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IMPROVING THE QUALITY OF INFORMATION SYSTEMS RESEARCH

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ABSTRACT

The quality of information systems research has been questioned in the literature. This paper discusses several methodological problems that have compromised past research: making variables operational, omission of key variables, and inappropriate inferences. Strategies and examples are presented for coping with these problems.

INTRODUCTION

One of the characteristics of an emerging field is that research in it often appears to lack rigor. This criticism has been made frequently about research in information systems (Ginzberg, 1975; Larcker and Lessig, 1980). The purpose of this paper is to discuss three methodological issues that have obfuscated the results of many studies. While these three issues do not represent a comprehensive set of problems or even a representative set, they are problems frequently encountered and infrequently addressed.

A research strategy and design to compensate for these defects is presented. While the results of a study making use of these approaches cannot be compared directly with previous findings to assess the magnitude of errors introduced by failing to resolve these issues, the results can be used to illustrate the importance of these issues. An awareness of them should improve the quality of future research. In short, this paper is a plea for more careful research design.

THE NATURE OF INFORMATION SYSTEMS RESEARCH

Information systems research deals with the characteristics of information systems that effect users, the process of building information systems, and the organizational and social consequences of these systems (Kling, 1980). As such, information systems research is much closer to that done in the social sciences than to pure science research. In contrast to pure science, the phenomena being studied in social science exhibit a lack of regularity in underlying processes and a seeming reluctance to be represented in neat analytic forms.

The methods used for investigation in social science also differ from those used by pure science researchers. Since the phenomena being studied by the social scientist usually are altered when brought into the laboratory, the researcher relies heavily on field studies. Imagine the difficulty for pure science researchers if they had to go out into space to produce a high vacuum.

Field studies imply gathering data through observation, interview, questionnaire, or by direct parameter monitoring. All of these data sources are subject to significnt error, including bias, definition, measurement, and deception errors.

Unlike the pure scientist, the social science researcher often neglects to declare a model. Besides aiding in hypothesis formulation, models, as Kuhn (1970) notes, form the context or paradigm for interpreting new ideas. Models are the framework for evaluating research results.

In place of models, social science researchers frequently rely on data analysis techniques to reveal patterns in the data that then suggest causal explanations. Without the aid of testable hypotheses to guide the analysis, it is too easy to rationalize findings on the basis of plausible explanations.

Reliability and validity (Kerlinger, 1973) are two frequently mentioned methodological concepts. It is unfortunate that many information system studies have not directly considered these issues. As Larcker and Lessig (1980) observe, the survey instruments used in studies are seldom validated and their reliability is usually not substantiated.

Another neglected area is in the selection of statistical procedures. Too often analytical methods are applied without first determining whether the assumptions required by the procedure are met. In many cases where they obviously are not met, there is no discussion of how the findings may be compromised.

But these are general methodological criticisms that apply to all social science research (1). What about problems that are specific to information systems research?

There are three particular difficulties that have plagued information systems research design: the way that variables are made operationl, the omission of key variables, and inappropriate inferences. These problems form the subject of this paper.

MAKING VARIABLES OPERATIONAL

In many research studies, investigators attempt to determine the consequences of information system use. For instance, whether workers making use of information systems have more positive attitudes towards their jobs than do workers who do not use computer systems. In these situations, computer use is often an independent variable. However, as Kling (1978) has observed, computer use has been treated in the previous research, as a dichotomous variable; either a worker did or did not use a computer system. There was no provision made for graduation in the degree of computer use. Clearly, this is a simplification (and restriction) of what occurs in real world situations where a worker may use a system for only a portion of the tasks performed and consequently for only a portion of the work time. It is reasonable to expect that if computer use produces an effect, this effect will be related to the degree of computer use rather than just whether or not a computer is used in the job.

In most of the prior research, computer use was not directly measured. For instance, Whisler's (1970) frequently referenced study used one manager per insurance company to report the extent to which workers in the company used (and were affected by) computer systems. Not only did Whisler use second hand reports, but the source of these reports were department managers rather than the worker's first line supervisors. If the managers in Whisler's insurance companies were no more informed than most managers are, the accuracy of these reports must be questioned.

In another study, Shepard (1971) used different jobs, specifically computer operators and clerical workers, to introduce degrees of automation use. The weakness of this research design is that any change in the dependent variable, in this case alienation, may be just as easily attributed to differences in job content between the two jobs, than to differences in the degree of computer use implied by the two jobs.

Probably the most blatant example of indirect measures was a study by Swart and Baldwin (1971). They surveyed personnel directors in a number of firms to ascertain whether clerical workers had changed as a result of computer use. Why personnel managers should have any idea about detailed job content is never explained. One might surmise that if a firm used formal job descriptions, then personnel directors might have a basis for comparing the content of two jobs. However, in this study there were no controls for job descriptions. Even if job descriptions existed, this is a weak research design. To write a job description is one thing, to believe that it accurately reflects job content is another.

Indirect measures of computer use have the disadvantage of never assuring that any particular worker actually makes use of the system, thus weakening the logical link between dependent and independent variables.

One way to remedy this situation is to design a study that incorporates a direct measure of computer use intensity. The measure could either be based on the proportion of time a worker uses a computer system or the frequency of use. The soundest research strategy is to use actual system logging. However, in many work situations the structure of the system does not permit capturing this data. For instance, where the user prepares data for input to a batch system or receives printed reports from the system. Even with some interactive systems, a user may not be required to identify himself to the system. In this situation, self reports of usage, while less reliable than usage logs, provide a usable alternative (2).

OMISSION OF KEY VARIABLES

Much of the information systems research assumes that it is the very existence of a system, rather than the specific characteristics of the system, that produce the effects found. For instance, in Whisler's (1970) study, no allowance is made for the differences among the information systems used by the various insurance firms. Similarly, Kling (1978) makes no attempt to measure characteristics of information systems in his study of the impact of computer use on the character of jobs in municipal governments (3).

There is an implicit assumption in these research designs: that users respond to all information systems in the same way regardless of form of the system. That is, such factors as performance or processing structure do not influence a worker's reaction to the system. If these assumptions are incorrect, than alternate explanations may exist for some findings. In support of the notion that information system characteristics are important variables, Bjorn-Andersen (1976) found that clerical workers doing the same job responded differently to batch oriented application systems than they did to interactive systems. This suggests that worker's reactions to these systems are not likely to be independent of the system's characteristics. This problem of key variable omission is part of a more general problem of model misspecification.

One way to deal with this specific issue is to develop an application system taxonomy that permits differentiating among systems that perform similar functions. This implies identifying dimensions that are meaningful to both users and systems designers and methods for their measurement.

INAPPROPRIATE INFERENCES

A frequent problem in information systems research is the appropriateness of the explicit or implied model to the problem being investigated. In general, models may be constucted at the micro or macro level. One important aspect of model building is aggregation. The act of aggregation refers to any process of combining either models or data at the micro level (Winer, 1980). This aggregation results in the creation of models and data at the macro level. As Winer (1980) notes, it is important to resolve three fundamental issues relating to aggregation in building models:

1. Determining the level of aggregation at which the model is to be constructed.
2. Specifying the structure of the model.
3. Determining the appropriate level of aggregation for data to be used in the model.

The best guide for determining the model's level of aggregation is to select a model that matches the research objectives. If the purpose of the research is to investigate the consequences of workers using computer systems, then the model should be defined at the micro (individual) level. If the purpose is to investigate the consequences for firms, then the model should be defined at the macro (firm) level.

Frequently these issues are not satisfactorily resolved. For instance, Swart and Baldwin (1971) gathered data on each firm's use of computer systems and inferred effects on individuals from it. As Robinson (1950) has observed, significant error is often introduced when macro data are used to infer micro effects (4).

Errors in model structure have two main components. The first involves specification error. A macro model is applied to the micro level without first considering whether the model and the variables contained in the model make sense at this level. As Cronbach (1978) notes, variables at one level of analysis may bear little resemblance to variables at another level. One may propose a model where at the group level, satisfaction is a function of leadership style, group function, and worker demographics. Furthermore, one may assume that these variables map directly to the micro level. However, at the micro level, the real model of individual satisfaction may be a function of task variables and individual expectations. In this case, group function is a different variable than the individual task variables and leadership style is not meaningful at the individual level. Clearly satisfaction at the individual and group levels are different concepts.

Another class of specification error is the omission of important variables from the model. This topic was covered in the previous section.

In contrast to errors of specification, the second component of model structural errors is aggregation bias. This occurs when the grouping of cases at one level alters the relative variance of independent and dependent variables at another level, thereby effecting the values of standardized measures (Langbein and Lichtman, 1978). This effect constrains the direct mapping of variables.

With regard to the third issue, the level of data used in the model, it should match the aggregation level of the model being estimated. If macro data are employed to estimate a micro model, then specification error is likely to occur (Winer, 1980). This is because the model estimated will, in effect, be macro but specified from micro theory. In this case, there may be vast dissimilarities between the estimated and true macro models. Similarly, macro models can not be estimated with micro data because of the introduction of specification error (Winter, 1980). However, macro data used to estimate a macro model could be explicitly aggregate micro data. If this is done, the ability to draw implications about the behavior of the micro unit is lost in most cases (Gupta, 1971).

One approach to dealing with this problem is for the researcher to consider explicitly the appropriateness of the level of the model to the problem under investigation and the level of the data to the model being estimated.

THE STUDY

These three problems, how variables are made operational, capturing variables likely to influence dependent variables, and cross level inference were specifically considered in the design of a study to investigate the change in performance, attitudes, and tasks that take place when computer based application systems are used to perform clerical jobs (Turner, 1980). The population surveyed was the 100 largest mutual savings banks in the United States.

Questionnaires were used to gather data on the same routine clerical function, mortgage loan servicing, in each bank. In addition, data were gathered about the information systems used by these groups.

Two models were developed from the behavioral and organizational literature: one at the individual or micro level and the other at the macro or group level (5). Responses were received from 71% of the banks for an N of 1420 workers (6).

COMPUTER USE INTENSITY

A direct measure of computer use intensity was developed by asking workers the extent to which they made direct use of computer systems, that is, used a terminal for data entry or output, or used computer prepared reports in performing their job. Responses were scored on a five point grounded scale. Although it would have been a stronger research design to use system monitoring data instead of self reports, the batch processing organization of many of these systems did not permit the gathering of monitoring data.

Because of the similarity in job content among workers within the same work group resulting in about the same relative use of computer systems, respondents were also asked the extent to which others in their work group made use of computer based systems in performing their job. A relatively high correlation ($r=0.66$) was obtained between the two variables. A multiple item index was constructed by averaging the item scores over the case.

AN INFORMATION SYSTEMS TAXONOMY

Although many different frameworks have been proposed to describe computer application systems (Lucas, 1974), none capture those aspects of a system that are likely to influence individual workers. For instance, Gorry and Scott Morton (1971) used two dimensions, the purpose of the system (or the organizational level supported) and the degree to which decisions in the system are structured. If such a framework were used to classify application systems performing similar functions, all of the systems would likely fall into one cell.

As Ginzberg (1975) notes, although researchers have a general notion of what factors distinguish one computer based information system from another, few good operational measures have been specified. A framework with greater precision is needed to differentiate among systems that perform similar functions.

Ginzberg (1975) introduced the notion of complexity as a way to differentiate information systems. The approach taken in this study expands on his suggestion. The complexity concept was separated into three components believed to be independent. The first, system type, represents the processing structure of the system. It can be thought of as both the extent to which the system permits concurrent activities to take place and the user's perception of system accessibility. Low values of system type represent structured processing organizations while high values represent interactive processing organizations.

The second complexity component, technical complexity, describes the internal structure of the application system. It is a representation of the volatility and processing dynamics of the system. For example, systems that are continually changing their data base place severe demands on back up and recovery processing, thus making design and operation more difficult.

The third part of complexity, organizational complexity, represents the external complexity of the application system. It is a description of the network of users served by the system and the extent to which this network is homogeneous. Applications with high external complexity place additional demands and constraints on designers and users of the system.

DISCUSSION

Three questions pertain to the methodological issues that were raised previously. First, was there variation in computer use across the sample? What evidence was there for the reliability and validity of this measure?

VARIATION IN USE

The standard error of the computer use scale was equal to or greater than any other micro level variable; in this study computer use intensity has the same relative variation as the other variables. While this result does not permit concluding whether this is adequate variation, it does mean that computer use is no worse, in this regard, than the other variables in the study.

Cronbach's coefficient alpha, a measure of the extent to which test items are homogeneous, was used as a indicator of scale reliability. The value of alpha for the computer use intensity scale was 0.80 while the average value of alpha for all of the micro level variables was 0.70 suggesting that the computer use intensity scale is relatively more internally consistent than the other measures used in this study. While the reliability of this measure cannot be compared directly with other measures of this concept, it does compare favorably with that of the other variables in the study which were measured using instruments that have been validated by other researchers.

Group supervisors were asked to rate the extent to which members of their work group made use of computer based systems. A strong correlation (r=0.50) was found between this measure and the aggregate group measure of computer use intensity. This finding provides support for the validity of the computer use intensity measure.

Taken together, these findings demonstrate the practicality and utility of a direct measure of computer use intensity.

INFORMATION SYSTEM TAXONOMY

The second question pertains to the information system taxonomy. What evidence was there of scale reliability? Were any associations found between the variables in the taxonomy and those in the remainder of the macro model?

The values of alpha for the taxonomy indices were as good or better than those of the other variables in the model (7). This indicates that these measures are internally consistent. It is worth noting, also, that these measures are largely independent.

Yes, associations were found between the information system variables and the other variables in the model. Using path analysis techniques (Billings _et al._, 1977, (8)), system type was found to influence work load negatively. That is, systems that have an interactive processing organization were associated with a decrease in work load while systems with a batch organization were associated with an increase in work load.

A negative association was found between system technical complexity and group job satisfaction. Systems that were more complex were positively associated with group job dissatisfaction.

A positive association was found between organizational complexity of the system and group mental strain symptoms. Systems that served a larger and more heterogeneous community were associated with increased group mental strain symptoms.

Furthermore, the strength of all these associations were equal to or greater than those among the other variables, supporting the earlier contention that the characteristics of information systems are important variables in this class of research. In omitting them, the researcher runs the risk of having an incomplete model.

MICRO AND MACRO MODELS

The third question concerns the differences between the micro and macro models. Were the two models the same or were new variables introduced at the macro level?

The two models definitely are different. At the micro level, the pathways by which the effects take place were reasonably clear. At the macro level, these pathways tended to be obscured. It would have been difficult, if not impossible, to infer the micro model from the macro model. In addition, new variables were entered into the model at the macro level that accounted for much of the model variation. From these findings it is concluded that the two models are different and complementary.

CONCLUSION

The methodology issues identified in this paper are likely to have an important impact on information systems research. An approach to dealing with each of these problems has been presented. More care should be taken in making variables operational; a lack of precision at this level is likely to compromise later results.

Information systems do differ. There is a need to develop frameworks that capture these differences in order to introduce them into our models. The taxonomy used in this research is only a beginning. Hopefully others will become interested in this line of research so that some consensus will emerge on the key variables and how to make them operational. It is important that we build on the work of others in developing these frameworks so that the similarities and differences between frameworks become clear.

More care must be taken in determining the level of analysis of research design. Often the convenience of obtaining data determines the level of the model rather than the question under investigation. When inferential limitations exist, they should be made explicit. The micro and macro levels of analysis are really different.

Most of all, errors made at the research design stage are difficult, if not impossible, to correct at a later point. Being more aware of these problems and taking more care with research design should improve the quality of information systems research.

NOTES

(1) Useful general references are: Kerlinger (1973) or Babbie (1973) for a general discussion of social science research methods, Kuhn (1970) on the role of paradigms in research, Campbell and Stanley (1963) on research design, Edwards (1957) for scale construction techniques, and Winkler and Hays (1975) for statistical methods.

(2) Lucas (1976) reported a reasonably strong association ($r=0.61$, $p=0.01$ or better, $N=39$) between self reports of computer system use and actual monthly usage derived from system statistics. In another study, Ginzberg (1979) reported a reasonably strong association ($r=0.50$, $p=0.002$ or better, $N=30$) between self reported level of use and system reported number of functions used.

(3) Studies that have made use of information systems characteristics include Ginzberg (1975) and Bjorn-Andersen (1976).

(4) Consider the difficulty of using national income accounts to infer the situation of individual families.

(5) The micro model related job satisfaction and mental strain symptoms to the degree of computer application system use. Two task and two structural variables intervene the dependent and independent variables. The macro model related productivity, group job satisfaction, and group mental strain symptoms to group intensity of computer system use and the information system variables. Again, two task and two structural group level variables intervene. For a more detailed discussion of the models, see Turner (1980).

(6) Missing data reduced the N of 1420 to 1020 for the micro model. Of the 71 banks responding, 35 or 49% also returned the information systems questionnaire. Missing data reduced this to 23 or 32% of the original responding group for an N of 23 at the macro level.

(7) The value of alpha for the system type index was 0.52 (significant at the 0.1 level). The value for alpha for technical complexity was 0.84 and the value for organizational complexity was 0.79 (both significant at better than the 0.05 level).

(8) Path analysis is a form of multiple linear regression analysis that permits decomposing covariation into direct, indirect, and spurious components. A weak ordering of variables is defined and regression equations written for each node in the network. A set of rules are used to decompose the coefficients.

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MODEL MANAGEMENT SYSTEMS: AN APPROACH TO DECISION SUPPORT IN COMPLEX ORGANIZATIONS

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1. INTRODUCTION

Recent years have seen an increased interest in developing interactive computer-based systems for supporting decisions that must be made in complex environments. Many of these systems are designed and built for decisions that relate to a specific problem (1,10) -- portfolio management, manpower planning, etc. Each of these systems center around a single model that a decision maker can use to explore various problem characteristics and solutions. The model, the user interface, and the model solution process are tightly coupled into a self-contained system. As a result, such systems lack flexibility and are difficult to adapt when there are changes in the problems they are designed to deal with. Modifications due to changes in the environment or because of learning on the part of decision makers may introduce the need to incorporate new policies, goals, or data into the analytic framework of the decision support system. This paper discusses an extension of the decision support system concept that we term "Model Management Systems" (MMS). These systems support decisions relating to a variety of problems that arise in a complex decision making environement.

In particular, the major objectives of a MMS are:

1. to facilitate the structuring of a decision so that analytical tools, possibly several in combination, can be used in generating possible solutions,

2. to facilitate the use of the analytical tools that have been brought together through a structuring process.

Thus, rather than being a predefined decision aid, a MMS can be viewed as a system that dynamically constructs a decision aid in response to a particular problem. This is accomplished by drawing on a knowledge base of models that reflects the technical expertise of a management scientist and the organizational experience with the activities involved in a given decision making environment.

This knowledge can be diffused throughout the decision making environment and adapted as necessary to support a decision maker in structuring as well as analyzing a problem. Knowledge representation, diffusion of knowledge, and adaptation of this knowledge in solving problems are basic characteristics of a MMS.

The remainder of this paper will discuss the MMS concept in depth. Organizational factors that have created a need for a MMS are discussed in the next section. Section 3 discusses the user roles involved with the MMS, and Sections 4, 5, and 6 build upon our experiences with prototype systems to discuss a structure of each MMS component. Section 7 presents our conclusions.

2. MODEL MANAGEMENT: WHY IS IT NEEDED?

A common characteristic of all decision makers is the use of a "model" as a basis to gather data, analyze this data, and eventually make a choice. These models may be intuitive or externalized, i.e., formulated in some symbolic manner. Even those models that have been externalized may not be in a form that