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상황 데이터 품질이 의사결정 성과에 미치는 영향*

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Investigating the Impact of Contextual Data Quality on Decision Performance

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The effects of information quality and the importance of information have been reported in the Information Systems (IS) literature. However, little has been learned about the impact of data quality (DQ) on decision performance. Recognizing with this problem, this study explores the effects of contextual DQ on decision performance. To examine them, a laboratory experiment was conducted. Based on two levels of contextual DQ and two levels of task complexity, this study had a 2 x 2 factorial design. The dependent variables used to measure the outcomes of decision performance were problem-solving accuracy and time. The results demonstrated that the effects of contextual DQ on decision performance were significant. The findings suggest that decision makers can expect to improve their decision performance by enhancing contextual DQ. This research not only extends a body of research examining the effects of factors that can be tied to human decision-making performance, but also provides empirical evidence to validate and extend DeLone and McLean's IS success model.

Keywords : Contextual Data Quality, Task Complexity, Decision Performance

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Ⅰ. Introduction

The knowledge management literature describes distinctions among data, information, and knowledge. Tuomi [1999] states: "The generally accepted view sees data as simple facts that become information as they are combined into meaningful structures, which subsequently become knowledge as meaningful information is put into a context and when it can be used to make predictions" (p. 103). Similarly, Davenport [1997] note that data are simple observations of states of the world, and information is data endowed with relevance and purpose. Wiig [1993] also emphasizes that information consists of facts and data that are organized to describe a particular situation or condition. Based on these views, it seems clear that data is a prerequisite for information and information can be created from its raw data.

In the IS literature, information quality is one of two major dimensions for evaluating the success of information systems [DeLone and McLean, 1992; 2003] and decision quality is a function of information quality [Stephenson, 1985]. While the effects of information quality and the importance of information have been studied in IS literature, little has been learned about the impact of data quality (DQ) on decision performance. In addition, while there are many empirical studies about the factors that can be tied to decision performance, such as information technologies (e.g., DSS) [Benbasat *et al.*, 1993; Eierman *et al.*, 1995; Sharda *et al.*, 1988], decision-maker capability [Benbasat and Taylor, 1982, Dhaliwal and Benbasat, 1996; Gregor and Benbasat, 1999; Nah *et al.*, 1999], and decision strategy [Silver, 1990], little empirical evidence and understanding of the impact of data quality on decision performance has been documented. Thus, the purpose of this study is to empirically examine the relationship between data quality (DQ) and decision performance. The research question of this study is: how does data quality influence decision performance?

Wang and Strong [1996] conducted a two-stage survey and a two-phase sorting study to develop a hierarchical framework for organizing data quality dimensions. This framework captures four dimensions of data quality that are important to data consumers. *Intrinsic DQ* denotes that data have quality in their own right. *Contextual DQ* highlights the requirement that data quality must be considered within the context of the task at hand. Specifically, they define high-quality contextual data as data that can add value because it is relevant, timely, complete, and appropriate in terms of amount. *Representational DQ* and *accessibility DQ* emphasize the importance of the role of systems.

Strong *et al.* [1997] studied 42 data quality projects and found contextual DQ problems in practice. Their closer examination revealed three underlying causes for data consumers' complaints that available data does not support their tasks: missing data, inadequately defined or measured data, and data that could not be appropriately aggregated. Since it is not well understood whether these contextual DQ problems affect problem-solving performance in decision-making settings, it would be worth investigating the effects of contextual DQ. For this study, we chose to focus on a single aspect of data quality, namely contextual DQ. In addition, incomplete and irrelevant data could increase the level of task complexity, which in turn has a negative impact on decision performance. Thus, this study empirically explores how contextual DQ and task complexity simultaneously affect decision performance.

The remainder of this study is organized as follows. In section Ⅱ, literature review and hypotheses are presented in detail. Section Ⅲ describes the research methodology adopted for this study. In section Ⅳ, the results and findings are discussed. Finally, section Ⅴ concludes and discusses the study.

Ⅱ. Theoretical Background and Hypothesis Development

2.1 Information Quality

Since the beginning of the computer age, IS researchers have addressed the issue of the quality of information. During the earlier phases of information quality research, IS researchers focused on the quality of the information systems output primarily in the form of reports [DeLone and McLean, 1992]. Gallaher [1974] used several information quality items to measure the value of a group of IS reports. The items included relevance, informativeness, usefulness, and importance. Larcker and Lessig [1980] measured the perceived importance and usableness of information presented in reports for their study. Other IS researchers considered report format as an information quality measure [Zmud, 1978; Olson and Lucas, 1982]. In addition, IS researchers highlighted the multifaceted nature of information quality. Ahituv [1980] used five information characteristics to measure information value: accuracy, timeliness, relevance, aggregation, and formatting. To develop a composite measure of information value, King and Epstein [1983] used various information attributes such as sufficiency, understandability, freedom from bias, reliability, decision relevance, comparability, and quantitativeness.

Iivari and Koskela [1987] used various information quality criteria to measure users' information satisfaction. Their items included relevance, comprehensiveness, recentness, accuracy, credibility, convenience, timeliness, interpretability, and adaptability. More recently, IS researchers examined the relationship between information quality and individual performance [Etezadi-Amoli and Farhoomand, 1996; Seddon and Kiew, 1994; Teo and Wong, 1998; Wixom and Watson, 2001]. Their studies provided strong support for the effects of information quality on individual performance. However, since this large base of previous research on information quality has given little consideration to the effects of contextual data quality on decision performance, this study may add incremental information to existing information quality research.

2.2 Decision Performance

Many IS researchers have investigated the impact of information (systems) on decision performance. In an experimental study of the impact of information presentation, Lucas and Nielsen [1980] measured learning, or rate of performance improvement, as a dependent variable. Other researchers adopted decision effectiveness as the dependent variable in their information systems laboratory experiments. Various dimensions of decision effectiveness within the context of laboratory experiments include the average time to make a decision [Benbasat and Dexter, 1986; Benbasat and Schroeder, 1977; Chervany and Dickson, 1974], the confidence in the decision made [Chervany and Dickson, 1974], the number of reports requested [Benbasat and Dexter, 1979], and member participation in group decision making [DeSanctis and Gallupe, 1987].

On the other hand, DeLone and McLean [1992] provided a comprehensive literature review on individual performance (see <Table 1>). In their study, they stated that "individual impact" could be an indication that an information system, which produces information, has given the user a better understanding of the decision context, has changed the decision maker's perception of the importance or usefulness of the information, and has improved his or her decision-making productivity. Furthermore, they concluded that "information (systems) quality" and "individual impact" are interrelated and interdependent. That is, their IS success model shows that system quality and information quality singularly and jointly affect both system use and user satisfaction that are direct antecedents of individual impact, which in turn impacts organizational performance.

With the primary purpose of empirical testing and validation of the D&M IS Success Model, the several studies that tested the relationships between "information quality" with "user satisfaction" and "individual impact" found those associations to be statistically significant [Seddon and Kiew, 1994; Etezadi-Amoli and Farhoomand, 1996; Igbaria and Tan,

<Table 1> Empirical Measures of Individual Impact [DeLone and McLean, 1992]

Authors	Description of Study	Type	Description of Measure(s)
DeSanctis and Jarvenpaa [1985]	Table vs. graphs: 75 MBA students	Lab	Decision quality, forecast accuracy
Dickson, DeSanctis, and McBride [1986]	Graphics Systems; 840 undergraduate students	Lab	Interpretation accuracy, decision quality
Vogel, Lehman, and Dickson [1986]	Graphical presentation system; 174 undergraduate students	Lab	Change in commitment of time and money
Watson and Driver [1983]	Graphical presentation of information; 29 undergraduate business students	Lab	Immediate recall of information, delayed recall of information
Aldag and Power [1986]	DSS; 88 business students	Lab	User confidence, quality of decision analysis
Goul, Shane, and Tonge [1986]	Knowledge-based DSS: one university, 52 students	Lab	Ability to identify strategic opportunities or problems
Grudnitski [1981]	Planning and control system: 65 business students	Lab	Precision of decision maker's forecast
King and Rodriguez [1981]	Strategic system; one university, 45 managers	Lab	Worth of information system, quality of policy decisions

1997; Guimaraes and Igbaria, 1997; Yuthas and Young, 1998; Torkzadeh and Doll, 1999].

Despite many decision performance studies that examined the effects of information (systems) on individual performance, there is still no empirical support for the relationship between data quality and individual performance. Therefore, this research examines the effects of data quality, especially contextual DQ, on decision performance by employing the conceptual framework of DQ proposed by Wang and Strong [1996].

2.3 Contextual Information

Context information is most useful for not only information retrieval (IR) functions [Brown and Jones, 2001; 2002], but also browsing tasks [Dourish *et al.*, 1993; Park and Kim, 2000]. IR systems are concerned with the finding of information, often in the form of text documents [Brown and Jones, 2001]. According to Brown and Jones, at one time, IR systems were almost exclusively the domain of the librarian. However, the advent of the World Wide Web (WWW) has changed this situation radically, and many people are now familiar with the use of IR systems in the form of web search engines. In a later study, they found that the use of context information leads to improvements in precision and retrieval speed [Brown and Jones, 2002]. Jul and Furnas [1997] also asserted that context information plays an important role for effective information retrieval because each retrieval process takes place in a particular information environment and is tied to the specificity of the environment. Dourish *et al.* [1993] studied two information systems, one paper-based and one electronic, managing similar information within the same organization. In addition to the fact that the availability of contextual information makes browsing much more productive, they also found that information retrieved from these systems is interpreted subjectively by individuals, and point to contextual information contributing to this interpretation. That is, they addressed the importance of contextual information, which causes the same information to be interpreted in different ways once retrieved. Since this interpretation is critical in decision-making, it must be perceived to be correct and pertinent if information is to be of use to an individual. Thus, they emphasized that contextual information acts as resources in the process of interpreting the information.

Based on these views, it could be possible to infer that decision-makers can benefit from high-quality contextual information because it can increase the efficiency and effectiveness of browsing and retrieval processes, as well as information interpretation processes. In other words, if the system provides high-quality contextual information, then problem-solving performance may be improved due to the improved efficiency and effectiveness of browsing, retrieval, and interpretation processes for the information necessary to make decisions. In the same way, if the system provides high-quality contextual data, then the better efficiency and effectiveness of browsing, retrieval, and interpretation processes may also act as resources in the process of decision-making, which make the difference between a person with high-quality contextual data and a person with low-quality contextual data. Therefore, when a person is given high-quality contextual data for the experimental problem-solving tasks, a positive effect of contextual data quality on decision performance is expected. Based on the above discussion, the following hypotheses are proposed.

H1: Regardless of the levels of task complexity, subjects with high-quality contextual data will require less time than subjects with low-quality contextual data.

H1a: Subjects with high-quality contextual data for simple task will require less time than subjects with low-quality contextual data for simple task.

H1b: Subjects with high-quality contextual data for complex task will require less time than subjects with low-quality contextual data for complex task.

H2: Regardless of the levels of task complexity, problem-solving with high-quality contextual data will lead to an increase in problem-solving accuracy compared to problem-solving with low-quality contextual data.

H2a: Problem-solving with high-quality contextual data for simple task will lead to an increase in problem-solving accuracy compared to problem-solving with low-quality contextual data for simple task.

H2b: Problem-solving with high-quality contextual data for complex task will lead to an increase in problem-solving accuracy compared to problem-solving with low-quality contextual data for complex task.

2.4 Task Complexity

Task complexity is defined as the degree of cognitive load or mental effort required to identify and/or solve a problem [Payne, 1976]. Wood [1986] 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 [Campbell, 1988; Newell and Simon, 1972]. Rossano and Moak [1998] also suggest that mental workload increases as more data are evaluated and retained in working memory.

In addition, multi-criteria tasks are considered more complex than the elementary tasks [Crossland *et al.*, 1995; Jankowski, 1995; Swink and Speier, 1999]. Since multi-criteria tasks have a set of alternatives and a set of criteria, the decision maker must perform a series of information acquisition tasks and a series of information evaluation tasks. As more alternatives and criteria are added to the problem, more information must be processed and the task becomes more difficult [Newell and Simon, 1972].

Information systems are widely used to support decision-making tasks, particularly when solving complex problems. These complex tasks typically involve high cognitive loads that require significant attention and efforts, which provide detrimental influence on computer-based decision making [Baccker *et al.*, 1995; Robinson and Swink, 1994; Swink and Robinson, 1997]. In their data warehousing study, Speier and Morris [2003] demonstrated that decision maker performance was more accurate when task complexity was low. More recently, Roberts *et al.* [2004] investigated the effect of varying project complexity on the group interaction processes of IT project teams. The projects had two complex tasks and a less complex development task. They found that project complexity can affect the group interaction process. That is, as IT projects become more complex, more problems can lead to project failure.

Prior research has shown that as task complexity increases, task difficulty increases and at the same time decision makers take more time and produces less accurate outcomes. Based on the above discussion, the following hypotheses are presented.

H3: Regardless of the levels of contextual data quality, subjects with simple task will require less time than subjects with complex task.

H3a: Subjects with high-quality contextual data for simple task will require less time than subjects with high-quality contextual data for complex task.

H3b: Subjects with low-quality contextual data for simple task will require less time than subjects with low-quality contextual data for complex task.

H4: Regardless of the levels of contextual data quality, subjects with simple task will make more accurate decisions than subjects with complex task.

H4a: Subjects with high-quality contextual data for simple task will make more accurate decisions than subjects with high-quality contextual data for complex task.

H4b: Subjects with low-quality contextual data for simple task will make more accurate decisions than subjects with low-quality contextual data for complex task.

Ⅲ. Research Methodology

3.1 Experimental Design

Since a laboratory environment provides the control necessary to understand the causal relationship between the aspect of data quality (DQ) and the effects on decision performance, a laboratory experiment was appropriate for this study. In order to examine the proposed relationship, contextual data at two levels of quality (e.g., high vs. low) for both simple and complex tasks was given to subjects. That is, based on the two factors, contextual DQ (high vs. low) and task complexity (simple vs. complex), a2 x 2 factorial design was implemented to test the hypotheses. The various attributes of data quality (e.g., aggregated data, missing (incomplete) data, and irrelevant data) were used to map to the data type. Thus, contextual data at two levels of quality for both simple and complex tasks was operationalized by using these attributes of data quality.

Because different groups of subjects used data in the different combinations of contextual DQ and task complexity, decision performance was expected to vary depending on the combinations of data quality and task complexity. Each subject's decision performance was assessed based on predetermined measurement, and decision performance referred to solution time and the accuracy of problem-solving that most accomplished the objective for the decision task. Thus, the goal of the experiment to identify the effects of data quality on decision performance could be achieved.

A Web-based simple system to deliver the contextual data 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 data access tools that are being used in various functional areas in industry because the subjects accessed data through this system.

3.2 Procedures

The experimental task for this study asked subjects to solve a decision problem. The decision task and a set of data were given to them. The data set given to the subjects was fit for the decision task and delivered to them by a Web-based simple data access system developed for this study. 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 data set and the task, the subjects made decisions. Finally, this study observed the effects of the various treatments on decision performance.

3.3 Controls

Kerlinger and Lee [2000, 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 [Kerlinger and Lee, 2000]. 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.

One of important sources of extraneous variance is the possible effect of the measurement procedure, which is called *reactive* measures because they themselves cause the subject to react [Campbell, 1957]. For example, participants can learn in any given time, and the learning may affect dependent variable measures. That is, if participants are exposed to more than one experimental treatment condition, then they are more likely to learn later things that were included in the experiment. Consequently, participants become more efficient over time, and thus the later measurements are more accurate than earlier one. In short, if participants are exposed to more than one treatment condition, performance on later trials is affected by performance on earlier trials. Hence, observed changes in dependent variable measures may be due to learning effects. Because of learning effects, the subjects participated in this experiment were exposed to only one out of four experimental treatment conditions.

3.4 Independent Variables

Two levels of task complexity and two levels of contextual DQ were operationalized as independent variables.

3.4.1 Task Complexity

The decision task created by Jarvenpaa [2003] was used for this laboratory experiment, with some minor adjustments. It asks subjects to select a site for the construction of a Chinese restaurant. While the complex task asked subjects to select a site from among five alternative sites in which to locate a Chinese 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 were very important in deciding where the restaurant should be located. The scores for the factors were predetermined.

Two levels of task complexity (high and low) were used for this study. 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 the scores over the 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 the scores over the 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.

3.4.2 Contextual Data Quality

Attaining high-quality contextual data is a research challenge [Madnick, 1995; Strong *et al.*, 1997], because tasks and their contexts vary across time and data consumers [Wang and Strong, 1996]. Strong *et al.* [1997] found three main causes in general for data consumers' complaints that available data does not support their tasks: missing (incomplete) data, inadequately defined or measured data, and data that could not be appropriately aggregated. Based on their findings, it seems possible to infer that providing data consumers with relevant, complete, and aggregated data may add value to the tasks of data consumers and may be one of the ways to solve the contextual DQ problems. In addition, according to the framework of data quality [Wang and Strong, 1996], one of the contextual DQ attributes is an appropriate amount of data. Therefore, providing problem solvers with an appropriate amount of data relevant to the tasks of data consumers could be another way to solve the contextual DQ problems.

The second independent variable is contextual data at two levels of quality, referred to as high and low. The subjects supported with an appropriate amount of relevant, complete, and aggregated data were considered as being assigned to the experimental treatment of high-quality contextual data. On the other hand, the subjects considered as being assigned to the treatment of low-quality contextual data were given a limited amount of contextual data. That is, no aggregated data was given to the subjects who were assigned to the treatment of low-quality contextual data. In addition, they used irrelevant and incomplete data (see Appendix A). For example, a couple of numbers in the data set given to the subjects was missing. Therefore, the subjects had to go through extra steps to infer the information necessary to make decisions.

3.5 Dependent Variables

The dependent variable of this study is decision performance. Decision performance was operationalized as the accuracy of problem-solving and solution time. Problem-solving accuracy was measured by the number of correct answers from the correct solutions. That is, problem-solving 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 solution time as the total time in seconds the subjects required to select the best site from the candidates. That is, solution 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.* [2003] 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. Because time factors, pressure or constraints, affect decision-making [Ahituv *et al.*, 1998; Austin, 2001; Zakay and Wooler, 1984; Dukerich and Nichols, 1991], subjects were not informed of any time expectation for this experiment.

Ⅳ. Research Findings

A total of 40 undergraduate students from various academic programs at two large universities participated in the experiment and they were randomly assigned to one of the four treatments. Of the participants, 60 percent were male, and 71 percent were younger than age 25. The average age of participants was 23.9 years. The number of years in college was 2.5

years. Two-thirds of the participants were majoring in business administration.

Problem-solving accuracy and time were each analyzed with two-way ANOVAs. The tests were carried out at a 95% confidence level. SPSS 12.0 for Windows was used for the data analysis. Between-groups analysis of variance (ANOVA) tests were performed to capture any between-group variation across treatments. The descriptive statistics for the dependent variables are summarized in <Table 2>.

The interaction effect on problem-solving time between task complexity and contextual DQ was significant (p = .029, see <Table 3>). In addition, the results of the two-way ANOVA for time showed that the main effects of task complexity (p = .000) and contextual DQ (p = .000) were significant (see <Table 3>). Since the interaction effect on problem-solving time between task complexity and contextual DQ was significant, two one-way ANOVAs were performed for these variables. The one-way ANOVAs for time confirmed the significant main effects of task complexity (F = 108.549,

<Table 2> Descriptive Statistics for Problem-Solving Performance

Measures	Treatment Conditions			
	Simple Task		Complex Task	
	High Cont. DQ	Low Cont. DQ	High Cont. DQ	Low Cont. DQ
Solution Accuracy: (a higher score implies greater accuracy)				
Mean	97.917	47.500	97.917	74.444
Std. Dev.	4.0493	25.1692	1.6536	16.2993
n	10	10	10	10
Solution Time: (minutes: seconds)				
Mean	0:07:59	0:12:45	0:22:22	0:33:18
Std. Dev.	0:02:40	0:02:09	0:06:59	0:03:01
n	10	10	10	10

<Table 3> ANOVA Table for Two-Way Analysis of Problem-Solving Time: Task Complexity by Contextual DQ

Source	Type III Sum of Squares	Mean Square	F	Sig.
Corrected Model	24092401*	8030800	88.791	.000
Intercept	132295964	132295964	1462.71	.000
COMP	18018663	18018663	199.221	.000
CONT	5730386	5730386	63.357	.000
COMP * CONT	343351	343351	3.796	.029
Error	6873879	90445		
Total	163262245			
Corrected Total	30966280			

Note) * R Squared = .232 (Adjusted R Squared = .202)

<Table 4> ANOVA Table for Two-Way Analysis of Problem-Solving Accuracy: Task Complexity by Contextual DQ

Source	Type III Sum of Squares	Mean Square	F	Sig.
Corrected Model	18256*	6085.347	7.658	.000
Intercept	271833	271833.472	342.069	.000
COMP	483	483.472	.608	.438
CONT	17750	17750.868	22.337	.000
COMP * CONT	21	21.701	.027	.869
Error	60395	794.674		
Total	350484			
Corrected Total	78651			

Note) * R Squared = .232 (Adjusted R Squared = .202).

p = .000) and contextual DQ (F = 17.712, p = .000). The results indicated that the simple task was solved more quickly than the complex task. Therefore, H3 was supported. Also consistent with expectations, subjects using high contextual DQ took less time than subjects using low contextual DQ. That means, regardless of the levels of task complexity, problem-solving times with high contextual DQ were significantly shorter than with low contextual DQ. Therefore, H1 was supported.

The two-way ANOVA for problem-solving accuracy revealed no significant interaction effect between complexity and contextual DQ (p = .869, see <Table 4>). However, the ANOVA on problem-solving accuracy found a significant main effect for contextual DQ (p = .000, see <Table 4>). Therefore, H2 was supported. Surprisingly, the results of ANOVA for problem-solving accuracy showed that there was no significant main effect of task complexity for problem-solving accuracy (p = .438, see <Table 4>). Subjects completing the complex task had comparable problem-solving 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 problem-solving accuracy. Thus, H4 was rejected.

<Table 5> Summary of Hypotheses Testing

Hypotheses	Statistics		Evaluation
H1	F = 17.712	P = .000	Supported
H1a	F = 19.222	P = .000	Supported
H1b	F = 20.693	P = .000	Supported
H2	F = 22.337	P = .000	Supported
H2a	F = 39.112	P = .000	Supported
H2b	F = 18.474	P = .001	Supported
H3	F = 108.549	P = .000	Supported
H3a	F = 36.037	P = .000	Supported
H3b	F = 311.0	P = .000	Supported
H4	F = .608	P = .438	Rejected
H4a	F = .923	P = .349	Rejected
H4b	F = 3.775	P = .069	Rejected

However, it is interesting to note that the main effect of task complexity was significant for problem-solving 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 problem-solving 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. <Table 5> presents the results of testing the hypotheses of this study.

Ⅴ. Conclusions and Discussion

5.1 Discussion of Findings

For problem-solving accuracy, the interaction between task complexity and contextual DQ was not significant ($p = .869$), indicating these two variables do not jointly affect problem-solving accuracy. This is likely due to the insignificant main effect of task complexity ($p = .438$) on problem-solving accuracy. A more in-depth investigation was performed to see how the effect of contextual DQ might differ in different levels of task complexity. There was a significant mean difference between high (71.250) and low (40.417) contextual DQ in the effect of the simple task (see <Table 6>). That means, problem-solving using low contextual DQ led to lower problem-solving accuracy compared to problem-solving using high contextual DQ. There was also a significant mean difference between high (75.125) and low (46.375) contextual DQ in the effect of the complex task (see <Table 6>). That means, problem-solving using low contextual DQ led to lower problem-solving accuracy compared to problem-solving using high contextual DQ. Based on these results, it could be possible to infer that these significant differences resulted from the significant main effect of contextual DQ on problem-solving accuracy.

However, the difference between the contextual DQ effect in the simple task effect (e.g.,

<Table 6> Table for Mean Values of Problem-Solving Accuracy: Task Complexity by Contextual DQ

Comp.	Cont. DQ	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Simple Task	High	71.250	4.286	62.705	79.795
	Low	40.417	4.286	31.872	48.962
Complex Task	High	75.125	4.286	66.580	83.670
	Low	46.375	4.286	37.830	54.920

<Table 7> Table for Mean Values of Problem-Solving Time: Task Complexity by Contextual DQ

Comp.	Cont. DQ	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Simple Task	High	10:09	04:13	08:11	12:06
	Low	16:53	06:11	14:56	18:50
Complex Task	High	23:47	05:38	21:50	25:44
	Low	34:53	03:31	32:56	36:50

71.250 - 40.417 = 30.833) and the contextual DQ effect in the complex task effect (e.g., 75.125 - 46.375 = 28.750) was not significant (e.g., 30.833 - 28.750 = 2.083). It appears that this insignificant difference resulted from the insignificant main effect of task complexity. Thus, the insignificant main effect of task complexity on problem-solving accuracy led to the insignificant interaction between task complexity and contextual DQ despite the significant contextual DQ effect on problem-solving accuracy.

A two-way interaction between-groups ANOVA was executed to capture any interaction between-group variation across treatments for problem-solving time. The interaction between task complexity and contextual DQ was significant ($p = .029$), indicating these two variables jointly affect problem-solving time. The significant interaction effect between task complexity and contextual DQ indicates that there was significant difference in the effect of contextual DQ on problem-solving time for both simple and complex tasks (see <Table 7>). More time was needed for both simple and complex tasks with low contextual DQ than for those tasks with high contextual DQ. Based on these results, it could be possible to infer that low contextual DQ made the decision tasks more difficult to solve, which in turn required more time. The potential explanation for these results probably lies in the low quality contextual data used. As expected, the low quality contextual data used in this study includes irrelevant and incomplete data. In addition, no aggregated data was provided. As a result, subjects using the low quality contextual data needed additional time to deal with the low quality contextual data as well as the decision tasks.

Another finding, the interaction effect, is that the mean difference between high and low contextual DQ in the effect of the complex task is greater than the difference between high and low contextual DQ in the effect of the simple task (see <Table 7>). This indicates that in comparison to the simple task, low contextual DQ might make the complex task more difficult to solve, which in turn detrimentally affects problem-solving time.

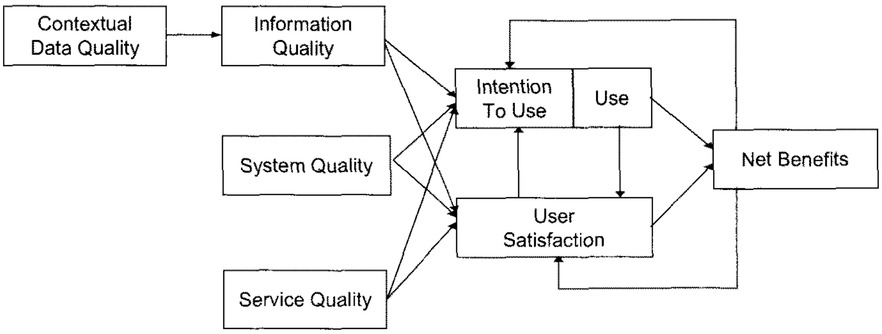
5.2 Implications for Research

The findings of this study may help IS researchers see the impact of contextual DQ on problem-solving performance from a theoretical point of view. The perspective offered by several of the authors cited earlier in this paper sees data as a set of simple, discrete, objective facts that become information as they are combined into meaningful structures or endow relevance and purpose [Tuomi, 1999; Davenport and Prusak, 1998; Spek and Spijkervet, 1997; Wiig, 1993]. Based on this perspective, this research assumed that data is a prerequisite for information and information can be created from its raw data. DeLone and McLean [1992] defined information quality as the quality of the information system output and postulated that system quality and information quality singularly and jointly affect both system use and user satisfaction that are direct antecedents of individual impact. In their later study [2003], they reviewed and analyzed over 285 articles that referenced the original IS success model in order to examine recent contributions to IS success measurement. After reviewing these studies, they proposed an updated IS Success

Model that includes those contributions. The changes in the updated IS Success Model are the addition of service quality and the integration of individual and organizational impacts into net benefits. According to them, as a result of system use and user satisfaction, certain net benefits will occur. In addition, there are many empirical studies to support the effects of information quality on individual performance [Etezadi-Amoli and Farhoomand, 1996; Guimaraes and Igbaria, 1997; Igbaria and Tan, 1997; Seddon and Kiew, 1994; Torkzadeh and Doll, 1999; Teo and Wong, 1998; Wixom and Watson, 2001; Yuthas and Young, 1998]. Thus, based on DeLone and McLean's model, the assumption mentioned above, and a review of the relevant literature, this study predicted that improved data quality would positively affect information quality, which affects both system use and user satisfaction, which in turn have an impact on net benefits including user performance.

The results of this study showed that the effect of contextual DQ influence problem-solving efficiency and effectiveness. Thus, the findings of this study are consistent with the IS success model. However, what is lacking is a detailed model for describing how data (quality) is transformed into information (quality), the strength of the relationship between data (quality) and information (quality), and the strength of the relationship between information (quality), once transformed, and user performance. One area for future research would be to develop a model examining the transformation of data (quality) into information (quality).

In summary, although there is no considerable empirical evidence in the IS literature discussing how data (quality) transforms into information (quality), with the assumption that information can be created from its raw data, the results of this study partially support the IS success model [DeLone and McLean, 1992; 2003] in suggesting that information quality has an impact on user performance. That means, the analyses of research into the performance of contextual DQ on problem-solving accuracy and time show that data quality as an antecedent of information quality has an impact on user performance. <Figure 1> presents a model for extending the updated IS success model by recognizing and including the contextual aspect of DQ into the model.



<Figure 1> IS Success Model with Contextual Data Quality

5.3 Implications for IS Practitioners

The observed main effect of contextual DQ on problem-solving performance has important practical implications for enhancing the efficiency and effectiveness of problem-solving. In order to improve users' ability to analyze data and make decisions, systems designers and managers should not only make data available to users, but also enable users to access better (high-quality) data. To accomplish this, it is recommended that systems designers and managers examine the nature of the task to be performed. They should then support the task by providing users not only with high-quality representational data that matches the task [Vessey, 1991], but also with high-quality contextual data that are complete and relevant to the task. Large database management systems such as data warehouses have continued to be well ingrained into the business environment as one of the most important strategic initiatives in the information systems field [Watson, 2001] and a dedicated source of data to support decision-making applications [Gray and Watson, 1998]. As organizations increasingly adopt distributed repositories such as data warehouses, it seems clear that various kinds of valuable information can be dispersed across the information systems in an organization. Strong *et al.* [1997] also found some contextual DQ problems caused by integrating data across distributed systems. Thus, in order to enable users access high-quality data, systems designers, builders, and database administrators should ensure the integrity of data in such distributed data warehouses.

5.4 Limitations and Future Research

Although this study provided a number of findings and conclusions that will be useful for improving our understanding of the impact of contextual DQ on problem-solving performance, 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 subjects' capability and characteristics, the decision support applications, the task type, and the set of data 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.

In addition, data were collected from a small sample of 40 students. The findings of this study might not generalize to a broader population. Because a single empirical study is not sufficient to validate the findings, further research should address these limitations and apply the findings of this study in specific contexts, population, and decision support technology as a whole.

Finally, this study used college students as subjects, many of who had no significant problem-solving experiences as compared to decision makers in practice. When significant results are obtained in the college laboratory using students, it is useful to replicate the experiment with subjects from organizations to determine if the results still hold. Therefore, a replication study adopting the same research design could be useful as a future research project. But, the future research should be conducted with ongoing subjects from organizations. This future study may extend this study in more detail by examining two different types of problem solvers. Moreover, decision makers in practice frequently meet much more complex decisions and the information necessary to make decisions in practice may vary among organizations and decision types. Future research should test whether the findings of this study still hold in more complex decision environments.

〈참 고 문 헌〉

[1] Ahituv, N., "A Systematic Approach Toward Assessing the Value of an Information Systems," *MIS Quarterly*, Vol. 4, No. 4, December 1980, pp. 61-75.

[2] Ahituv, N., Igbaria, M., and Stella, A., "The Effects of Time Pressure and Completeness of Information on Decision Making," *Journal of Management Information Systems*, Vol. 15, No. 2, 1998, pp. 153-172.

[3] Aldag, R.J. and Power, D.J., "An Empirical Assessment of Computer-Assisted Decision Analysis," *Decision Sciences*, Vol. 17, No. 4, Fall 1986, pp. 572-588.

[4] Austin, R.D., "The Effects of Time Pressure on Quality in Software Development: An Agency Model," *Information Systems Research*, Vol. 12, No. 2, 2001, pp. 195-207.

[5] Baccker, R.M., Grudin, J., Buxton, W.A.S., and Greenberg, S., "Readings in Human-Computer Interaction: Towards the Year 2000," San Francisco: Morgan Kauffman, 1995.

[6] Benbasat, I., DeSanctis, G., and Nault, B.R., "Empirical Research in Managerial Support Systems: A Review and Assessment," In *Recent Developments in Decision Support Systems*, Holsapple, C. and Whinston, A.H .(eds.). NATO ASI Series F: Computer and System Sciences, Vol. 101, Springer-Verlag Publishers, 1993, pp. 383-437.

[7] Benbasat, I. and Dexter, A.S., "Value and Events Approaches to Accounting: An Experimental Evaluation," *The Accounting Review*, Vol. 54, No. 4, October 1979, pp. 735-749.

[8] Benbasat, I. and Dexter, A.S., "An Investigation of the Effectiveness of Color and Graphical Information Presentation Under Varying Time Constraints," *MIS Quarterly*, Vol. 10, No. 1, March 1986, pp. 59-83.

[9] Benbasat, I. and Schroeder, R.G., "An Experimental Investigation of Some MIS Design Variables," *MIS Quarterly*, Vol. 1, No. 1, May 1977, pp. 37-49.

[10] Benbasat, I. and Taylor, R.N., "Behavioral Aspects of Information Processing for the Design of Management Information Systems," *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. SMC-12, No. 4, July-August, 1982, pp. 439-450.

[11] Brown, P.J. and Jones, G.J.F., "Context-aware Retrieval: Exploring a New Envi-

ronment for Information Retrieval and Information Filtering," *Personal and Ubiquitous Computing*, Vol. 5, No. 4, Jan. 2001, pp. 253-263.

[12] Brown, P.J. and Jones, G.J.F., "Exploiting Contextual Change in Context-Aware Retrieval," *Proceedings of the 2002 AGM Symposium on Applied Computing*, March 2002, pp. 650-656.

[13] Campbell, D., "Factors Relevant to the Validity of Experiments in Social Settings," *Psychological Bulletin*, Vol. 54, 1957, pp. 297-312.

[14] Campbell, D.J., "Task Complexity: A Review and Analysis," *Academy of Management Review*, Vol. 13, No. 1, 1988, pp. 40-52.

[15] Chervany, N.L. and Dickson, G.W., "An Experimental Evaluation of Information Overload in a Production Environment," *Management Science*, Vol. 20, No. 10, June 1974, pp. 1335-1349.

[16] Crossland, M.D., Wynne, B.E., and Perkins, W.C., "Spatial Decision Support Systems: An Overview of Technology and a Test of Efficacy," *Decision Support Systems*, Vol. 14, 1995, pp. 219-235.

[17] Culnan, M., "The Dimensions of Accessibility to Online Information: Implications for Implementing Office Information Systems," *ACM Transactions on Office Information Systems*, Vol. 2, No. 2, 1984, pp. 141-150.

[18] Davenport, T.H., "*Information Ecology: Mastering the Information and Knowledge Environment*," New York: Oxford University Press, 1997.

[19] Davenport, T.H. and Prusak, L., "Working Knowledge: How Organizations Manage What They Know," *Boston: Harvard Business School Press, 1998.*

[20] DeLone, W.H. and McLean, E.R., "Information Systems Success: The Quest for The Dependent Variable," *Information Systems Research*, Vol. 3, No. 1, 1992, pp. 60-95.

[21] DeLone, W.H. and McLean, E.R., "The DeLone and McLean Model of Information Systems Success: A Ten-Year Update," *Journal of Management Information Systems*, Vol. 19, No. 4, Spring 2003, pp. 9-30.

[22] DeSanctis, G. and Gallupe, R.B., "A Foundation for the Study of Group Decision Support Systems," *Management Science*, Vol. 33, No. 5, May 1987, pp. 589-609.

[23] DeSantis, G. and Jarvenpaa, S.L., "An Investigation of the 'Tables Versus Graphs' Controversy in a Learning Environment," *Proceedings of the Sixth International Conference on Information Systems*, December 1985, pp. 134-144.

[24] Dhaliwal, J.S. and Benbasat, I., "The Use and Effects of Knowledge-Based System Explanations: Theoretical Foundations and a Framework for Empirical Evaluation," *Information Systems Research*, Vol. 17, No. 3, Sep. 1996, pp. 342-362.

[25] Dickson, G., DeSanctis, G., and McBride, D.J., "Understanding the Effectiveness of Computer Graphics for Decision Support: A Cumulative Experiment Approach," *Communications of the ACM*, Vol. 29, No. 1, January 1986, pp. 40-47.

[26] Dourish, P., Bellotti, V., Mackay, W., and Ma, C.Y., "Information and Context: Les-

sons from a Study of Two Shared Information Systems," *Proceedings of the Conference on Organizational Computing Systems*, December 1993, pp. 42-51.

[27] Dukerich, J.M. and Nichols, M.L., "Causal Information Search in Managerial Decision Making," *Organizational Behavior and Human Decision Making Processes*, Vol. 50, 1991, pp. 106-122.

[28] Eierman, M.A., Niederman, F., and Adams, C., "DSS theory: A model of Constructs and Relationships," *Decision Support Systems*, Vol. 14, 1995, pp. 1-26.

[29] Etezadi-Amoli, J. and Farhoomand, A.F., "A Structural Model of End User Computing Satisfaction and User Performance," *Information and Management*, Vol. 30, No. 2, 1996, pp. 65-73.

[30] Fisher, C.W., Chengalur-Smith, I., and Ballou, D.P., "The Impact of Experience and Time on the Use of Data Quality Information in Decision Making," *Information Systems Research*, Vol. 14, No. 2, June 2003, pp. 170-188.

[31] Gallagher, C.A., "Perceptions of the Value of a Management Information Systems," *Academy of Management Journal*, Vol. 17, No. 1, March 1974, pp. 46-55.

[32] Goul, M., Shane, B., and Tonge, F.M., "Using a Knolwedge-Based Decision Support System in Strategic Planning Decisions: An Empirical Study," *Journal of MIS*, Vol. 2, No. 4, Spring 1986, pp. 70-84.

[33] Gray, P. and Watson, H.J., *Decision Support in the Data Warehouse, Upper Saddle River*, New Jersey: Prentice Hall, 1998.

[34] Gregor, S. and Benbasat, I., "Explanations from Knowledge-based Systems: A review of Theoretical, Foundations and Empirical work," *MIS Quarterly*, Vol. 23, No. 4, 1999, pp. 497-530.

[35] Grudnitski, G., "A Methodology for Eliciting Information Relevant to Decision-Makers," *Proceedings of the Second International Conference on Information Systems*, December 1981, pp. 105-120.

[36] Guimaraes, T. and Igbaria, M., "Client/Server System Success: Exploring the Human Side," *Decision Sciences*, Vol. 28, No. 4, 1997, pp. 851-875.

[37] Iivari, J. and Koskela, E., "The PIOCO Model for Information Systems Design," *MIS Quarterly*, Vol. 11, No. 3, September 1987, pp. 401-419.

[38] Igbaria, M. and Tan, M., "The Consequences of the Information Technology Accenptance on Subsequent Individual Performance," *Information and Management*, Vol. 32, No. 3, 1997, pp. 113-121.

[39] Jankowski, P., "Integrating Geographical Information Systems and Milti Criteria Decision-Making Methods," *International Journal of Geographical Information Systems*, Vol. 9, 1995, pp. 251-273.

[40] Jarvenpaa, S.L., "Additive-Difference Task: Ying-Yang Corporation Site Selection," Indiana University Kelley School of Business, (available online at *http://kelley.iu.edu/bwheeler/ISWorld/index.cfm*; accessed Nov. 1, 2003).

[41] Jul, S. and Furnas, G.W., "Navigation in Electronic Worlds," *Nav 97 Report*, 1997.

[42] Kerlinger, F.N. and Lee, H.B., *Foundation of Behavioral Research*, Harcourt College Publishers, 2000.

[43] King, W.R. and Epstein, B.J., "Assessing

Information Systems Value," *Decision Sciences*, Vol. 14, No. 1, January 1983, pp. 34-45.

[44] King, W.R. and Rodriguez, J.I., "Participative Design of Strategic Decision Support Systems," *Management Science*, Vol. 27, No. 6, June 1981, pp. 717-726.

[45] Larcker, D.F. and Lessig, V.P., "Perceived Usefulness of Information: A Psychometric Examination," *Decision Sciences*, Vol. 11, No. 1, January 1980, pp. 121-134.

[46] Lucas, H.C. and Nielsen, N.R., "The Impact of the Mode of Information on Learning and Performance," *Management Science*, Vol. 26, No. 10, October 1980, pp. 982-993.

[47] Madnick, S., "Integrating Information from Global Systems: Dealing with the "On- and Off-Ramps" of the Information Superhighway," *Journal of Organizational Computing*, Vol. 5, No. 2, 1995, pp. 69-82.

[48] Nah, F.H., Mao, J., and Benbasat, I., "Effectiveness of Using Expert Support Technology for Individual and Small Group Decision Making," *Journal of Information Technology*, Vol. 14, 1999, pp. 137-147.

[49] Newell, A. and Simon, H.A., *Human Problem Solving*, Englewood, Cliffs, NJ: Pretice-Hall, 1972.

[50] Olson, M.H. and Lucas, H.C., "The Impact of Office Automation on the Organization: Some Implications for Research and Practice," *Communications of the ACM*, Vol. 25, No. 11, November 1982, pp. 838-847.

[51] Park, J. and Kim, J., "Effects of Contextual Navigation Aids on Browsing Diverse Web Systems," *Proceedings of SIGCHI Conference on Human Factors in Computing Systems*, Vol. 1, No. 6, April 2000, pp. 257-264.

[52] Payne, J.W., "Task Complexity and Contingent Processing in Decision Making: An Information Search and Protocol Analysis," *Organizational Behavior and Human Performance*, Vol. 16, 1976, pp. 366-387.

[53] Roberts, T.L., Cheney, P.H., Sweeney, P.D., and Hightower, R.T., "The Effects of Information Technology Project Complexity on Group Interaction," *Journal of Management Information Systems*, Vol. 21, No. 3, Winter 2004-2005, pp. 223-248.

[54] Robinson, E.P. Jr, and Swink, M., "Reason Based Solution and the Complexity of Distribution Network Design Problems, *European Journal of Operational Research*, Vol. 76, 1994, pp. 393-409.

[55] Rossano, M.J. and Moak, J., "Spatial Representation from Computer Models: Cognitive Load, Orientation Specificity and the Acquisition of Survey Knowledge," *British Journal of Psychology*, Vol. 89, No. 3, August 1998, pp. 481-497.

[56] Seddon, P.B. and Kiew, M.Y., "A Partial Test and Development of the DeLone and McLean Model of IS Success," in J.I. DeGross, S.L. Huff, and M.C. Munro (eds.), *Proceedings of the International Conference on Information Systems*, Atlanta, GA: Association for Information Systems, 1994, pp. 99-110.

[57] Sharda, R., Barr, S.H., and McDonnell, J.C., "Decision Support System Effectiveness: A Review and an Empirical Test," *Management Science*, Vol. 34, No. 2, 1988, pp. 139-159.

[58] Silver, M.S., "Decision Support Systems:

Directed and non-directed change," *Information Systems Research*, Vol. 1, No. 1, 1990, pp. 47-70.

[59] Speier, C. and Morris, M.G., "The Influence of Query Interface Design on Decision-Making Performance," *MIS Quarterly*, Vol. 27, No. 3, 2003, pp. 397-424.

[60] Spek, R.V.D. and Spijkervet, A., *Knowledge Management: Dealing Intelligently with Knowledge*, Utrecht: Kenniscentrum CIBIT, 1997.

[61] Stephenson, B.Y., "Management by Information," Information Strategy: *The Executive's Journal*, Vol. 1, No. 4, 1985 Summer, pp. 26-32.

[62] Strong, D.M., Lee, Y.W., and Wang, R.Y., "Decision Support for Exception Handling and Quality Control in Office Operations," *Decision Support Systems*, Vol. 8, No. 3, 1997, pp. 217-227.

[63] Swink, M. and Robinson, R.P., "Complexity Factors and Intuition-Based Methods for Facility Network Design," *Decision Sciences*, Vol. 28, 1997, pp. 583-614.

[64] Swink, M. and Speier, C., "Presenting Geographic Information: Effects on Data Aggregation, Dispersion, and Users' Spatial Orientation," *Decision Sciences*, Vol. 30, No. 1, Winter 1999, pp. 169-196.

[65] Teo, T.S.H. and Wong, P.K., "An Empirical Study of the Performance Impact of Computerization in the Retail Industry," *Omega - The International Journal of Management Science*, Vol. 26, No. 5, 1998, pp. 611-621.

[66] Torkzadeh, G. and Doll, W.J., "The Development of a Tool for Measuring the Perceived Impact of Information Technology on Work," *Omega - The International Journal of Management Science*, Vol. 27, No. 3, 1999, pp. 327-339.

[67] Tuomi, I., "Data Is More Than Knowledge: Implications of the Reversed Knowledge Hierarchy for Knowledge Management and Organizational Memory," *Journal of Management Information Systems*, Winter, Vol. 16, No. 3, 1999, pp. 103-117.

[68] Vessey, I., "Cognitive Fit: A Theory Based Analysis of The Graphs Versus Tables Literature," *Decision Sciences*, Vol. 22, 1991, pp. 219-241.

[69] Vogel, D., Lehman, J.A., and Dickson, G.W., "The Impact of Graphical Displays on Persuasion: An Empirical Study," *Proceedings of the Seventh International Conference on Information Systems*, December 1986, pp. 240-254.

[70] Wang, R.Y. and Strong, D.M., "Beyond Accuracy: What Data Quality Means to Data Consumers," *Journal of Management Information Systems*, Spring 1996, Vol. 12, No. 4, pp. 5-34.

[71] Watson, H.J., "Recent Developments in Data Warehousing," *Communications of the Association for Information Systems*, Vol. 8, 2001, pp. 1-25.

[72] Watson, C.J. and Driver, R.W., "The Influence of Computer Graphics on the Recall of Information," *MIS Quarterly*, Vol. 7, No. 1, March 1983, pp. 45-53.

[73] Wiig, K.M., "*Knowledge Management Foundations: Thinking About Thinking - How People and Organizations Create, Represent, and Use Knowledge*," Arlington, TX: Schema Press, 1993.

[74] Wixom, B.H. and Watson, H.J., "An Em-

pirical Investigation of the Factors Affecting Data Warehousing Success," *MIS Quarterly*, Vol. 25, No. 1, 2001, pp. 17-41.

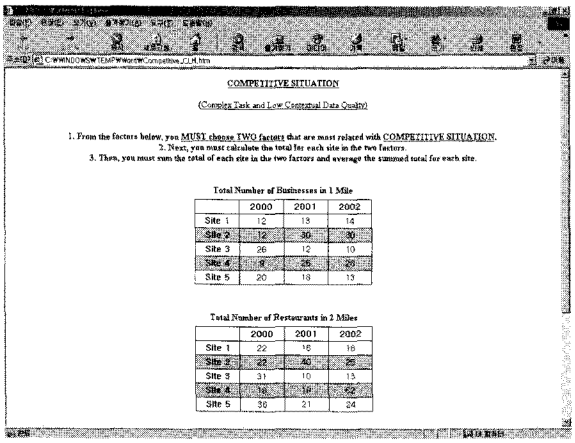
[75] Wood, R., "Task Complexity: Definition of the Construct," *Organizational Behavior and Human Decision Processes*, Vol. 37, 1986, pp. 60-82.

[76] Yuthas, K. and Young, S.T., "Material Matters: Assessing the Effectiveness of Materials Management IS," *Information and Management*, Vol. 33, No. 3, 1998, pp. 115-124.

[77] Zakay, D. and Wooler, S., "Time Pressure, Training, and Decision Effectiveness," *Ergonomics*, Vol. 27, 1984, pp. 273-284.

[78] Zmud, R.W., "An Empirical Investigation of the Dimensionality of the Concept of Information," *Decision Sciences*, Vol. 9, No. 2, April 1978, pp. 187-195.

Appendix A



COMPETITIVE SITUATION

(Complex Task and Low Contextual Data Quality)

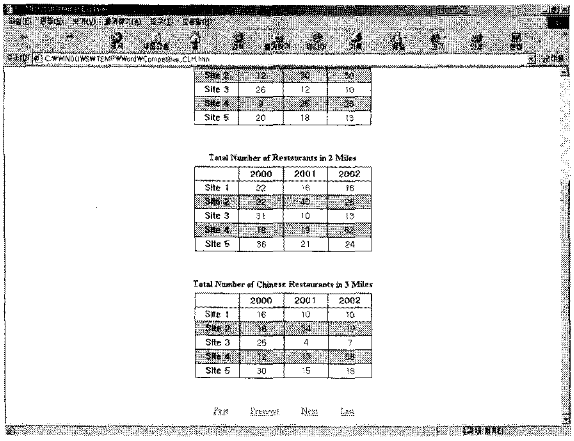
1. From the factors below, you MUST choose TWO factors that are most related with COMPETITIVE SITUATION.
2. Next, you must calculate the total for each site in the two factors.
3. Then, you must sum the total of each site in the two factors and average the summed total for each site.

Total Number of Businesses in 1 Mile

	2000	2001	2002
Site 1	12	13	14
Site 2	12	30	30
Site 3	26	12	10
Site 4	9	25	28
Site 5	20	18	13

Total Number of Restaurants in 2 Miles

	2000	2001	2002
Site 1	22	16	16
Site 2	22	40	25
Site 3	31	10	13
Site 4	18	19	62
Site 5	36	21	24



Site 2	12	30	30
Site 3	26	12	10
Site 4	9	25	28
Site 5	20	18	13

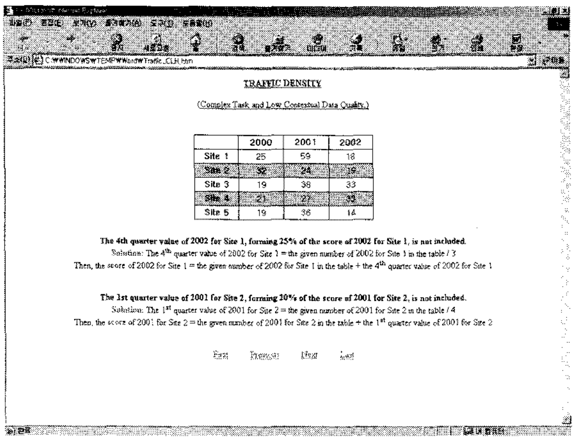
Total Number of Restaurants in 2 Miles

	2000	2001	2002
Site 1	22	16	16
Site 2	22	40	25
Site 3	31	10	13
Site 4	18	19	62
Site 5	36	21	24

Total Number of Chinese Restaurants in 3 Miles

	2000	2001	2002
Site 1	16	10	10
Site 2	18	34	19
Site 3	25	4	7
Site 4	12	13	58
Site 5	30	15	18

First Previous Next Last



TRAFFIC DENSITY

(Complex Task and Low Contextual Data Quality.)

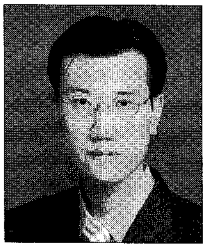
	2000	2001	2002
Site 1	25	59	18
Site 2	32	24	19
Site 3	19	38	33
Site 4	21	27	33
Site 5	19	36	14

The 4th quarter value of 2002 for Site 1, forming 25% of the score of 2002 for Site 1, is not included.
Solution: The 4th quarter value of 2002 for Site 1 = the given number of 2002 for Site 1 in the table / 3
Then, the score of 2002 for Site 1 = the given number of 2002 for Site 1 in the table + the 4th quarter value of 2002 for Site 1

The 1st quarter value of 2001 for Site 2, forming 20% of the score of 2001 for Site 2, is not included.
Solution: The 1st quarter value of 2001 for Site 2 = the given number of 2001 for Site 2 in the table / 4
Then, the score of 2001 for Site 2 = the given number of 2001 for Site 2 in the table + the 1st quarter value of 2001 for Site 2

First Previous Next Last

◆ 저자소개 ◆



정원진 (Jung, Won-jin)
수원대학교 전자계산학과를 졸업하고, University of Wisconsin - Milwaukee에서 석사, Claremont Graduate University에서 박사학위를 받았다. 현재 단국대학교 상경대학 경영정보학과에 재직하고 있다. 주요 관심분야는 데이터 품질, 데이터 웨어하우징, 의사결정지원 시스템, 지식정보 시스템, e-비즈니스 등이다.

김종원 (Kim, Jong-Weon)
인하대학교 경영학과를 졸업하고, University of Nebraska-Lincoln에서 MBA와 박사학위를 취득하였으며, 현재 동의대학교 경영정보학과의 부교수로 재직하고 있다. Asia Pacific Management Review, 경영학연구, 경영과학, 대한경영학회지 등에 논문을 게재하였으며, 주요 관심분야는 정보기술의 수용 및 응용, 지식경영, e-비즈니스, DSS 등이다.

◈ 이 논문은 2004년 10월 7일 접수하여 1차 수정을 거쳐 2005년 5월 30일 게재확정되었습니다.