provides the repository of information used for decision support [54] and a data warehousing project is a quite expensive undertaking. According to Watson and Haley [53], the typical project costs over $1 million in the first year alone. Many organizations expect that a data warehouse as a dedicated source of information [26] will provide high quality information, which leads to the improvement of decision quality. Based on their expectations, many organizations might have made investments in such expensive data warehousing projects. Since the findings of this study showed that information visualization brought decision effectiveness and efficiency improvements, improving information visualization by investing in database practices would improve information quality and appear to be beneficial for organizations' performance. Thus, this study may provide evidence that helps organizations to justify their efforts to improve information quality.

Although this study provided a number of findings and conclusions that will be useful for improving our understanding of the impact of different information visualizations on decision quality, it is subject to the limitations of laboratory research. Thus, a number of limitations should be considered in terms of the methods used when interpreting the findings. It is almost impossible to control the influence of all potential extraneous variances by the nature of the experimental setting, the subject population, the task type, the structure of the task, the set of information, the information visualization types, and the application development tools to make the Web-based system used in this study. For example, data were collected in different experimental sessions held in different computer laboratories. Although every effort was made to provide the subjects with the same instructions consistently on how to complete the task, it is possible that the subjects might not receive the same instructions due to different laboratory circumstances. Another example is that the subjects have different cognitive abilities and cognitive styles. That means, a particular treatment group may have more introvert subjects than other groups or vice versa. In that case, the results of this study would be different than the results described above. However, it was believed that proper randomization was accomplished, the influences of those independent variables extraneous to the purposes of the study might be minimized or isolated.

Kerlinger and Lee [34, p. 170] state : "An 'ideal' experiment is one in which all the factors or variables likely to affect the experimental outcomes are controlled." According to them, if we know all these factors in the first place, and can make efforts to control them in the second place, then we will have an ideal experiment. However, we can neither know all the pertinent variables, nor can we control them even if we know them. The variables that were expected to influence the experimental outcomes of this study were subjects' capability, characteristics, and decision strategy. The best way to control these factors was to keep almost all of these potential extraneous variances at a minimum. Randomization was expected to accomplish this goal. The basic purpose of random assignment is to apportion subjects (objects, groups) to treatments [34]. For the experiment, every effort was made to apportion subjects to treatments randomly. Therefore, it was believed that individuals with varying characteristics were spread approximately equally among the treatments so that variables that might affect the dependent variable, other than the experimental variables, had equal effects in the different treatments.

Second, data were collected from a small sample of 40 students and they were undergraduate students. Therefore, the findings of this study might not generalize to a broader population. In addition, there are hundreds of thousands of different platforms (PC, Macintosh, Unix etc.), different monitors, different browsers, and different versions of browsers. The website can look drastically different depending on which platform it is viewed. However, the experiment for this study cannot be conducted with every single platform and every single browser. This is an area of concern for external validity. External validity defines representativeness or generalizability and it is a difficult criterion to satisfy. When an experiment has been completed and a relation found, one should ask to what populations it could be generalized. This important scientific question should always be asked and answered. Because a single empirical study is not sufficient to validate the findings, further research should address these limitations (i.e., subject characteristics and experimental tools) and apply the findings of this study in specific contexts and decision support technology as a whole.

6. CONCLUSIONS

This study empirically investigated the interaction effects of different information visualizations and task complexity on decision quality by conducting a laboratory experiment. The results demonstrated that the effects of information visualization on decision-making effectiveness and efficiency are significant. The findings provided empirical evidence to validate the cognitive fit theory and the integrated model of user satisfaction and technology acceptance. Therefore, this study may be useful for informing the academic communities about the effects of information visualization and task complexity. However, a number of limitations should be considered in terms of the methods used when interpreting the findings and future researchers would be wise to further examine and extend the findings of this study. Finally, it is postulated that despite these limitations, practitioners should be able to facilitate the design of database management systems such as data warehouses to improve their decision quality by enhancing information visualizations.

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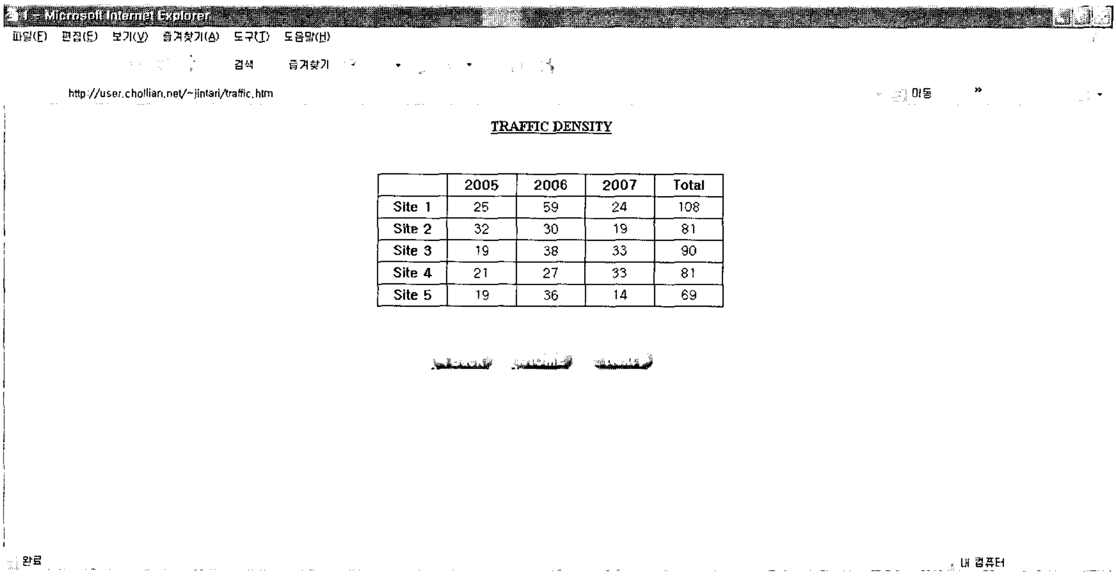
Appendix A



TRAFFIC DENSITY

	2005	2006	2007	Total
Site 1	25	59	24	108
Site 2	32	30	19	81
Site 3	19	38	33	90
Site 4	21	27	33	81
Site 5	19	36	14	69