METHODOLOGICAL ISSUES IN INFORMATION SYSTEMS SURVEY RESEARCH

by

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Abstract

Empirical survey research has been extremely popular in the information systems field. However, survey researchers encounter a number of methodological problems in conducting their studies. This paper presents a model of the research process and uses it to organize a discussion of the difficulties encountered in doing IS survey research. The paper concludes with suggestions on how to improve the quality of IS survey research and improve the information systems field at the same time.

Introduction

A significant amount of information systems research can be classified as empirical, that is, a researcher collects and analyzes data to answer a question. There are two major empirical research designs, experimental and survey. Most frequently experimental work takes place in a laboratory setting while empirical research is conducted in the field in actual organizations.

The purpose of this paper is to discuss survey research in the information systems field. We define survey research in IS to be studies which collect data systematically from more than a few entities and which conduct some sort of statistical analysis of the data. The paper focuses on methodological problems in IS survey research. A review of methodological difficulties leads to the conclusion that there are certain research designs which produce better results than others. The paper concludes by comparing strong and weak designs and suggests strategies to improve the quality of IS survey research.

Survey Research

Why Conduct Research?

Most researchers probably never stop to ask why they conduct research; it has become a part of their work. Some academics might claim that they began doing research for promotion and tenure, and that the behavior became ingrained. While promotion might be the immediate motivation for an individual, research serves several important functions. Through research we understand more about our environment and we make economic, technological and social progress.

How does information systems survey research contribute to knowledge? In less than four decades, information technology has become pervasive in all aspects of the economy of industrialized countries. IS research helps to evaluate, implement, manage and understand systems with respect to individuals, organizations and the economy as a whole.

One encounters two major types of published survey research in the IS field. The first type of research presents information without trying to test a model. A researcher might wish to understand if a problem exists and the extent to which there is agreement about the problem. For example, one might try to determine how many individuals in a sample of organizations actually use personal computers or retrieve data from a mainframe using a Fourth Generation Language. Such surveys may provide useful information, but I feel they do little to advance the perceived quality of research in the IS field.

The most rigorous survey research is devoted to finding causal relationships among variables. It would be nice to know that a certain feature of a user interface caused managers to adopt a technology; another helpful finding would be that the use of a particular system contributed a certain amount of revenue to an organization. Drawing causal inferences from survey research is a very difficult task due to the nature of most survey research designs. Typically survey research shows the potential for a causal relationship, but provides little evidence that the relationship actually exists. We shall discuss the causality problem later in more depth.

The Process

There are a variety of models of the empirical research process, for example, see Stone (1978). The discussion in this section is organized around the following steps in conducting survey research:

Research Question

- Define research area
- Locate relevant theories
- Develop research model
- Delineate hypotheses

Research Design

- Develop research design
- Determine what and how to measure
- Identify the sample
- Design data collection instruments
- Collect the data

Analysis and Write Up

- Analyze the data and test hypotheses
- Interpret the results
- Develop the implications
- Write up the results

Typical Research Designs

Survey research is often considered to be synonymous with a cross sectional design in which all data are collected at once; however, there can be other designs for survey research. Using the notation of Campbell and Stanley (1963), a cross sectional design appears as:

X O

where O is an observation and X a "treatment" like the introduction of a new system.

One can also consider a control group where there is no treatment:

X	O
	O

Finally, a very strong design for survey research involves a longitudinal strategy in which data are collected at more than one point in time with a control group:

O	X	O
O		O

The advantage of this latter design is in the evidence it provides for causality. Pure cross sectional research is the weakest design for drawing causal inferences; one can only show that two variables are correlated at one point in time. Usually we can not claim that one variable caused a change in the other, nor in general can we argue for the direction of the causal relationship. The absence of a correlation, if the research is sound, is evidence that a causal relationship does not exist.

A longitudinal design provides greater evidence of causality as one can measure changes in variables over time. If one introduces a computer-based workstation and user productivity increases after installation, there is good evidence that the workstation contributes to productivity. An even stronger design includes a control group that does not have the workstations yet; it might be that the firm changed to employee ownership during workstation installation and that the new form of ownership is responsible for higher productivity. Comparing the experimental and control groups should allow the researcher to isolate the impact of the workstation.

Can we ever "prove" causality in IS survey research? My own view is that the answer to this question is "no;" we can only provide evidence for a reasonable observer to consider. The better the research design and overall quality of the research, the stronger the evidence for a causal relationship.

Problems In IS Survey Research

This section of the paper follows the model for research presented above and discusses typical methodological problems encountered in conducting IS survey research. Why do researchers in other areas frequently find fault with IS research in general and IS survey research in particular? See Table 1.

Research Question

One of the major problems with IS survey research is the questions addressed; does anyone care about the topic of the research? One researcher published a study of whether information centers in companies followed the model for information centers suggested by IBM (Carr, 1987). An observer outside of the IS field might find it hard to see exactly how the results of this survey contribute to advancing knowledge or practice. The paper certainly does not make it clear why anyone should be interested in IBM's model of an information center.

Once the researcher has found an interesting problem to study, the task is to locate relevant theories. Too frequently IS survey research is labeled "exploratory" and the researcher argues that there is no applicable theory. Since the IS field is broad and interdisciplinary, developing a research model from theories is quite difficult because one must synthesize theories from a number of different fields.

Failure to find a theory often leads to survey research that lacks hypotheses testing and rigor. Too often IS survey research presents descriptive statistics of some phenomenon, such as how users have worked with personal computers (Guimaraes, 1986).

The lack of relevant theories is a problem in survey research. While it is always desirable to derive hypotheses from a known theory, the researcher can not always do so. One way around the theory problem is to develop one's own research model inductively based on existing studies. I have conducted a number of survey studies of the implementation process for information systems; in 1981 these and other studies provided the ideas for two models of implementation. The major point of a 1981 monograph was to take two diverse approaches (possibly even theories) to implementation known as factor and process models, and combine them into one framework or model for implementation (Lucas, 1981).

Hypotheses are another source of problems for the IS survey researcher. Lacking a firm theory, it is difficult to come up with hypotheses; when present, hypotheses can be very uncooperative. First, a hypothesis should come from one's research model or theory; it should also be significant. I have reviewed a number of hypotheses in doctoral dissertation proposals and find that too often, candidates develop hypotheses that do not capture the major relationship among variables that make a research model interesting.

Hypotheses sometimes manage to become tautologies or they are untestable as stated. Given a good hypothesis, the researcher has to make it operational; in fact, a single hypotheses may generate several operational hypotheses for testing. If the researcher's hypotheses are disproved, does it have an impact on the theory or research model? If not, then the hypotheses probably are not really hypotheses derived from the model or theory.

The research model can be of great help in moving from theory to hypotheses. In survey research one is usually interested in different variables and how they are related; a model which shows the relationship diagrammatically is of great help in planning, organizing and presenting the results of the research.

My dissertation lacked a good research model, at least in the beginning. After having collected data I was faced with the problem of how to analyze a large number of variables; a model seemed like a good idea. There are simply too many relationships to consider in most survey research; a model tells the researcher where to concentrate.

The model is the place where a serious error can be introduced which will become evident later in the study; the omission of a confounding variable. If the researcher believes there is a relationship between variables X and Y, but in fact there is a confounding variable Z that causes both X and Y to move together, the model is misspecified. The specification error is not thinking of Z, a problem that may become evident in data analysis or when an individual not involved in the research reads a report of the results.

One research problem is to determine how much to include in a model and how complex the model should be. In an attempt to encourage a new direction in implementation research, we have proposed a rather complex, structural model of the implementation process (Ginzberg, Schultz and Lucas, 1984). Randy Schultz first suggested the idea of such a simultaneous equation model to me a number of years ago; the model is based on similar types of research in marketing and to some extent, economics. The model is rather large and studies to support it have been criticized by reviewers because of their complexity. We are planning to present the model and at least two studies in a monograph to provide a stronger case for the approach.

In developing a research model, then, one has to keep in mind the complexity of the model and the practicality of collecting enough data to test the model. One of the great disappointments in testing our structural model was that the data showed only weak relationships and it did not make sense to present the results through the simultaneous equation model, a major purpose of the research. Both model complexity and the general problems of obtaining precise, self-report data on surveys contributed to problems with the model. The economist with excellent data on interest rates, GNP and so on is in a much better position to propose a simultaneous equation model than is the IS survey researcher who includes behavioral, self-report variables in a study.

Research Design

The research design is crucial in determining the credibility of a study. As discussed earlier, in survey research often the design is purely cross sectional which offers the least evidence for causality. In only one of my field studies was it possible to use a longitudinal design with a control group (Lucas, 1978). In this instance user satisfaction decreased with the use of a new information system over time; the decrease was evident in both the experimental and control groups, but was much more pronounced in the experimental group. Even though the results were contrary to our expectations, the research design provided a great deal of confidence in what was observed due to the presence of the control group.

Design includes determining how to measure variables in the model, that is, the researcher operationalizes the variables. In the overall model, variables might be at the level of "management support;" in the design we must identify what operational variables will be used to measure management support.

In addition to operationalizing variables, one must deal with a number of measurement problems. Two familiar difficulties are the issues of reliability and validity. While there are measures of reliability like Cronbach's alpha, one ideally would like to assess test-retest results. A survey is reliable if an individual would answer in exactly the same way at some later time. Of course, in a longitudinal study, we expect to find differences in response after a treatment; as a result, longitudinal studies generally let several months elapse between observations so they are measuring more than test-retest reliability.

Validity is a difficult problem; extensive validation of a research instrument is a major research project in itself. Validity simply asks the question, "does the survey measure what the researcher says it measures?" If we ask about management support, does the answer we get in some way measure actual management support?

The researcher can reduce questions about validity by using a standard survey form that has been validated by someone else. To the extent that the standard survey asks the questions relevant to the present study, such a strategy works well.

Lately I have had some serious disagreements with editors and referees over the issue of standard survey instruments. Much of my research focuses on a single information system; as a result I need to survey users about very specific aspects of the system. Using a "standard" user satisfaction instrument would provide information about a respondent's satisfaction with IS in general; for my research model, I need to know about satisfaction with specific aspects of a single system.

It is not possible to validate an instrument for a single system using existing validation techniques unless there is an extremely large number of users of the system. To accept a requirement that one use only standardized, validated instruments means that research dealing with individual information systems is likely to be precluded.

Another point of criticism of instruments comes from single-item scales. A single-item may be all the researcher wants to ask, but looking at any of the reliability measures shows that it is unreliable. Thus, one is well-advised to have multiple items for each operational variable in a study if that variable is behavioral in nature.

The discussion above concerns primary sources of data in which the researcher collects the data. It is also possible to conduct survey research using secondary data alone, or in combination with primary data. Secondary data exist already; the researcher collects the data from other than its original source. Secondary data collection is often easier than primary and it can provide increased credibility for findings. In several studies I have been able to collect secondary data on system usage and to compare it with self-reports (Lucas 1976). Recently Rice and Shook (1988) found a high correlation in most instances between reported and monitored use of an electronic mail system. Kauffman (1988) did an excellent job of using secondary data in a survey to discover the impact of automatic teller terminals in Pennsylvania.

In general, multiple, independent sources of data reduce suspicion that the results of survey research come from an artifact of the data collection instrument or the halo effect from completing a survey. Multiple data sources may be self-report measures from different individuals; in (Lucas and Walton, 1988) we included data from three individuals in companies using a packaged program and from the vendor's representative to the companies.

A final problem in operationalizing variables and creating survey instruments comes in asking the hypothesis. Stating the hypothesis as a part of the question does not allow one to draw a relationship among variables. As an example consider the following question:

> Since the XYZ system was installed, how much time does it take you to do your job?
>
> 1. Less time
> 2. The same
> 3. More time

If the predominant answer is 1, the unwary researcher is likely to draw a conclusion that the system has saved user time. Such a conclusion is not warranted unless the user has kept track of time required to do his or her job before and after the system. All one can legitimately conclude from the question above is that users perceive that the system has reduced the time required to do their job, not that the system has saved user time. The strongest evidence on the impact of the system would be if a control group of non-users showed no change.

The researcher must decide what population to sample and arrange for data collection. Arranging a sample can be difficult and requires a great deal of effort. One also must decide the unit of analysis which influences the sample. Does the survey deal with firms, or with individuals in the firm? Generally one has many fewer organizations than individuals in a study. If the sample is focused on an entity like a firm, how are multiple respondents in that firm to be represented? Are their results to be averaged to form a score for the firm, a typical strategy?

Most of the statistics that we use in analyzing survey data rely on a random sample. Unfortunately, none of my studies that comes to mind employed a random sample, not because randomness was not desired, but because it was not practical to obtain it. Generally survey research is done in situations where subjects agree to participate. The researcher may select a company or series of companies because they are willing to cooperate.

If the researcher focuses on a single system, the users of that system become the sample, hardly a random group. With a sufficient number of users, the researcher could take a random sample of users, but the underlying population is all users of the specific system, not all users of systems. How representative are these users and the system? The researcher must argue that the sample in the study does not differ from a random sample in any meaningful way and the reader must evaluate the soundness of that claim.

Data collection is a major challenge in survey research, though conceptually it is a simple task. One sends an instrument to or interviews individuals to collect primary data. For secondary data the researcher makes arrangement with whomever has the data to obtain it. I have had the most luck in data collection when studying a single system, particularly if a company official sends a cover letter with the survey form. In a study where multiple companies were involved, obtaining cooperation from the firms and sending several assistants to visit plants took two to three times the length of time originally envisioned (Lucas, 1984).

In the packaged program study mentioned earlier, we relied on the package vendor's sales representative to collect data from customer sites. We were assured that the vendor representatives would cooperate; of course, they did not. As a result, a few month data collection task turned into more than a two-year effort that involved sending an assistant into the field (which seriously damaged the project budget).

Analysis and Write Up

If the researcher has developed a research model, data analysis will allow him or her to test the model and hypotheses. If there is no model, analysis becomes a frustrating exercise in hunting for relationships. The typical result is a set of frequency distributions and descriptive statistics about a survey (Guimaraes, 1986, Carr, 1987). An equally disturbing outcome from the lack of a well-specified model is that the researcher often collects data on an extremely large number of variables so that interpretation becomes very difficult (Hiltz, 1988).

The researcher is also confronted with the problem of what statistics to use; in most instances the survey will have violated enough assumptions that parametric statistics are not appropriate. However, since one can do a lot more with parametric statistics and since the assumptions do not seem to matter as much as n gets to 50, most of us use them anyway. In the case of the package study, we managed to extract over seventy responses, but our unit of analysis was the company of which there were 18 represented. We used nonparametric statistics because of the small sample size. (A referee who complained about the small sample size criticized the paper for using nonparametric statistics.)

Baroudi and Orlikowsky (1989) have recently called our attention to the lack of power of many IS survey research projects. Usually power becomes a problem in small samples. Power is the ability of the research design to avoid accepting the null hypothesis when the null hypothesis is false. We generally set an alpha of .05 or .10 saying that the null hypothesis will be rejected incorrectly only 5 or 10% of the time. Power looks at the other side of testing; did the researcher accept the null hypothesis when it was false? How well does the research design allow the researcher to discriminate between the null and alternative hypotheses?

Small sample size also presents serious problems in data analysis and hypothesis testing, particularly when the researcher wants to use analysis techniques like regression. The rule of thumb for a regression is that there should be at least 10 observations per independent variable in the equation. Some studies have violated this rule of thumb to the point that their results must be suspect (Leonard-Barton and Deschamps, 1988).

Another data analysis problem comes under the heading of obscure statistical tests. In an effort to show statistical significance, some researchers turn to little known tests. While such an approach may salvage statistical significance, we should be concerned with the practical significance of the results. The lack of results is often an interesting finding and should not be hidden from readers.

A related problem is using statistical methods with survey data that suggest the data show causality; it is possible the data do, but the research design probably does not. In particular path analysis has become popular in survey research; it is an excellent technique for presenting results. However, it can not do anything more than regression analysis or the use of partial correlations to provide evidence of causality.

In thinking about appropriate statistical tests, we should keep in mind the ways in which results will be used. Typical IS research hypotheses deal with the existence and direction of a relationship among variables. The presence of a strong correlation is often enough to support a hypothesis. The econometrician asked to predict whether GNP will grow at 2% or 3% next year given a particular fiscal policy has a much greater problem with precision than the typical IS survey researcher.

Once satisfied with the data analysis, the researcher must interpret the results, develop implications and prepare a write up of the study. At this point, specification error in the original model may appear as one looks at the data. Creativity is needed to explain unexpected results.

For the researcher who would like to claim causality, all the evidence is now at hand. Blalock (1964) offers a number of suggestions about how one can provide the strongest evidence for causality. If, in a cross sectional design, the researcher finds a positive correlation and can demonstrate that one variable preceded another in time and can also discount confounding variables, he or she may argue for a causal relationship. In IS research, the time ordering of variables often does not lend itself to these arguments.

In most of my studies the conservative approach was to say that the reader has now seen the evidence for the model. The survey data can not prove causality; however, if the reader is willing to accept the model, what are its implications? The model itself is most often causal; we are saying that there is evidence to support, but not prove the model. If the reader feels the model is valid, he or she must decide whether or not to accept its implications based on evidence from the current study and from other research.

Conclusions

We have presented an inventory of steps in IS survey research and some of the issues encountered at each stage in the research process. It is difficult to say that any one step is more important than another; the conclusion may be that to produce high quality research, the researcher must do well at each stage. The norms for different stages based on past IS survey research vary. For example, most reviewers are more concerned about instrument validity than the non-randomness of a sample. In general, however, we should attempt to achieve the highest possible standards for each component.

Will attention to each stage guarantee good research? No, it will guarantee competent research. Performing the research tasks above well does not necessarily result in research that is interesting or creative; it will not guarantee that the product of the research effort will be perceived as outstanding by other researchers.

Weaknesses in IS Survey Research

Why does not IS survey research get any respect? There are a number of reasons why individuals outside of the information systems field often find our research lacking. It is indeed unfortunate that these individuals often represent the dominant power structure of business schools in the 1980s; finance, economics and management science faculty.

The first problem in Table 2 is that empirical survey research is often thought to be equivalent to behavioral research, an area that is not held in a great deal of regard in many business schools today. To some extent, this association of IS survey research with behavioral research is not justified; most of my studies include behavioral variables, but they also include other factors as well. Kauffman's work has no behavioral variables at all, yet could be considered survey research (Kauffman, 1988). It appears that much IS research in general is behavioral; a faculty participant in the 1987 ICIS doctoral consortium indicated that he thought he had come to the wrong conference seeing the titles of the doctoral research proposals. The consortium looked more like a meeting of a behavioral science or psychology group than a gathering of IS Ph.D. candidates.

The use of information systems involves behavior, but I think it would be a mistake if the IS field became a branch of applied behavioral science (or applied computer science). The information systems field is multidisciplinary and draws its theory from many fields. If we concentrate on one of these fields and become narrow specialists in it, the IS field will suffer as our research becomes unrepresentative of the issues in IS.

Another reason IS survey research is not highly regarded is either the subject matter addressed or the trivial nature of the results. We continue to publish papers in highly rated journals with no research model, no hypotheses or theory, and which present their results in the form of frequency distributions and descriptive statistics (Martin, 1983, Benson, 1983). Compare these papers with the articles that appear in first rate finance or management science journals and the differences will be painfully obvious. There is a place for surveys that help identify current issues for researchers, but they should not be published as highly refereed research contributions.

There are many important topics in IS for which survey research is appropriate. If topics are not interesting to us in the field, how can they be perceived as interesting by non-IS faculty who sit on promotion and tenure committees? We seem to have the idea that a poorly designed study on an uninteresting topic which produces significant results advances the field. I would much prefer to see a well-designed study of a hard problem produce modest results.

Strengthening IS Survey Research

How do we improve the quality of IS survey research and improve the entire IS field in the process? See Table 3. First researchers have to develop standards so that they can identify and judge high quality research. Quality has a number of dimensions, many of which have been discussed above. Quality means finding an interesting research problem, developing a compelling model, hypotheses, and a rigorous research design to test the model.

We should strive for research designs which have a large sample size to allow for greater statistical power and the use of multivariate analysis procedures. Multiple sources of data increase credibility of results; today with more and more data being monitored and collected there should be opportunities to have both primary and secondary data in survey research.

If the research design can move beyond cross sectional approaches to longitudinal with a control group, the researcher can provide much more compelling evidence for the causal implications of the research model. Multidisciplinary research can also strengthen the field by bringing multiple methodologies to bear on the same problem (Jarke, et. al., 1985).

Conclusions

The first task, of course, is to do research. Second is to aim for the highest possible quality in the research. Quality benefits the researcher directly and benefits all of us by advancing our knowledge and the information systems field, itself. The challenge for survey researchers in the IS field is to set new standards for research. In the academic environment, quality research is a requirement for a field to survive and flourish. The future of the IS field as an academic area depends very much on the quality of the survey research we undertake.

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Research Question

Does anyone care about the answer?

Is there any relevant theory?

Develop a research model; beware of complexity

Hypotheses are often uncooperative, tautologies or untestable.

Look for omitted variables.

Research Design

Can the research go beyond a cross sectional design?

Determine operationalized variables and how to measure them.

Assess reliability and validity of the instruments.

Consider standard surveys, but think about their limitations.

Beware of single-item scales and of asking the hypothesis.

Can you find secondary data? Multiple sources?

Is there ever a random sample?

Try to collect the data.

Analysis and Write

Can the research model guide analysis?

Determine what statistics are appropriate.

Does your design have adequate power?

Are the statistical tests appropriate for the sample size?

Are the statistical tests obscure or do they raise misleading claims of causality?

Can you interpret the findings and do they support the model?

Problems in IS Survey Research
Table 1

Does Is survey research equal behavioral research?

Is the subject matter trivial?

Is there any theory or are there hypotheses?

Is there any statistical analysis beyond frequency distributions?

Does the research do anything to advance the IS field?

Weaknesses in IS Survey Research
Table 2

Develop standards to judge IS survey research.

Find interesting problems to research.

Develop compelling models and hypotheses.

Construct rigorous research designs to test the model.

Look for multiple sources of data.

Can the design include a longitudinal study and control group?

Try for a large sample size, good statistical power and multivariate analysis.

Consider multidisciplinary research.

Strengthening IS Survey Research
Table 3