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컴퓨터 정보의 부하가 시장분류 의사결정에 미치는 영향: 실험연구

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Effects Of Computer-Based Information Load On Market Categorization Decision: An Experiment

As the use of information technology continues to bring a dramatic increase in the amount of data available to managers, researchers have noted that having too much data can be as much of a problem as having too little. It becomes very important to understand the effects of "information explosion" on the way managers perform their work. This study examines the effect of the amount of available data on the process and outcome of thinking within a context where managers are equipped with computing tools. The purpose of this study is to better understand how managers respond cognitively to increased information availability.

In this experiment with 104 MBAs three groups of subjects were asked to identify high and low potential market categories for effective direct mail sales based on three different amount of computer-based socioeconomic data designed based on existing research on cognition and information overload. Analyses of the outcomes showed that the group with medium amount of data used data and computer-based analysis tools most effectively and efficiently. We expect that the study will provide us a base to relate future MIS research to theories on cognition in such related fields as psychology and organizational behavior.

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1. Introduction

The widespread use of computer-based technology has brought a dramatic increase both in the amount of data available to managers and in the sophistication of the tools used to analyze these data. It is anticipated that "information availability will continue to increase at least in the near future as technologies mature and become more widely used" [Huber and Daft, 1987]. As this trend continues, researchers have noted that having too much data can be as much of a problem as having too little. It becomes very important to systematically understand the effects of "information explosion" on the way managers perform their work and make decisions.

Vast amounts of data are now collected from varioussources using information technologies. During the same period of time, the adoption of personal computers, workstations, and user-friendly data management anddecision support software have presented managers with a substantial increase in data manipulation capacity.

These changes in information environment bring managers both new opportunities and new threats.One promising expectation is that the "informated" managers may think and make sense more rapidly and more smartly [Zuboff, 1988]. Further, the increased data availability and the enhanced capacity to manipulate data may enable managers to judge and interpret situations differently [Rockart and DeLong, 1988].

The increase of data, however, has not always been considered desirable. Individualsoverloaded byexcessive information may misinterpret or bias its meaning so that outcomes of organizational activity are affected [Huber and Daft, 1987].

This study examines the effect of the amount of available data on the process and outcome of thinking within a context where managers are equipped with computing tools. The purpose of the study is to better understand how managers respond cognitively to increased information availability and how theyuse data manipulation tools in the process of thinking.

We expect that improved understanding of the relationship between information availabilityand managers' cognition will contribute to improving the use of new technologies and can facilitate managers' thinking [Ramaprasad,1987; Rockart and DeLong, 1988]. The result will also provide us with practical guidelines for managing data provision.

2. Conceptual Background

2.1. Information Technology and Cognition

The role of managers' cognition and its importance in organizational activities have long been discussed. Managerial cognition includes complicated cognitive processes including problem solving, decision making, interpretation, and sense-making [Simon, 1960; Isabella, 1990; Lave, 1988]. Cognitive organization theory explains how the memberswithin an organization produce, process, and share information and its meaning [Bougon, Weick, and Binkhorst, 1977]. In the organizational information processing (OIP) paradigm, individual's cognitive processes were considered to play an important role in interpreting and sharing the meaning of environmental signals in coping with uncertainty [Daft and Weick, 1984].

Recently, managerial cognition has also received much attention among researchers in more applied disciplines such as strategic management and marketing. According to Ginsberg (1989), "… not the markets, technologies, or number of businesses, etc., but the logic that managers use determines business strategy." For this reason, cognition is considered to have the potential to explain the "missing-link" between individual and organizational level phenomena [Stubbart, 1989]. In marketing management, researchers in the "cognitive sales" paradigm studied how sales managers organize and store information about customers, sales situations, and sales strategies. They found that sales managers' cognition and knowledge are closely related to selling effectiveness [Szymanski and Churchill, 1990; Sujan, Sujan, and Bettman, 1988].

Effects of using technological artifacts on such aspects as managers' thinking, mental models, and sense making has only recently emerged as an issue of interest among information systems researchers. For example, in their study on executive information systems, Rockart and DeLong (1988) observed evidence that an increase in available data caused by the use of information technology enhanced managers' cognition or mental models. The use of decision aiding tools, graphics management tools, and spreadsheets can help managers aggregate, modify, and transform the contents and forms of data more efficiently by speeding up these processes [Sharda, Barr, and McDonnell, 1988].

Recently a series of research was performed that focused on the internal cognitive process of information processing among systems users. The major question being probed by the researchers in this stream is "what happens while users perform their tasks using computer-based information through information systems". For example, Todd and Benbasat(1991, 1992) extended Payne's(1976) "cognitive effort" study on preference choice behavior by computerizing experimental instruments and by focusing on user's attempt to minimize cognitive efforts in solving a similar problem. They found that in solving a preference choice problem, subjects tried to use information search strategies that minimize cognitive efforts(e.g. Elimination By Aspects or EBA strategy) rather than pursuing strategies that ensure decision quality(e.g. Additive-Compensatory or Additive-Difference strategy).

Based on "cognitive fit" model, Vessey and Galletta(1991) and Umananth and Vessey(1991) suggested that focusing on task differences will be more effective in imporving performance than focusing on individual differences. They suggested that a fit between problem representation and problem type produce high performance, and studied the effect of problem representation(form of data: e.g. graph or table) on the cognitive process and problem solving performance. They found that a match between task and problem representation (spatial repretation to spatial problems, symbolic rpresentation to symbolic problems) improved performance [Vessey and Galletta, 1991]. They also found that their subjects preferred tables and symbolic problems to graphs and spatial problems.

Mackay and Elam(1992) performed a protocol analysis study to examine the effects of task and spreadsheet knowledge on problem solving processes. They found that strategies used by individuals were affected by spreadsheet skill. The strategies used by subjects who had expertise in the functional area but did not have enough spreadsheet skill were different from those who had expertise both in the functional area and spreadsheet. Further, the strategies used by subjects who were functional area experts/spreadsheet novices were closer to the strategies used by functional area novices/spreadsheet novices or functional area novices/spreadsheet experts.

In summary, managers face two on-going trends: increasing volume of data (especially, computer–based data) and the formation of information technology–based task environment. Both the two trends are considered closely related to managers' thinking. Considering these factors at the same time, we will focus our research on managers' cognition by examining the information technology–based information environment and the information overload issue simultaneously. Specifically, we will study how managers perform a cognitive task using data manipulation aids when they receive varying amount of computer–based data.

2.2. Information Provision and Overload

Although individuals' processing capacity may vary depending on such aspects as the amount of prior knowledge, information handling skills, expertise, repetition, training, or ability to make chunks of information [Sternberg, 1986], they may not benefit from the provision of information exceeding their bounded capacity or the "integrative complexity" of a system to process information [Driver and Streufert, 1969]. If the information processing needs exceed an individual's processing ability, an "information overload" would occur, and it could result in undesirable consequences such as a decrease of performance [Miller, 1977]. Driver and Streufert(1969) suggested that an optimal level of input load exists for every system, and system's performance show a curvilinear pattern.They said productivity would increase only until the input load reaches this "characteristic level of integrative complexity".

Inspite of the extensive list of psychological research on information overload, it has not been easy to draw enough implcation for information systems research in management context [Chervany and Dickson, 1974]. Several management researchers have also investigated into the overload phenomena. Most of these studies used an experimental method in their research with the premise that if subjects were overloaded in the experimental settings, which have a relatively simplified information environment, overload would also occur under more complex real–world circumstances [Jacoby, 1984]. Some representative results from communications and consumer behavior research are summarized in [Table 1].

O'Reilly(1980) found a negative correlation($r = -.12$ and $-.19$ at $p < .05$) between a perceptual measure of overload and supervisor rated performance, and a positive correlation($r=.20$ at $p<.05$) between reported overload and error rate. He further found some positive relationships between overload and several job satisfaction measures(between .11 and .34 at $p<.01$). Since he used broad measures of information load, performance, and job satisfaction, he had difficulty in understanding how certain uses of information caused overload effects.

In an effort to find implications of information overload for information systems design, Chervany and Dickson(1974) experimentally examined the effect of summarizing on decision making. They presented hard copies of raw and summarized production management data, and asked subjects to make operating decisions on production schedule and raw material order. They found evidence that users of statistically summarized data produced better decision output($p=.18$), took longer time($p=.05$), and were less confident($p=.12$). While no formal operational definition of overload was used, both the amount of raw and summarized data used in the experiment were fairly large: the raw data was ten pages report of computer output with 1040 data items, and the summarized data was seven pages long with 449 data items.

Researchers of consumer behavior have studied the relationship between the amount of information provided and consumer's purchasing decisions [Bettman, 1979]. Experimental research methods were used to examine the effect of information load.A two dimensional format of information(alternatives by attributes) has been commonly used in the "overload paradigm" of consumer behavior research [Malhotra, 1984]. Values were usually presented as a form of dichotomous data: either high or low calories contained in each cereal, for example.

Malhotra(1982) found that when the number of alternatives and attributes increased from 5 to 15 by an increment of 5, the probability of correct choice decreased significantly.He also found some interaction effects between the increase of the number of alternatives and the number of attributes. In a later experiment, Keller and Staelin(1987) focused on the effect of increasing only the number of attributes to avoid the interaction problem.They increased the number of attributes from 4 to 12 by an increment of 4, and kept the number of alternatives constant at 5. The result of the experiment showed that given fixed quantity of information, an increase

Study	Subjects	Task	Information Load	Result
Chervany and Dickson (1974)	n=22, graduate students	Production Scheduling	449 (statistically summarized) and 1040 (raw) data items, computer output	Summarized data users had lower total cost (better performance) ($p<.18$), and took longer time ($p<.05$), and were less confident ($p<.12$)
Payne (1976)	Study I, n=6 under-graduate	Apartment Selection	2, 6, 12 Alternatives by 4, 8, 12 Attributes	% of available information searched has declined (no statistical test, protocol analysis)
ibid	Study II, n=12 under-graduate	Apartment Selection	2, 4, 8, 12 Alternatives by 4, 8, 12 Attributes	% of available information searched has declined (no statistical test, protocol analysis)
O'Reilly (1980)	Study I, employees (Two Surveys) n1=579, n2=814	Overall navy aviation unit acitvities	Measured using 7 point Likert scale	As information load increased performance decreased ($n=151$, $r=-.12$ and $-.19$, $p<.05$), and satisfaction increased ($p<.01$). (separate communication, pay, promotion, work, supervisor, co-worker satisfaction produced between $r=.11$ and $r=.34$)
ibid	Study II, employees (Survey) n=163	Welfare agency activities	Measured using 7 point Likert scale	As information load increased error rate (inverse of performance) increased ($r=.20$, $p<.05$), and job satisfaction increased ($r=.20$, $p<.01$).
Jacoby, Speller, and Berning (1974)	192 Housewives	Buying rice and prepared dinner products	4, 8, 12, 16 brands (alternatives) by 4, 8, 12, 16 attributes	Interaction between number of alternatives and number of alternatives, decision accuracy decreased when the total amount of information was high. Time spend increased then ceased. Need for more information decreased as infomation increased ($r=-.443$ and $-.218$).
Malhotra (1982)	300 heads of households (interview)	Buying a house	5, 10, 15, 20, 25 Alternatives by 5, 10, 15, 20, 25 Attributes	Probability of correct choice decreased when the number of alternatives went over 10, or when the number of attributes went over 15 ($p<.05$). Level of confusion increased as number of alternatives increased (p: not reported)
Keller and Staelin (1987)	53 MBA students	Job selection	5 Alternatives by 4, 8, 10, 12 Attributes, Different quality (content)	Decision effectiveness and confidence decreased when quantity increased (Log N) holding quality fixed ($p<.015$), and increased as quality (Log TQ and TQ^2) increased holding quantity fixed. ($p<.04$)

〈Table 1〉 Summary of the selected management research on overload of quality caused performance increase, while a quantity increase given constant quality resulted in a performance decrease.

In research on choice behavior, Payne (1976) used protocol analysis to investigate the relationship between the internal process of cognition and task complexity. He varied the number of alternatives from 2 to 6 to 12, and the number of attributes from 4 to 12 by increments of 4. He found that as the task complexity increased, subjects used a smaller percentage of the total available information.

From the review of the research on information overload, we could draw the following observations. First, the effect of information load can be meaningfully examined using an experimental method. Based on Miller's(1956) findings regarding the "magical number seven, plus or minus two" the number of alternatives or attributes were varied from four to over ten. The underlying premise of the experimental studies on information over load was that if subjects are overloaded in the experimental settings, which have a very simplified information environment, "overload would also occur under more complex real-world circumstances." [Jacoby, 1984].

Second, existing information systems research on this aspect needs more rigor in designing information provision.The operationalization of information load should be determined so that results of experiments in information systems research can be compared to the results from other disciplines. This way we can both draw theories and designs from the related or underlying disciplines and can contribute to the development of knowledge in a broader academic context.

Third, while preference choice is meaningful for consumer choice behavior research, the context may be somewhat different in managerial thinking. Although each consumer can choose any alternative in terms of their own taste [Meyer and Johnson, 1989], managers have to rely more on explicit goals determined exogenously, such as share increase and profit maximization. Thus, managers have to be less subjective in making decisions. The difference in the thinking context and goals can affect thinking practices.

Fourth, the information environment where subjects have computational aids has not been considered in overload research. It is common among today's managers to use computational aids in performing their tasks, and the trend toward managers' using data manipulation tools for themselves will rapidly increase [Huber, 1990]. As Ackoff(1967) discussed, the role of information systems should be the provision of relevant information to its users and the compression of irrelevant information. Unless we understand more about the way information is used in current technological contexts, we will not be able to successfully provide good guidelines for planned provision of relevant information.

2.3. Categorization as a Cognitive Process of Decision Making

For the reason we discussed in the previous section, instead of using a preference choice decision, we chose to examine decision making using categorical cognition. Categorical cognition, being relatively new in management research, has not yet received much attention from researchers of information overload or information systems. Categorization, however, has been considered closely related to various important managerial decision making activities.

Purposeful categorization within a specific domain is considered highly important in managerial contexts, and "creating useful categories which are related to human intentions" is closely tied to problem-solving activities and "intentional learning" [Stubbart, 1989]. For example, the purposeful categories used by managers play an important role in determining business strategy [Ginsberg, 1989], and sales managers' categorization of their customers and sales situations is closely related to their performance [Sujan, Sujan, and Bettman, 1989].

First, categorization has been considered to be an important fundamental cognitive process. It is involved in most of the cognitive processes like sense-making, interpretation, problem solving, and decision making [Nisbett and Ross, 1980], and the categorical representation of stored information is one of the most widely adopted models of the structure of the contents of human cognition [Lurigio and Carroll, 1985]. Categorization is also considered important for complex managerial activities [Stubbart, 1989].

Second, categorization has been considered closely related to various important managerial decision making activities. On the one hand, Categorization is closely related to the "intelligence" phase of decision making [Simon, 1960], which has not been extensively explored by information systems research. Since most of the IS research on decision making has focused on the later, "design" and "choice" phases of decision making, an improved understanding of the intelligence phase is considered necessary for an effective support of management decisions [Keen, 1987]. On the other hand, categorization is by itself a complicated and unstructured mental activity, which includes many elementary decision making components [Szymansky and Churchill, 1990].

Third, categorization research has provided us with evidence that it is closely related to managerial tasks and managers' performance [Ginsberg, 1989; Sujan, Sujan, and Bettman, 1989; Szymanski, 1988]. For these reasons, categorization is considered as one of the most important and relevant cognitive issues for management research [Stubbart, 1989].

Fourth, categorization has many practical implications for managers by itself. For example, such tasks as categorization of markets based on demographic data for direct-mail marketing, categorization of credit card members based on their credit history for membership management, categorizing subordinates for performance appraisal, and categorization of companies in which to invest, based on their financial information, are important business problems that managers encounter repetitively [Feldman, 1981; Gluck and Bower, 1988; Martin and Klimoski, 1990].

Finally, many categorization tasks within management context involve the use of numeric data. For this reason, the research subjects can easily benefit from using computer-based data manipulation tools in this context compared to the preference choice settings mostly using nonnumeric dichotomous data such as "high in vitamin A". Many functional managers in practice are currently receiving large amount of numeric data(e.g., the sales volume, number of items in stock, amount of orders, and market share) and make decisions based on those numbers.

3. Research Hypotheses

We examined the effect of increased information availability with the premise that there exists an optimal amount of data available to managers given a relatively limited amount of time. As reviewed in previous sections, research on information load reported conflicting results. One way to interpret the inconsistent results is that it could be caused by the existence of an optimal load of information, which Driver and Streufert(1967) called a "characteristic level". The level of outcome shows a curvilinear pattern around the characteristic level. Specifically, Driver and Streufert suggested that the pattern have the shape of inverted U. In most cases with a more complicated context, however, the result ceased to improve when the amount of information increased beyond some level.

H1a : The task outcome will improve as the amount of available information increases to some level(from small to medium).

H1b : Then the task outcome will decrease or not increase if the amount of information increased further(from medium to large).

The time spent to perform a task reflects the amount of effort to perform the task [Bettman, Johnson, and Payne, 1990]. The increase in the complexity of a problem requires decision makers to devote more effort to solve it. As the components of the problem space increase, more cognitive operations should be performed to analyze data and to evaluate alternatives. However, the amount of cognitive effort devoted may not increase proportionally to the increase in the amount of data to be analyzed, as individuals try to use certain cognitive strategies to optimize the amount of effort [Payne, 1976]. Thus, we propose that the total amount of time will increase as the amount of data increases only upto certain level. If the amount of data increased beyond this level, the subjects should feel a stronger need to save their efforts, and thus, the total amount of time should not increase further.

H2a: The time to perform the task will increase as the amount of available information increases to some level(from small to medium).

H2b: Then the time to perform the task will decrease or not increase if the amount of information increased further(from medium to large).

Satisfaction with information is user's behavioral response to the provision of data, and confidence in the task result is a self-perception of the goodness of the outcome [Keller and Staelin, 1987]. In survey research on the effect of information load on managers' behavior, O'Reilly(1980) reported that the levels of information satisfaction and confidence have increased as the task load increased even after the increase in the amount of data caused a decrease in outcome. His interpretation was that managers might want to have more evidence on hand and to save the unused portion of the data for a later reference.

Since our research strategy is different from O'Reilly's and the subjects in our study will not think they will use the data again for a later task, we will be able to clarify his interpretation.

H3: As the amount of available information increases, satisfaction with information provision will increase.

H4: As the amount of information increases, confidence in task results will increase.

Each element of data used in making decision provides input cues to perform the task. As the need of data for the task is better fulfilled, the need for additional information should decrease. Thus, we propose that as the amount of available data increases, the need for additional data will decrease [Payne, 1976]:

H5: As the amount of information increases, the perceived need for additional information will decrease.

Since we will give the subjects data manipulation aids, we will observe the degree to which the subjects utilize the computational aids. As the amount of data increases, the need to analyze data will increase. This will lead users to use more diverse data manipulation functions and try to explore the data from more diverse angles. However, as the amount of information increases beyond a certain level, the effort required to analyze the data from diverse perspectives will increase rapidly. The subjects will thus try to minimize their cognitive efforts devoted in the task [Todd and Benbasat, 1991]. They should feel more need to summarize, filter, or simplify the data to make sense. They may not try to create more new numbers such as ratios and percentages, although those new numbers could surface nontrivial additional meanings. They may use a limited number of functions focusing more on compressing and summarizing the data. They may try to reduce the data to a more manageable size.

H6a: The diversity of the use of data manipulation function will increase as the amount of available data increases to some level(from small to medium).

H6b: Then the diversity of the use of data manipulation function will not increase if the amount increased beyond the level(from medium to large).

We finally examined how much proportion of the data available was used in the process of decision making. Malhotra (1982) noted that "under the overload condition, the respondents did not make detailed comparisons of all the alternatives on all the attributes but adopted some simplifying strategies or heuristics." One type of biased use closely related to information overload will be ignorance of part of the data provided. Payne(1976) found that as complexity of a task increased(more alternatives, more attributes or both), individuals used a smaller proportion of the available data and ignored considerable amounts of data available to them. Thus,

H7: As the amount of available information increases, less proportion of the total amount of data will be used in performing the task.

4. Research Methodology

4.1 Experimental Context

Task Context: Marketing Management

A marketing management context was used in the experiment Because of the high level of uncertainty facing marketing managers and the nature of their role requiring the use of diverse and abstract market data, interpreting and drawing meaning out of data takes critical importance. In addition, recent developments in the scanner-based technology and the widespread diffusion of user-friendly software enabled these mamagers to access and explore tremendous amount of market data to draw meaningful market signals.

The subjects were told that they were marketing managers for a computer manufacturing company, which is trying to launch a new model of home computer into specific areas. They were responsible for allocating advertising resources across different areas. In an attempt to make an effective advertising plan, they were told to categorize the selected areas into two groups differing in their potential to absorb the direct mail advertising and selling efforts.

Technological Context: Data Manipulation Tool

We furnished the subjects with a spreadsheet software(Lotus 1-2-3) as a data manipulation aid. Spreadsheet software provides a set of relatively nondirected computational aids. In contrast to the directed decision aid, which implies a normative model of decision process, a nondirected decision aid provides information processing capabilities which a decision maker decides if and how to use (Silver, 1990). Since our focus is the cognitive strategies that individuals employ for themselves, we avoided providing a normative logic of thinking to follow. By using general purpose spreadsheet software, subjects would be minimally driven by certain rules and be able to follow their own logic both in selecting the operations they want to perform and in determining the sequence of operations.

4.2. Experimental Treatment: Data availability

Following the tradition of information overload research, we used the "alternatives by attributes" format of two dimensional data. The availability of information was manipulated by varying the number of attributes for a constant number of alternatives. Specifically, three sets of data were prepared by increasing the number of attributes for the same 9 areas. The number of attributes included in each report varied from 4 to 14. We chose to fix the number of alternatives(areas) in order to avoid the interaction problem between alternatives and attributes [Keller and Staelin, 1987]. In addition, it closely resembles the data used in practice, where different marketing reports are frequently prepared for an identical set of target markets by varying the depth, number, and types of data attributes. The variation in the number of attributes is consistent with those frequently employed in existing overload research [Jacoby, 1984; Malhotra, 1984].

To select the data attributes, we followed the procedure used by Keller and Staelin (1987) and Malhotra (1982). We asked three marketing professors to suggest attributes which were considered important. To help them we provided them a list of data attributes appearing in the Zip Code Data Book (Bureau of Census, 1990). In a second pass, we presented the three reviewers the list of attributes compiled from their first suggestions, and asked them to evaluate the importance of each data attribute on a 7 point scale, 1 being not important at all and 7 being extremely important. We used the first fourteen attributes considered highly important in terms of the average importance score. The attributes used in each data set are listed in [Table 2]. According to Keller and Staelin (1987) the total importance scores and average importance scores respectively represent the information content included in each data set and per data attribute within a data set.

4.3. Study Procedure

4.3.1 Subjects and Pretests

Boston University MBA students taking

computer-based information systems courses from the School of Management served as research subjects.

They were motivated to participate in the experiment as part of class requirements. Three rounds of pretest (9 DBA, 9 MS/MIS, and 27 MBA students respectively) were performed prior to performing the actual experiment. Through the pretest we checked whether the experimental context and instructions were clear and understandable, and whether the subjects performed the experimental task without confusion and as appeared in the instruction sheet.

4.3.2 Experimental Procedur

The "posttest-only control group design" was used in the experiment. The subjects were randomly assigned into one of three groups. The three treatment groups each had a different level of information availability. The subjects were not informed about the amount of data stored in the computers they used.

The subjects were asked to perform the categorization task twice. The first categorization was performed with small data set (5 areas and 2 attributes), and was used for a practice to help subjects become familiar with the experimental procedure, and gain a better understanding of the experimental task. After completing the practice task, the subjects were allowed to ask questions, and then the instructions for the actual task were given.

In the actual task, the subjects were asked to categorize nine areas into two groups. All subjects were asked to study the data using the spreadsheet software provided, and identify two groups of areas: high potential and low potential groups. The subjects were instructed that the task was not a test of any marketing knowledge nor spreadsheet skill. They were told to use their common sense as much as possible.

The instruction was given in written form as a task instruction sheet and was read aloud by the experimenter. To help the subjects describe the categories they identified, a set of category description sheets were distributed. They were told to press the special completion key (Alt-F: a command to record the completion time and clear the screen) and raise a hand when they completed the task. Then a post-experimental questionnaire was administered. The subjects were told that they could use sufficient time to complete the task.

Attributes	Inportance Score
% Who have bought high-price technical items through mail order	7.0
Median Household Income, 1990	6.0
Median Years of Education	5.0
Median Age, 1990	4.7

Attributes included in the level 1 data set (small data)

Average importance score: 5.67 Total importance score: 22.7

Attributes	Inportance Score
% Who have bought high-price technical items through mail order	7.0
Median Household Income, 1990	6.0
% Household income \$50,000 to \$74,999	5.3
Annual Growth Rate of median household income 80-90	5.0
% Unemployed	5.3
% White collar	5.3
Median Years of Education	5.0
Median Age, 1990	4.7
% Ages 25 - 44	5.0

Attributes included in the level 2 data set (medium data)

Average importance score: 5.4 Total importance score: 48.6

Attributes	Inportance Score
% Who have bought high-price technical items through mail order	7.0
Median Household Income, 1990	6.0
% Who have bought high-price items through mail order	6.0
% Who have bought any item through mail order	5.7
% Unemployed	5.3
% White collar	5.3
% Household income \$50,000 to \$74,999	5.3
Median Years of Education	5.0
% Ages 25 - 44	5.0
Annual Growth Rate of median household income 80-90	5.0
Median Age, 1990	4.7
Median Age, 1980	4.7
% Household income \$75,000 or more	4.3
Subscriptions to PC Magazine or PC World (% of household)	4.3

Attributes included in the level 3 report (large data)

Average importance score: 5.26 Total importance score: 73.6

〈Table 2〉 Attributes included in each report and their importanceImportance on a 7 point scale(1:Not important at all 7:Extremely important)

4.4. Instruments to Measure Outcomes

The dependent variables used in the study include the task outcome, task completion time, subjects' confidence in their results, need for more information, satisfaction with information provision, the use of data, and the degree subjects utilized manipulation aids. A composite understanding of the task outcome, time taken to perform the task, and other perceptual states will help us understand the overall performance of the task.

Task Outcome:

The outcome of our experimental task is the amount of understanding the subjects gained while performing the categorization. One of the most used methods to evaluate an individual's level of understanding with regard to categorization is to evaluate the amount of description about the categories provided by the individuals. This method is based on the findings in categorization research, which indicate that one who has better knowledge of the categories s/he developed can provide a "richer" description. Following Sujan, Sujan, and Bettman(1988), we asked subjects to write down the characteristics of the categories they identified, and then counted the number of distinct descriptive statements to use this count as a measure of outcome.

Time Spent:

To measure the time spent to perform the task, we used a macro program running behind the spreadsheet in the background. This program automatically recorded the time when the subjects first retrieved the data file. The subjects were told to press a special key(Alt-F) and raise a hand when they finished the task. The finishing time was recorded when the subjects pressed this special key.

Information Satisfaction:

Four items in the post-experimental questionnaire were used to measure subject's satisfaction with information. Three items were related to subject's perception of the precision, sufficiency, and relevancy of the information. These items were a adopted from Baroudi and Orlikowski's (1988) measure of user's information satisfaction(UIS) with "Information Product". Items related to EDP staff, service, system, and involvement were considered irrelevant, because all environmental conditions were kept identical except for the amount of data. One item was a direct probe of subject's satisfaction for the information provided [Ives, Olson, and Baroudi, 1983; Doll and Torkzadeh, 1988].

Confidence in results:

Three items of the post-experimental questionnaire were used to measure subject's confidence in their results. This variable was usually probed by a single item in previous research and questions tended to be context dependent. In addition to an item which directly asked for the level of confidence, one item probed subject's self-evaluation of the quality of the task outcome, and the other asked about confidence more indirectly. Need for more information : The need for more information was a single item in Pearson's long-form UIS measure. We expanded the "need for more information" item to six questions that reflect the experimental task and context. This construct was emphasized in our study since our research focus was on the load of information. The questions probed subject's self-reported evaluation of the need for more types, detail, and amount of data on a seven-point scale.

Use of Data and Use of Manipulation Functions:

Questions regarding the use of data are highly dependent on, and sometimes unique for, the specific experimental context [Keller and Staelin, 1987]. We asked the subjects how much they used each data attribute using a seven-point scale. Since the three groups used different amounts of data, these questions differ across the three groups.

The degree to which subjects used data manipulation functions was examined by asking them to evaluate their use of various spreadsheet functions on a seven-point scale; 1 being not used at all and 7 being extremely extensively used. Thirteen items were included in the questionnaire: 1. moving a column; 2. moving a row; 3. summing; 4. transpose; 5. regression; 6. sorting; 7. graph; 8. computing average; 9. computing standard deviation or variance; 10. retyping; 11. computing new column; 12. determining range using minimum and maximum; and 13. deleting.

5. Results of the study

In total 104 subjects participated through out the experiment. The number of the subjects per each treatment(about 35 subjects) was larger than the size with an acceptable statistical power level(1-beta=.80; 25 subjects) at the significant level of =.05(Baroudi and Orlikowski, 1989). The size was also larger than what has been used in previous overload studies such as Malhotra(1982), Jacoby, Speller, and Berning(1974), and Chervany and

Dickson(1974) who had 12, 12, and 11 subjects per treatment respectively.

Background data on the subjects were collected to examine the characteristics of the subjects' experience in computer and spreadsheet software. The background data includeed years of personal computer use, years of spreadsheet use, years of work experience, and a self-evaluation of spreadsheet skill. Analysis of variance on the background variables showed that the three groups with different amounts of data were not significantly different in any of the four variables.

Self-report multi-item measures of the three perceptual variables included satisfaction with information(4 items), confidence in the categorization result(3 items), and the need for more information (6 items). The reliability of the three self-report outcome measures(Cronbach's alpha) were 0.6877 for satisfaction, 0.8585 for confidence, and 0.7697 for information need. We think this value is acceptable considering that user information satisfaction is a relatively broad construct and we used only four items which we considered relevant for our experimental context.

Overall multivariate analyses showed that there exist significant differences among the three groups when all the dependent variables were considered in aggregate($p<.000$).(Pillai's statistics=1.003, $F=11.95$; Hotelling's statistics=11.248, related $F=65.38$; Wilks' statistics= .075, related $F=31.09$; p-value $<.000$ in all cases). Since we were interested in comparing the first two(small and medium data groups) and the second two(medium and large data groups), similar multivariate analyses were performed to see if there are aggregate differences in those two pairs. Analysis between the first two groups showed that significant differences do exist($p<.000$).(Pillai's= .943; Hotelling's=16.572; Wilks'= .057; exact $F=128.43$ and p-value $<.000$ in all cases). Analysis between the second two groups also showed that significant differences exist($p<.000$).(Pillai's = .891; Hotelling's=8.183; Wilks'= .109; exact $F=128.43$ and p-value$<.000$ in all cases).

A detailed analysis was performed to see which variables have significant differences using multiple t-test procedures. [Table 3] summarizes the means and standard deviations of the outcome variables across each of the three groups. [Table 4] summarizes results of the t-tests for each of the outcome variables[2].

Hypothesis 1 and 2: Task Outcome and

the Time Taken to Perform the Task

As we hypothesized, the number of statements the subjects in the medium data(9 attribute) group produced to describe the characteristics of the categories they identified was significantly greater than the number of subjects produced by the small data(4 attribute) group($p<.001$). A comparison between the large data(14 attribute) group and the medium data group, however, showed no significant difference in number of statements produced [Table 4]. The result followed a curvilinear form in which the outcome increased as the amount of data increased to a certain degree, but did not increase further thereafter. We did not observe, however, an inverted U-shaped curve in the outcome.

A similar pattern of asymptote as the ourcome was observed in the length of time the subjects devoted to perform the task. A comparison between the small data group and the medium data group showed that the amount of time spent by the medium data group was significantly greater than the amount of time spent by the small data group($p<.0065$) [Table 4]. However, the difference in the amount of time spent between the medium data group and the large data group was not significant.

Hypothesis 3 and 4: Information Satisfaction and Result Confidence

Based on O'Reilly's(1980) survey, we proposed that levels of these perceptual variables would increase as the amount of information provided increased, and this trend would be maintained even after the amount of data provided is increased beyond the level of overload. A test comparing the first two groups showed that the level of satisfaction of the medium data group was significantly higher than that of the small data group($p<.013$). However, the level of satisfaction of the large data group was not higher than that of the medium data group. Thus, hypothesis 3 was only partially supported.

The increase in the levels of confidence between the small and the medium data group was not significant, although it was close to significance($p<.072$). The level of confidence of the large data group was slightly lower than the level of confidence of the medium data group, but the rela-

2) Same result can also be obtained using Analysis of Variance for each dependent variable with internal contrasts or MANOVA for pairwise two-group comparison. In the case of ANOVA the constrast formula should be Contrast 1(gr1, gr2, gr3) $=(-1, 1, 0)$ and Contrast 2(gr1, gr2, gr3) $=(0, -1, 1)$.

Mean Standard Deviation	Small Data (n=35)	Medium Datd (n=36)	Large Data (n=33)
Number of Descriptions	4.2571 1.245	6.222 2.030	6.1515 2.293
Time Spent	31.5143 8.712	37.8056 11.851	37.6364 13.592
Satisfaction	4.0143 1.014	4.5417 .942	4.4167 1.091
Confidence	3.4476 1.544	3.9722 1.435	3.6162 1.362
Information Need	5.5571 .907	4.7778 .810	4.4899 1.264
Function Used	4.5143 2.418	5.4722 2.396	4.4242 2.372
Propotion of Data Used	.7429 .231	.6671 .206	.5588 .248
Number of Attributes Used	3.057 0.765	6.000 1.852	7.818 3.468

〈Table 3〉 Means and standard deviations of the outcome variables of the three groups

t-value(plevel)	Vetween Small and Medium Data Group(df=69)	Between Medium and Large Data Group(df=67)
Number of Descriptions	4.90(.000)***	-.14(.892)[1]
Time Spent	2.54(.007)**	-.16(.956)[1]
Satisfaction	2.27(.013)*	-.51(.306)
Confidence	1.48(.072)	-1.05(.148)
Information Need	-3.82(.000)***	-1.14(.130)
Function Used	1.68(.049)*	-1.82(0.37)*
Proportion of Data Used	-2.07(.021)*	-2.00(.025)*
♯of Attributes Used	8.71(.000)***	2.75(.004)**

〈Table 4〉 Result of t-tests for the outcome variables(1: two-tailed test)
(*** means $p<.001$, ** means $p<.01$, * means $p<.05$)

tion ship was not significant($p<.148$) [Table 4]. Thus hypothesis 4 was not supported.

Hypothesis 5: Need for More Information

In the fifth hypothesis, we proposed that the need for more data should be negatively related to the amount of task-related data provided. The comparison between the small and the medium data group showed that the need for more information felt by the medium data group was significantly lower than the need of the small data group($p<.0000$). The need for more information by the large data group was lower than the need of the medium data group, but the relationship was not significant($p<.130$).

Hypothesis 6: Use of Data Manipulation Functions

We expected that as the amount of data increased from small to medium, the subjects would try to explore the data using a more diverse set of functions, and that the subjects with large amount of data would find it difficult to use more diverse functions than those with medium amount of data. The results showed that the number of functions used by the medium data group was significantly larger than that of the small data group($p<.0490$), and that the number of functions used by the large data group was significantly smaller than that of the medium data group($p<.0365$). Overall we could observe an inverted U-shaped curve for the number of functions used, supporting the hypothesis we proposed.

A further analysis by each function(not shown) provided us some additional information. The Average function(AVG) was used significantly more by the first group than by the second group($p<.015$), and was used significantly less by the third group than by the second group($p<.039$). The Regression function was significantly more used by the second group than by the third group($p<.05$), but there was no significant difference between the first and second groups. Generation of new columns significantly decreased between the first two groups($p<.046$), but the decrease between the second and third groups was not significant($p<.159$). The large data group significantly less frequently typed in additional data than the medium data group($p<.046$), but the absolute response to this function was very low in all the three groups.

Hypothesis 7: Proportion of Data Used

We expected that as the amount of available data increases, the subjects would use a smaller proportion of the data available to them. We compared those attributes rated as highly important in performing the task(rated 4 or above on a 7 point scale) to those rated low in importance. The proportion of data used decreased significantly between the small and the medium data groups($p<0.021$) and between the medium and large data groups($p<0.025$). The absolute amount of

sithin group F p-level	Tears of PC use	Years of Lotus use	Self evaluated Lotus skill	Years of work experience
Number of Descirptions	7.307*** .000	2.218 .091 1	4.666** .004	4 .560** .005
Time Spent	4.410** .006	3.942* .011	3.580* .017	.623 .602
Satisfaction	2.823* .043	.534 .660	1.190 .318	1.264 .291
Confidence	.840 .475	.357 .784	3.210* .026	1.237 .300
Information Need	4.862** .003	3.358* .022	4.962** .003	2.633 .054
Function Used	1.759 .160	2.557 .059	3.464* .019	1.374 .255
Propotion of Data Used	3.918* .011	2.773* .045	3.474* .019	2.164 .097
Number of Attributes Used	15.354*** .000	11.207*** .000	19.293*** .000	15.558*** .000

〈Table 5〉 Within-group effects of the background variables

(*** means $p<.001$, ** means $p<.01$, * means $p<.05$)

Hypothesized relation (Result)	Between Group 1 and Group 2	Between Group 2 and Group 3
Number of Descriptions	Increase(Supported)	Not increase(Supported)
Time Spent	Increase(Supported)	Nor increase(Supported)
Satisfaction	Increase(Supported)	Increase(Not supported)
Confidence	Increase(Not supported)	Increase(Not supported)
Need for more Info.	Decrease(Supported)	Decrease(Not supported)
Function Used	Increase(Supported)	Decrease(supported)
Proportion of Data Used	Decrease(Supported)	Decrease(supported)

〈Table 6〉 Summary of test results for the proposed hypotheses

data used, however, increased as the amount of data increased. The number of attributes used by the medium data group was higher than that of the small data group($p<.000$), and the number of attributes used by the large data group was larger than that of the medium data group ($p<.004$).

Analysis of the Effects of Background Variables as Covariates

As a supplemental analysis, we examined the effects of the background variables, controlling for the treatment variable

[Table 5]. We found that subjects with more PC experience produced more descriptors in their task, spent more time on the task, wanted more information to perform the task, and used more and a larger proportion of the available data. A similar pattern held for those with more spreadsheet experience and with more self–rated spreadsheet skill. In addition, subjects with more work experience produced more descriptors and used more attributes in carrying out their analyses.

6. Discussion of the Results

Results of the analyses of the seven hypotheses are summarized in [Table 6]. The test results confirmed six out of seven hypotheses between the small and medium data groups and four out of seven hypotheses between the medium and large data groups.

The test results confirmed six out of seven hypothesized relationships between the first and the second groups. Four out of seven hypothesized relationships between the second and the third groups were supported. The changes in the number of descriptions, time spent, satisfaction, need for more information, the number of functions used, and the proportion of data used were significant between the first two groups(the small data group and the medium data group). We did not observe an increase in the number of descriptions or time spent between the second (medium data) and the third(large data) group as expected. The decrease in the number of functions used and the proportion of data used were significant between the second two groups(medium data group and the large data group), supporting the hypothesized relationships.

As Driver and Streufert(1969) and Miller(1977) speculated, strong evidence of overload might be a decrease in the level of response when the intensity of input stimuli has increased beyond the characteristics level(Driver and Streufert, 1969). In our study, we could observe inverted U–shape trends in five out of seven dependent variables(e.g. number of descriptions, time spent, satisfaction, confidence, and number of functions used)(Table 7.5 and Table 7.6). However, the "decrease" in those dependent variables between the second and the third group were not significant except in the case of the number of functions used. Thus, we actually observed an "asymptote" in the four dependent variables. For example, the outcome as measured by the extent of category description and the time the subjects spent in completing the task increased when the amount of data increased from small to medium level, but did not change significantly when the amount of data increased from medium to large levels. This lack of increase in these variables conforms to our expectations.

Although the content of data(from 22.7 to 48.6 to 73.6) increased propotionally to the quantity of data(from 4 to 9 to 14 attributes), the amount and content increases between medium and large data groups were not reflected in the number of descriptions of the categories nor in the amount of time subjects devoted to complete the task(Todd and Benbasat, 1991). The subjects with large amounts of data must have felt a need to optimize their efforts in solving the problem. Being overloaded with the large amount of data, they might ignored part of the data or used cognitive strategies that help them reduce their cognitive efforts.

Two interpretations for the asymptotic responses are possible. First, the decrease in outcome beyond characteristic level observed in research on elementary cognitive operations may not apply to complex thinking. Alternatively, the load of input stimuli was not high enough to see such a "decrease". Our results did however show that responses as measured by the various outcome variables did not increase proportionally to the increase in the input load. In this regard, two 7questions still remain to be answered: Would the outcome and time spent really decrease if the amount of data increased further? and What did the subjects with different amount of data actually do during task performance?

We observed that the level of satisfaction ceased to increase when the amount of information provided increased beyond the medium level. This result does not conform to O'Reilly's(1980) survey result, which showed that information satisfaction increased even after the level of load increased beyond the overload level. O'Reilly interpreted that the consistent increase in satisfaction might be caused by managers' belief that they might to use the unused data for later reference. His interpretation is consistent with the suggestion by Feldman and March(1981) in that managers may try to gather more information than they use.

Since the subjects in our study were involved in the experiment on a one time basis, they could not expect that they would use the data for a later work. In this sense, our results are consistent with the reasoning of O'Reilly(1980) and

Feldman and March(1981). Our result implies that the level of user information satisfaction(UIS) in the field may not be directly related to performance of a particular decision or task. That is, researchers may have to be very careful in relating the level of UIS to concurrent task performance(Melone, 1987).

Analysis of the number of functions and the level of data used conformed to our expectations. The number of functions used increased between the first two groups and decreased when the amount of data increased from medium to large. The proportion of data used out of the total available significantly decreased as the amount of data provided increased. The use of some functions(e.g. Average, Regression, or new column generation) showed interesting changes across the three groups(e.g. curvilinear forms, consistent increase or decrease). This result may represent the strategies the subjects employed in performing the task. However, an unambiguous interpretation of this result and its relationship to cognitive strategies is not possible without futher information on the internal procedures performed by subjects in completing the task(Todd and Benbasat, 1987; Chervany and Dickson, 1974). Although the use of cognitive strategies, manipulation functions, and the data provided must be closely interrelated, the exact internal processes used in completing the task can only be analyzed through a process-tracing method.

7. Conclusion and Implica- tions of the Research

In the recent studies on the cognition of information systems users(e.g. Todd and Benbasat, 1991 and 1992;Vessey and Galletta, 1991; Umananth and Vessey, 1991;Mackay and Elam, 1992), the load (amount) of information involved in decision making was an important issue. For Todd and Benbasat(1991, 1992) and Mackay and Elam(1992), load of information was an important consideration in determining the complexity of their experimental task. Umananth and Vessey(1991) found that information processing efficiency was related to the form by which the problem data were presented. For example, they found that whereas the problem solving performance with schematic faces was not sensitive to changes in information load, the performance with tables was significantly sensitive to load(ibid.).

This study focused on the load of information, and closely examined how the load of information affected the cognitive outdomes. Specifically, our study focused on individuals' cognitive outcomes when they received different amounts of computer-based data, along with computerized data manipulation aids. The study produced several interesting findings on the effects of increased information availability.

Our findings imply that there may exist a range of information load that optimizes individuals' use of information. At this level, individuals use their cognitive capacity efficiently and explore the provided data extensively, without being distracted by problems caused by lower or higher data levels.

The subjects with the medium-sized data set used the data provided most effectively, performed computations relevant to the task more extensively than the other two groups. The number of spreadsheet functions used and the proportion of data used by the small and large data groups were significantly lower than those of the subjects with medium data set. Subjects' understanding of the data as measured by the number of category descriptions provided, and the amount of effort devoted as measured by the time spent, and the level of satisfaction increased as the data amount increased from small to medium. However, these outcomes did not increase when the amount of data increased beyond the medium level.

Subjects with the small data set must have believed that the burden of the data was well below their cognitive capacity, their level of satisfaction with data was lowest, and their need for additional data was significantly higher than that of the subjects with medium or large data sets. The subjects with the large data set performed fewer functions than the medium-data group and used a significantly smaller portion of the available data than the subjects with small or medium sized data sets. We think the amount of data we used for the small data set was somewhat less than the optimal information load level. We think, on the other hand, that the large data we used in the study was somewhat beyond the cognitive capacity of the subjects.

The results imply that the amount of information may play the role of moderating factor for the cognitive effort model (Todd and Benbasat, 1991, 1992). We could observe evidence of attempts to minimize cognitive efforts from subjects with a large data. However, the tendency to minimize effort was not clearly observed among subjects with the small data set.

We think the model is most relevant in describing cognitive behaviors of users when the task complexity is higher than a certain level. We suggest that in order to make the cognitive effort model applicable to a generalized situation, load of information should be incorporated into the model as a moderating variable.

Our results also present an insight to the novice/expert model. The comparison among the functions used by the three groups of subjects show that the use of function varied significantly among the three groups, although our subjects were homogeneous across the three groups. Mackay and Elam (1992) showed that the use of functions depended on the level of expertise in the technology. We believe that to build a more complete and persuasive model task demand as well as subjects' expertise in the technological tools should be incorporated. We believe that by considering the role of information load, we can better understand the roles of different models and relate them to understand the cognitive behavior of information systems users more clearly.

Another interesting point we observed in this study is that the subjects in our study performed notably more complicated operations than subjects in other research, where similar types of data were used, but where computer support was not furnished (Payne, 1976; Jacoby, 1984; Malhotra, 1984; Keller and Staelin, 1987; Bettman, Johnson, and Payne, 1990). This could be an evidence that the use of a computer helped to increase individual's computational capacity. Our subjects, however, indicated that they felt burdened by large amounts of data. This fact implies that the computer-aided increase in subjects' computational capacity does not change their perception of the amount of data at which the information overload threshold occurs.

Implications for Practice

We think that some practical guidelines can be drawn from our findings that are helpful both for users and designers of software, especially spreadsheet tools. We suggest that managers and builders of software systems should understand that data sets of different sizes should be processed differently. Managers responsible for the support of information processing among users can help these users by letting them know the effects of data size. To achieve higher performance, guidelines can be taught to user managers so that they can process different amounts of data using different strategies and functions. For example, establishing a procedure to eliminate unnecessary attention or standard procedures to·reduce excessive task complexity will improve task efficiency.

We expect that managers, in most cases, will cope with large data sets rather than small ones. However, if the amount of data to be processed at a time was smaller than the optimal or "characteristic" level, they may use them less efficiently than desired. To avoide the lack of effciency in this case, for example, a guideline to deal with this kind of data can be prepared and taught to managers. Managers can then follow the guideline to improve the data usage efficiency and not to perform excessive unnecessary operations.

On the other hand, if a large amount of data were to be used at a time, functions that facilitate reduction of problem complexity and functions that help users to identify patterns of data quickly will result in better performance.

Limits of the Study and Implications for Future Research

This research has several limitations, in terms of both the methods we employed and the theoretical scope we focused on. First, the data we used in the study present two-dimensional table of numerical data. However, there are still several other types of important data and data manipulation tools. To make a more generalizable conclusion, future research will have to examine the effects of different types of data (e.g. verbal data, graphical data, or multimedia data) on information load and on task performance. Future research with similar types of data should also be performed which changes the number of attributes by smaller increments, in order to gain more precise knowledge around the effects of data amount.

Second, we used MBA students as research subjects and performed the research in a very controlled experimental context. In our study, the 14 by 9 (large) two-dimensional numeric data set showed some overload effects, and the 9 by 9 (medium) data set looked more appropriate. However, real managers may have a somewhat larger capacity to handle the data than our MBA subjects, and may know more about strategies to handle data. Future research should address this issue (related to external validity or generalizability) by using real managers and an actual task context.

In our study we focused on cognition at the individual level. Thus, the research scope does not include issues related to inter-personal interactions, such as negotiated cognition, the social construction of meaning, and other social influences on the process of knowledge creation (Feldman and March, 1982; Bar-Tal and Kruglanski; 1988). Future research should examine the cognitive processes shared among dyads and members of groups, especially among those who use a technology that involves computer-mediated communication tools such as group decision support systems.

Finally, and perhaps most importantly, future research should directly observe and analyze the internal cognitive processes and the cognitive strategies employed by the subjects. The structural approaches using input-output method such as the one used in this research measures only the input stimuli and the outcome results, and draw inferences on the interim decision making processes. Since this approace does not directly oibserve the intervening processes, ambiguities remain in interpreting the results (Chervany and Dickson, 1974; Malhotra, 1984). Future research can follow process-tracing approach employing such method as protocol analysis to explore the internal dynamics of cognitive processes of information overload (Todd and Benbasat, 1987).

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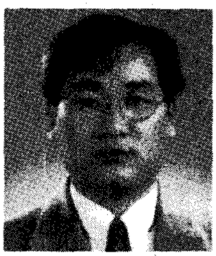
◇ 저자소개 ◇



저자 조남재는 82년 서울대학교 산업공학과를 졸업하고 한국과학기술원 경영과학과에서 석사, Boston University에서 MIS박사 학위를 취득하였다. 현재 한양대학교 상경대 학 경영학과 교수로 재직하고 있으며, 한남대학교 상경대학 교수와 한국외국어 대학교 대학원 강의, 한국과학기술원 대우교수를 역임하였다. 주요 관심분야는 정보기술의 조 직 영향, 경영자 인지과정, 정보기술의 마케팅활용, 조직정보처리(OIP)등이다.