

February 2002

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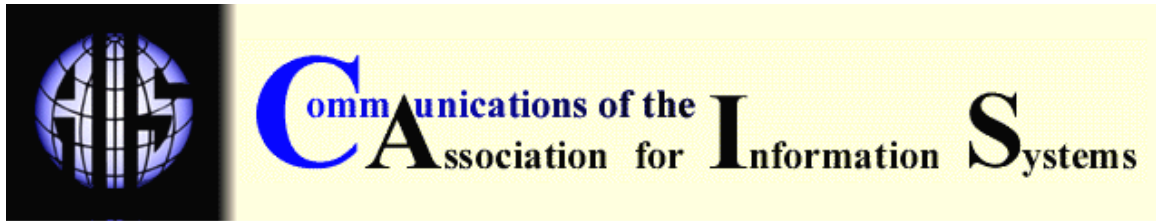
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Recommended Citation

Thomas, D., & Watson, R. (2002). Q-sorting and MIS Research: A Primer. *Communications of the Association for Information Systems*, 8, pp-pp. <https://doi.org/10.17705/1CAIS.00809>

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Q-SORTING AND MIS RESEARCH: A PRIMER

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ABSTRACT

Q-sort offers a powerful, theoretically grounded, and quantitative tool for examining opinions and attitudes. This article provides clear guidelines in an effort to facilitate successful understanding and application of Q-sort. Following a description of the steps of Q-sorting, an example Q-sort of MIS professors on the topic of PhD preparation is presented. The example includes details of Web-based data collection and data analysis using freeware tools. The use of Q-sorting in MIS research and issues surrounding the use of Q-sort are discussed.

KEYWORDS: Q-sort, Research Methodology, Q-Methodology, Survey Research, WebQ, Web-enabled Research

I. INTRODUCTION

Developed by William Stephenson over a lifetime of work beginning in the 1930s [Stephenson 1935], Q-methodology has been studied extensively, with over 1,500 works referencing it [Brown 1986]. It is used for behavioral research in various fields including psychology, sociology, and marketing. Through its techniques, primarily Q-sorting, it offers the IS researcher a systematic and rigorous quantitative means for examining human subjectivity.

Q-sorting consists of "a modified rank-ordering procedure in which stimuli are placed in an order that is significant from the standpoint of a person operating under specified conditions" [Brown, 1980, p. 195]. It results in the captured patterns of respondents to the stimulus presented, a topic on which opinions vary. Those patterns can then be analyzed to discover groupings of response patterns, supporting effective inductive reasoning [Stephenson, 1979].

Q-sorting offers IS researchers several benefits:

- Q-sort offers a means for an in-depth study of small sample populations;
- It can help with exploratory research;
- A well-developed theoretical literature guides and supports its usage;
- It captures subjectivity in operation through a person's self-reference;
- Participants need not be randomly selected;
- It may be administered over the Internet;

- Its analysis techniques help protect respondent self-reference from researcher influence.

Q-sorting use in MIS research goes back at least as far back as 1987 [e.g., Kendall, Buffington, et al. 1987]. Since 1987, several studies used Q-sorting effectively, but others employed techniques that cannot properly be termed Q-sorting because they violate the theoretical underpinnings. This article presents an example of Q-sorting as a way of introducing how to use Q-methodology and to help guide successful applications of Q-sorting in MIS research. Toward the end of the article, in Section V, several examples of Q-sorts in MIS research are identified and discussed briefly. Interested researchers will find the references section useful in exploring Q-methodology further.

II. Q-SORTING IN DETAIL

Q-sorting proceeds in stages similar to general survey methodology. First, the Q-study, that is the research in which Q-sorting will be used, must be properly designed. Second, the Q-sort must be properly administered. Third, the Q-sorts may be analyzed. Without completing the first two stages successfully, the validity of insights drawn from the analysis may be compromised (see Brown, 1980 for a more detailed and theoretical discussion of these stages.)

Q-STUDY DESIGN

A Q-study begins with identifying a topic on which people's opinions vary. Q-sorting requires that Q-samples, usually verbal statements, be collected that adequately represent the spectrum of opinions on a given topic. For example, if a study were looking at attitudes about Lotus Notes in a given organization, statements applicable to the viewpoints involved should be included. Collecting statements from personal interviews and questionnaires, asking experts, drawing quotations from relevant literature, and an investigator's own words can be used.

If a structure of responses can be forecast *a priori*, it can be used to facilitate selection of Q-samples across the population of thoughts available on the topic. In the Lotus Notes example, if one expects low-level users, executives, and IT staff viewpoints to differ on both maintenance and value to the organization, a block design of 3 x 2 produces 6 cells needing Q-samples. This basic design multiplied by its replicates yields the total sample size. The number of Q-samples adequate for a given Q-study depends on the distribution that will be used in Q-sorting. Generally, 30 to 60 Q-samples are used with respondents distribution their answers on a scale of from -4 to +4 or from -5 to +5 [Brown, 1980]. In addition to verbal statements, Q-samples can include other types of objects about which a researcher desires subjective feedback including Web sites, smells, and pictures.

Q-sorting response distributions generally follow a quasi-normal pattern. However, the distributions can differ depending on the topic. For example, Brown [1980] explains how a topic evoking strong, polar opinions would justify use of a flatter distribution.

Q-SORTING ADMINISTRATION

The Q-sorting procedure follows a fairly specific pattern. All Q-samples (statements, Web sites, smells, etc.) must remain accessible and sortable until the sorter (respondent) is finished and satisfied. Additionally, no outside source may guide the sorting, and no collaboration can be allowed unless the unit of analysis is a group. Usually, the Q-samples are placed in the center of the distribution, and the sorter must then go through the statements deciding which must be moved. For the Lotus Notes example, the -4 and +4 distribution anchors might be Strongly Disagree and Strongly Agree with gradations in between. Sorters would then read through, comparing the statements, and placing them. At first, the respondent might simply divide the items into three piles: disagree, neutral and agree. In the following iterative process, each pile would be examined carefully and distinctions made within the pile, eventually leading to each space in the distribution being filled.

Thus, the respondents compare each Q-sample to each of the others and arrive at a true comparative judgment on where to place each item based on self-reference rather than external factors. This self-referent response may then be termed accurate from the respondent's

perspective regardless of whether the 'universal pool' of Q-samples was represented. The sorter will have made the best choices possible within the options available. The forced distribution requires a decision. This decision impacts interpretation of the -1, 0 and +1 Q-samples in that they may be intentionally neutral or leftovers with little value. They are considered to contain no information [Stephenson, 1974].

Q-sorts can be affected by social desirability, an important piece of information for anyone studying subjectivity. To capture social desirability, Q-sorting conditions can be reframed. For example, the sorters in the hypothetical Lotus Notes example could be asked to sort (1) as themselves (2) as members of the other groups (e.g., IT staff as executives or simple users as IT staff).

After sorting, follow-up interviews can be conducted to capture the subjects' reasoning for ranking the various Q-samples in their unique way.

Q-STUDY DATA ANALYSIS

As Q-Method founder William Stephenson says, "the statements of a sample may interact" [1953, p.58]. They are analyzed with factor analysis, thereby allowing the capture of this interaction in factor loadings. Basically, Q-method factor analysis begins with an $n \times n$ correlation matrix of the Q-sorts, where n is the number of people who sorted the items. It proceeds to partial out the shared variance mathematically among the Q-sorts, converging on a first dimension or factor that accounts for the most shared variance. This process continues until all factors are identified.

The number of eigenvalues above one, produced at the correlation matrix stage (or all factors containing more than one Q-sort) can be used as heuristics to inform the number of factors. Special cases might point to factors satisfying neither of these guidelines and point to the inclusion of additional factors. For example, Brown notes that one is the customary but not absolute cut off for acceptance of the significance of a factor. He goes on to illustrate an occasion when an important factor represented by only one person's sort, the doctor in a medical ward, would have been left out if not for careful thinking and analysis by the researcher [Brown 1980]. With the Q-sorts as variables, the factors produced represent groupings of people with similar patterns of response during the sorting (e.g., attitudes, opinions, viewpoints), and the loading of a particular respondent on a given factor indicates the level of agreement or disagreement.

The use of factor analysis in Q-method assumes proper Q-study design and Q-sorting administration and aims at the discovery of patterns of response among the respondents. These patterns then provide a basis for induction and *abduction*, a logical search beginning with observed effects in a given context and in search of potential causes when expected relationships are found absent [Stephenson, 1979, Brown, 1980].

The use of factor analysis in research raises questions about the appropriate technique and the researcher's influence over the results, particularly when factor analysis aims to confirm or disconfirm hypotheses about data interrelations (Lance and Vandenberg 2001). To this end, exploratory applications of factor analysis might be influenced by the analyst's subjectivity, confounding deduction (Lance and Vandenberg 2001). A variety of factor analysis methods have been applied to Q-sort data. Though deductive research and confirmatory research may require mathematically driven factor analytic techniques to ensure objectivity through statistically maximized solutions, such techniques deny theoretical pursuit in favor of achieving representation for generalization purposes. Q-studies do not purport to achieve this end, and the use of judgmental techniques such as the Centroid method with judgmental rotation fits the needs of Q-method, facilitating theoretically driven searches for patterns of response leading to induction and abduction [Brown, 1980].

Q-method's application of factor analytic techniques focuses on preserving the respondents' self-reference and comparative choice relationships so that patterns can be discovered from responses without *a priori* formulation [Stephenson, 1953]. In terms of Q-sorting this objectivity requires that the data reflect the population's self-referent, subjective placement behavior during

the Q-sorting with minimal researcher influence. In an effort to establish the independence necessary for inferential statistical validity, researchers employing cluster analysis (or other inferential techniques) often ask respondents to choose a value such as “highly likely” from a scale, such as a Likert scale, so that the choice of one answer does not impact the ability to choose others. Thus, while Q-sorting respondents are *forced* to make the subjective value judgments from which the analysis proceeds, cluster respondents may or may not be forced to do so (i.e., the *ad hoc* nature). The underpinnings of Q-sorting, that the respondents make their choice based on a comparison with all available alternatives, preserves the self-reference, enabling Q-sort data’s factor analysis.

Researcher influence can become an issue during analysis through a lack of randomization leading to systematic comparisons due to ill-composed Q-samples [Brown, 1980]. Randomizing the ordering of Q-samples and formatting them all in the same manner, in the case of verbal statements, negates this problem.

III. Q-SORTING EXAMPLE

In August and September 2000, University of Georgia MIS professors participated in a browser-accessible Q-sort of verbal statements focusing on how best to prepare MIS PhD students. The goal of the exercise was to spur conversation by distinguishing attitudes within the department. The informal character of this Q-sort as a group focusing activity among colleagues reduced the need to apply a block design for demographic or contextual factors. This example is offered primarily as a hands-on introduction to the workings of a Q-sort and its analysis. In-depth and more sophisticated applications of Q-sort can be found in many of the articles cited.

The statements (Table 1) were collected from faculty via email and entered into an online JavaScript Q-sort freeware application called WebQ (see the next subsection). WebQ includes the ability to view Q-samples and move them throughout the sorting process. It also checks to ensure a forced distribution of answers before emailing them to the researcher, and it allows an elimination process for sorters to compare each Q-sample individually, and review, refine, and iterate their decision process. While some questions exist about whether Web-administration of the Q-sort will compromise the results, recent research found that Web-based Q-sorting showed no difference in terms of reliability or validity [Reber, Kaufman et al., 2000].

Table 1. The 14 Q-Sort Statements

1	At least one or two journal publications before they leave
2	Given an MIS problem or outcome, be able to create a good research design that addresses the issue
3	Be able to teach Core MIS classes well
4	Understand the role of existing theory in the process of developing new knowledge: as a vehicle for learning, challenging, expanding, and communicating knowledge
5	Methodologically well trained so they collect data wisely, and interpret it correctly
6	Good placements
7	Good faculty mentoring starting with the choices we make in admissions, through laying out the paths of coursework, through pairing of student and dissertation advisor based on the developing interests of the student
8	Strong foundation in research methods understanding and skills
9	A strong foundation in teaching methods understanding and skills
10	Produce high-quality IS researchers that will contribute to the field through knowledge creation
11	Produce high-quality IS educators that will contribute to the field through knowledge dissemination
12	To develop a high level of competence in the areas of conducting basic and applied research
13	To develop a high level of competence in university teaching
14	To demonstrate mastery of a large and complex body of knowledge

WEBQ Q-SORTING

WebQ is a freeware Q-sort administration Web application programmed in Javascript and available at <http://www.rz.unibw-muenchen.de/~p41bsmk/qmethod/webq/index.html>. For the source code and more about the capabilities and limitations of WebQ, visit the URL. The program currently runs on Javascript-capable browsers and handles Q-samples formatted as text statements. It could probably be modified for other objects. Since the MIS PhD preparation Q-study used verbal statements, WebQ could easily be used. To try out the MIS PhD preparation Q-study point your browser to <http://www.arches.uga.edu/~dominict/webq/samplewq.htm>.

WebQ randomizes the Q-samples for each sort to help reduce possible effects due to Q-sample order. If you reload the sample study at the preceding URL, you will see the statements are reordered.

Figure 1 shows the main sorting screen. All of the Q-samples can be seen and compared at once. Computer monitors at lower resolutions or Q-studies with more Q-samples might require scrolling, though pairs of Q-samples would almost certainly always be available to compare, allowing the sorting to take place. During sorting, WebQ keeps track of the status of the sorting using traffic signal-like markers to indicate empty slots (blue), occupied slots (green), and over-filled slots (red) in the forced distribution. If a sorter tries to send the results without all of the slots being occupied, WebQ displays Figure 2 and denies submission.

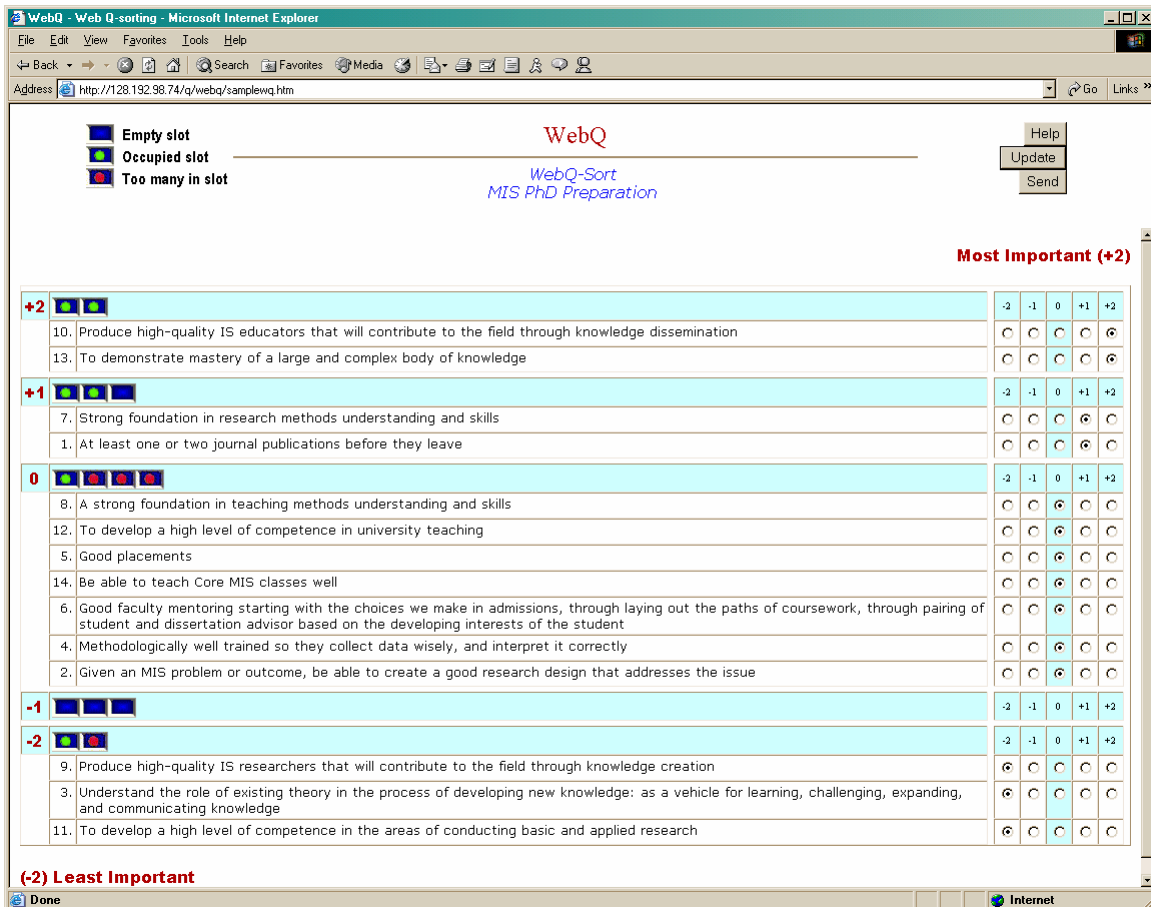


Figure 1. Webq Sorting Screen.

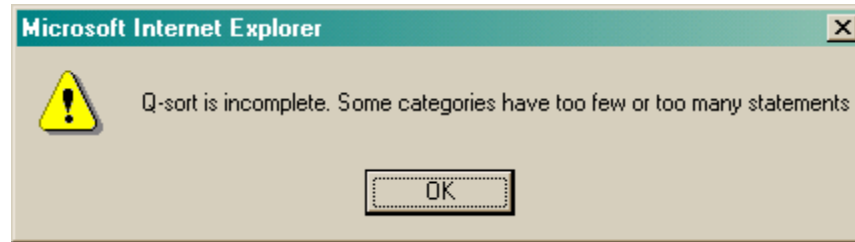


Figure 2. Flag that Forced Distribution is Not Satisfied.

WebQ submissions arrive via email and contain a code word to identify each sort, determined by the sorter, an array containing the sort, and any comments the sorter has about the process (Figure 3). The results can be copied and pasted into a text document to create the source data file for data analysis. The code word allows for anonymity to be introduced between the data collector and data analyzer if they are different people. Depending on the mail clients and browsers used by the sorters, line breaks and other formatting may be introduced or left out in the submission. As a result, data collection still requires scrutiny of the response arrays and perhaps some reformatting to prepare for data analysis.

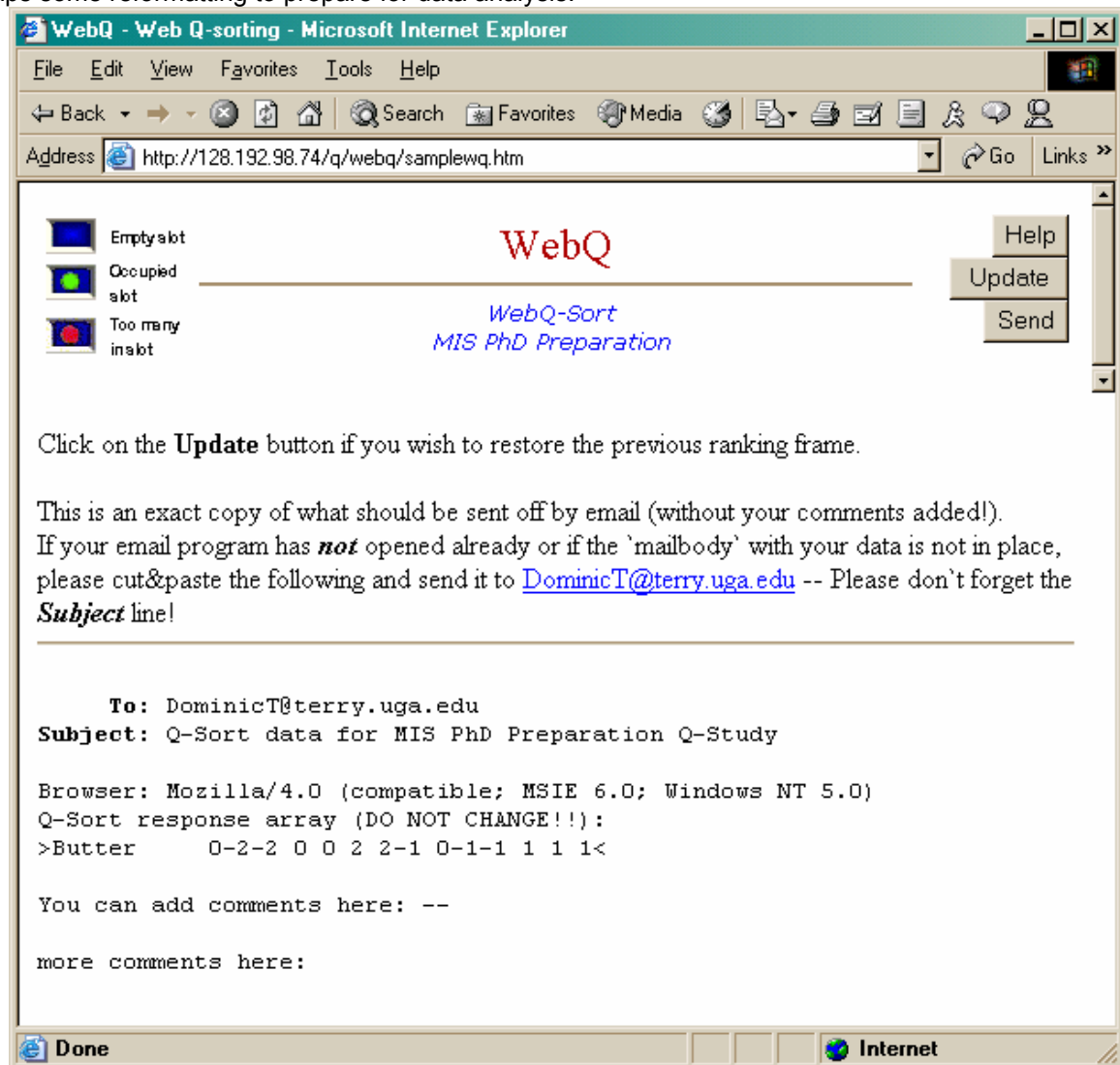


Figure 3. Submission Screen

Q-SORT ANALYSIS USING FREEWARE

With the Q-sorts completed, the analysis using MQMethod, a free statistical package geared to the specific needs of Q-method located at

<http://www.rz.unibw-muenchen.de/~p41bsmk/qmethod/index.html>),

begins with the output of a correlation matrix and eigenvalues for a series of potential unrotated factor groupings. The correlation matrix (Table 3) helps to show how Q-sort grouping works. Given the high correlation between sorts 1 and 6, one would expect them to be in the same group, even if rotation of the factors caused some shift in their level of agreement. Likewise, 8 and 3 are orthogonal (i.e., differ on their views), and any grouping of 8 with 3 would be suspect. A simple examination of the eigenvalues greater than one suggests that three significant factors are present, and that they account for 76% of the variation (Table 2).

Table 2. Eigenvalues from the Unrotated Factor Matrix

Eigenvalues	2.99	2.37	1.47	0.74	0.51
Variance Explained	33.2%	26.4%	16.1%	8.3%	6.2%

Table3. Correlation Matrix

Respondent	1	2	3	4	5	6	7	8	9
1	1.00								
2	.27	1.00							
3	.18	.27	1.00						
4	-.14	.64	.27	1.00					
5	-.32	-.05	.45	.36	1.00				
6	.77	.18	.09	-.27	-.32	1.00			
7	.00	.36	.55	.55	.64	-.14	1.00		
8	.27	-.18	.00	-.41	.05	.14	-.09	1.00	
9	.41	.45	.36	.09	.32	.27	.50	.23	1.00

Next, a three-factor limit guided a principal components factor analysis with rotations, which serves to distinguish the interactions between the Q-sorts and does not affect the pattern of response given by the sorters as it lies in the factor space. Changing the underlying pattern of response would violate the psychometric and operational principles of self-reference that guide and validate data collection and analysis in applications of the Q-method [Brown, 1980; McKeown and Thomas, 1988; Stephenson 1994]. This rule is in counter distinction to other grouping techniques such as cluster analysis that may allow more outside manipulations as they rely on a variety of data collection and validation techniques as well as multiple methods for calculating proximity. The differences between these two approaches are discussed later in this paper.

ANALYZING THE FACTORS (TABLE 4)

After several rotations to optimize the factor loadings, respondents are grouped distinctly (Table 4). Multiple sorts compose each factor. Because sorts represent the self-referent responses of individuals, the factors can be taken as groupings of respondents with similar responses with the exception of respondent eight on factor three whose strong negative loading on factor three clearly indicates an opposite attitude to other factor three members, namely respondents two and four. Meanwhile, in accordance with the data from the correlation matrix, respondents one and six are highly loaded on factor two, and respondents three and eight are loaded on different factors. Not surprisingly, faculty viewpoints differ on how PhD students should be prepared.

In addition to factor identification and loadings, MQMethod provides extensive output for comparing and contrasting factors. The normalized factor score tables provide a measure of the relative strength of importance attached by each factor or attitude to each statement on the scale used during the sorting, in this case from -2 to 2. A merger of the common variance among the members of a factor produces the normalized factor scores. A detailed mathematical description can be found in Brown's work [1980]. In discussing these outputs, the middle scores of each table were omitted because they are ambiguous in a forced distribution context. For example, the following can be observed in Tables 4 and 5.

Table 4. Factor Loadings

Q-sort	Factors		
	1	2	3
1	0.06	0.92	-0.08
2	0.29	0.44	0.73
3	0.72	0.14	0.10
4	0.39	-0.17	0.81
5	0.81	-0.43	-0.07
6	-0.09	0.87	-0.10
7	0.85	-0.07	0.29
8	0.21	0.25	-0.74
9	0.68	0.49	-0.02
Explained variation	29%	26%	21%

Note: Bolding indicates a significant factor loading

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1. (Table 5) Adherents to factor one feel strongly in favor of statement 12. They favor statement 7 less so and oppose statements 1 and 6. The researcher can infer that these respondents feel that PhD student preparation should focus on developing an ability to conduct research with the help of a mentor while specific placement and publication outcomes are not so important.
2. (Table 6) Those with the perspective captured by factor two agreed with statements 10 and 4, and demoted 13 and 11. An interpretation of their view is that PhD preparation should produce productive theory-based researchers, and they consider teaching relatively unimportant.

Table 5. Factor One Distinguishing Statements

	Most Important	Normalized Factor Score
12	To develop a high level of competence in the areas of conducting basic and applied research	1.92
7	Good faculty mentoring starting with the choices we make in admissions, through laying out the paths of coursework, through pairing of student and dissertation advisor based on the developing interests of the student	1.05
	<i>Least Important</i>	
6	Good placements	-1.44
1	At least one or two journal publications before they leave	-1.59

Table 6. Factor Two Distinguishing Statements

	Most Important	Normalized Factor Score
10	Produce high-quality IS researchers that will contribute to the field through knowledge creation	1.63
4	Understand the role of existing theory in the process of developing new knowledge: as a vehicle for learning, challenging, expanding, and communicating knowledge	1.32
	<i>Least Important</i>	
13	To develop a high level of competence in university teaching	-1.63
11	Produce high-quality IS educators that will contribute to the field through knowledge dissemination	-1.63

THE CONSENSUS VS. DISAGREEMENT TABLE

The Consensus vs. Disagreement table (Table 7) helps to distinguish the three viewpoints further. This table rounds the factor scores and forces them into the original distribution. For this example, five of the statements were omitted. Note that all three factors show a score of zero on statement five. (Table 7) Due to the forced distribution, the zero scores should be interpreted very carefully since they probably indicate indifference or unimportance rather than careful consideration leading to placement in the middle. The extremes may be interpreted with more confidence.

Examination of the Consensus vs. Disagreement Table (

Table) leads to a better understanding of how the different attitudes operate and interact. For example, factors one and three agree on most of the statements except 10, seven, and eight. On those items, factor one emphasizes more faculty responsibility in supervising PhD students through mentoring while de-emphasizing the role of specific outcomes on the part of the PhD student, seen in negative responses on statements one, 10, eight, and six. Factor three also disagrees with the tangible outcomes in statements one and six but finds skills-based outcomes in 12 and eight desirable. Several additional comparisons of the factors can be made with these data, but because this Q-sort is presented only for demonstration purposes, the authors leave further interpretation to the reader.

Table 7. Consensus vs. Disagreement

Statement	Factor Arrays		
	1	2	3
5 Methodologically well trained so they collect data wisely, and interpret it correctly	0	0	0
4 Understand the role of existing theory in the process of developing new knowledge: as a vehicle for learning, challenging, expanding, and communicating knowledge	1	2	1
11 Produce high-quality IS educators that will contribute to the field through knowledge dissemination	0	-2	0
12 To develop a high level of competence in the areas of conducting basic and applied research	2	0	2
1 At least one or two journal publications before they leave	-2	1	-1
10 Produce high-quality IS researchers that will contribute to the field through knowledge creation	-1	2	1
7 Good faculty mentoring starting with the choices we make in admissions, through laying out the paths of coursework, through pairing of student and dissertation advisor based on the developing interests of the student	2	1	-2
8 A strong foundation in teaching methods understanding and skills	-1	-1	2
6 Good placements	-2	1	-2

Q-SORT COMPARED TO CLUSTER ANALYSIS

Q-sorting is a distinct technique with its own strengths and weaknesses though it continues to be confused with other techniques [Brown, 1980], such as cluster analysis (e.g. Hair 1998, p.473). Cluster analysis, a multivariate technique for grouping responses statistically, differs from Q-sorting and Q-analysis in that it draws on traditional inferential statistical methodology rather than Q-methodology for its theoretical grounding [Brown, 1980]. One implication is that cluster analysis aims at achieving representation through random sampling and large numbers without regard to preserving self-reference. Its end result is homogenous groups of *objects* about which assumptions are made based on broad categorizations. Thus, a researcher using a cluster sample might select only a few members of a specific group, a homogenous population, as all members of the group would be assumed *by the researcher* to have similar responses within a margin of error (Babbie 1998). No such assumption is made in Q-sorting. Q-analysis does not allow selective manipulation of the criteria being used to judge variation and create groupings of *people* as such manipulation might interfere with the self-reference captured in the sorts. Thus, in cluster analysis the researcher's definition of the variates being sought is a "critical step" [Hair, 1998, p. 473]. In Q-sorting and Q-analysis the preservation of self-referent responses precludes such definition of the grouping criteria by the researcher.

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On a more practical level, "Factor analysis has an underlying theoretical model, while cluster analysis is more ad hoc" [SPSS Manual, 1999, p.293]. This difference affects any inferences drawn because the factor analysis fundamental to Q-technique allows the researcher to look deeper into how the data relate. To illustrate one such implication, the data from our example Q-sort were run through several cluster analyses to find a near identical fit with the Q-analysis. The results are shown in Figure 4. Comparing Table 4 and Figure 4 shows that a Hierarchical Cluster Analysis performed with SPSS and the Q-sorting factor analysis output similar groupings. A closer look at respondent eight reveals one surface difference. With cluster grouping the groups become clear in terms of only one dimension, proximity.

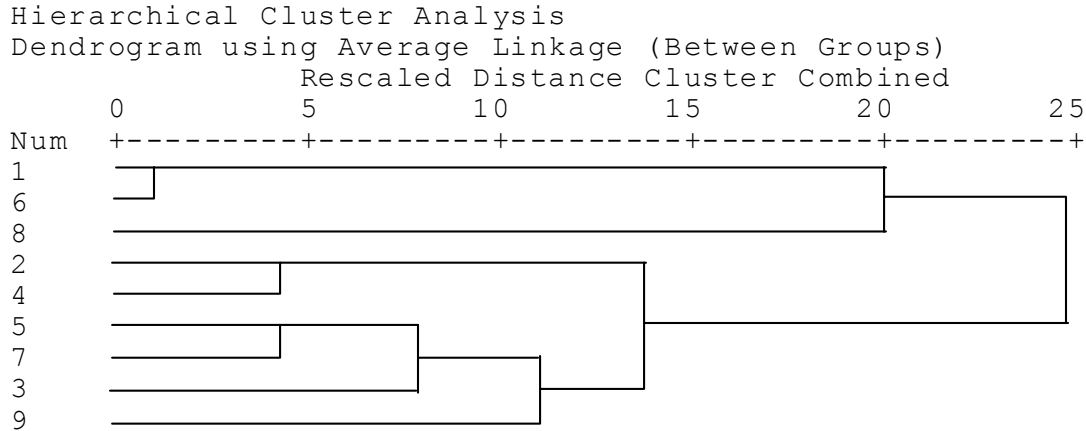


Figure 4. Cluster Analysis Tree Diagram

In Q-analysis the groups have both proximity and valence. Thus, we see in Table that respondent eight is actually a strong opposite view to factor three, a much more valuable relationship to discover than the weak relationship to factor two found in the distant connection at about 20 in the cluster analysis (Figure 4). It cannot be overstressed that the matching of a clustering method to the Q results required multiple attempts. Even when Q-sorting occurs in unstructured Q-studies lacking a block design, such as the MIS PhD preparation example, the theoretical grounding behind Q data collection and study design helps guide the discovery of actual agreements and disagreements in line with respondent attitudes. Without this guidance, the researcher can fish until relationships are found regardless of meaningfulness.

IV. Q-SORTING IN MIS RESEARCH

Q-methodology offers techniques to help address some of the weaknesses within MIS research. For example, MIS interpretive researchers currently have two particular weaknesses,

1. addressing the interaction between the researcher and the subjects, how they influence the results they collect, and
2. in addressing the dialogical reasoning, how the philosophical lens or preconceptions they are using for interpretation affects the outcome [Klein and Myers, 1999].

Q-sorting can address these shortcomings in two ways:

1. by helping to ensure a minimal influence by the researcher through the Q-sorting procedure and
2. by allowing readers to go back to the data and work through the logic of analysis themselves, thereby checking the researcher's interpretative preconceptions.

As noted in Section II, the Q-sort procedure follows a fairly specific pattern. Prior to the sort procedure, the researcher set the topic and collected the statements from relevant literature, experts, or from the sample population. In the case of Web sites, smells, or other non-verbal

sorting material, these will be selected. An appropriate environment is created and presented to the respondent, leading to confidence that the respondent compared each statement to each of the others and arrived at a true comparative judgment based on self-reference. This self-referent response truly depicts the respondent's subjective point of view given the context. Thus, judgments might be influenced by unusual and unexpected personal interpretation of the context or wording of the statements but are not inaccurate.

In the Q-analysis, all of a respondent's sorted statements must be included, and the use of eigenvalues and a well-defined factor analysis procedure limits outside manipulation of the data directed at forcing specific results. Inasmuch as a standard Q-analysis includes the presentation of

1. the normalized factor scores
2. the actual factor loading arrays
3. the statement(s) on which the arrays load,

the reader of such research may reinterpret and check the researcher's base logic.

Q-methodology requires that Q-sorting maintain the subjectivity of individual sorters from the initial data collection procedures to the ultimate analysis, interpretation, and presentation. Thus, the effect of the researcher's philosophical lenses on the respondents' answers is minimized throughout the process and presented in the outcomes, addressing the issues of interaction between the researcher and the subjects and of the dialogical reasoning.

USES OF Q-SORTING IN MIS RESEARCH

A search for articles in MIS research journals shows that use of Q-sorts by MIS researchers goes back at least 14 years (Table 8). Four of them are shown in Table 8 so that the interested reader can use them as examples.

Table 8. Examples of Q-Sorting in MIS Research.

Article	Statements generated from participants	Response type	Elimination sort process used	Forced distribution of sorts used	Aided the study
Kendall, Buffington et al. [1987]	Yes	Scaled Piles	Yes	Yes	Yes
Kaplan and Duchon [1988]	No	Unclear	Unclear	Unclear	No
Kendall and Kendall [1993]	Yes	Scaled Piles	Yes	Yes	Yes
Tractinsky and Jarvenpaa [1995]	No	Scaled Piles	Yes	Yes, Quasi-Normal	Yes

Tractinsky and Jarvenpaa [1995] use Q-sorting to look at the differing viewpoints among IT project managers with varying levels of global experience. Kaplan and Duchon [1988] aimed their Q-sort at the attitudes affecting computer system questionnaire designs, though this last Q-sort did not prove fruitful and was abandoned.

VALIDATION SORTING AND Q-SORTING

Q-sorting requires a forced distribution. As Brown states, "The nature of the Q-sorting operation is often misunderstood, especially as relates to the forced-distribution feature" [Brown, 1980, p. 201]. A number of MIS researchers used a non-forced-distribution sorting procedure in an effort to establish discriminant and convergent validity of constructs[e.g., Moore and Benbasat 1991; Turley and Bieman 1995; Teng and Calhoun 1996; Kettinger, Teng et al. 1997; Grover,

Teng et al. 1998; Segars and Grover 1998]. The validation sorting procedure seems to serve its purpose well and enjoy popularity in the MIS research community. Nevertheless, violation of the forced-distribution requirement during data collection invalidates the principles of psychological significance and choice equilibrium underlying self-reference and leads to questions about the applicability of the Q-method's theoretical foundation during data analysis [Brown, 1980]. Thus, these validation sorts should be labeled something other than "Q-sorts" to reduce confusion. This topic deserves closer scrutiny in another paper.

STRENGTHENING MIS RESEARCH

Studying subjectivity suffers from common method variance when the use of common methods allows the imposition of observed patterns that do not actually exist. Adding Q-sorting offers MIS researchers an additional method as well as a tool for exploring the subjective with minimal researcher interference. A research framework for integrating the subjective with interpretive and positivist approaches to research is presented in Lee [1991].

Q-sorting can help

- provide the group-specific subjective understanding upon which the interpretive sits,
- confirm or disconfirm predictions of subjective reality in a specific group, and
- support reformulation of the interpretive understanding of a specific group when called for by positivist disconfirmation.

In short, Q-sorting particularly fits situations in which the subjective understanding is critical to exploring or validating interpretive or positivist understanding, as in research dealing with user or group attitudes. For example, adding Q-sorting could result in more robust survey findings. A Society for Management Information Systems membership survey study reported by Ball and Harris [1982] reports only standard deviations and averages. Augmented with a Q-sort, the study might have found factions among the members and defined more clearly how they agree and disagree, as was done in the study by Morgado, Reinhard, and Watson [1999].

IV. OTHER ISSUES

THE 'NON-ISSUE' OF IPSATIVE SCALING [BROWN, 2001]

Some controversy surrounds the implementation of Q-sorting. Fundamentally, Q-technique bases itself on the in-depth examination of specific behavior of sample populations [Stephenson, 1953, Brown, 1980]. Q-technique includes examining the behavior of people in a particular company, the human issues related to a particular ERP implementation, or any other particular context in which attitudes may be assessed.

At issue in many researchers' minds is the value of Q-technique and Q-sorting to the development of general rules. Some researchers see Q-sorting as invalid due to its use of comparative measures that they associate with ipsative measures [Neuman, 1887, pp. 164-166]. Ipsative measures were first defined by Cattell in 1944 as distinct from normative and interactive measures. They are defined as "a method of assessing scale values that takes the individual's own characteristic behavior as the standard for comparison (e.g., rating a response as better or worse than is usual for the given individual is simple ipsative scaling)" [English, 1958], and have been termed rank measures that fail to show validity for use in inferential statistics [Cornwell and Dunlap 1994]. Q-sorting is not concerned with the issue of objective inferential generalization intrinsic to ipsative measures [Cattell, 1944]. Its measures are therefore intentionally of a different sort: subjective [Brown 1980, p.174].

Even with the understanding that Q-sorting does not use ipsative measures, debate over the validity of Q remains in the larger realm of psychometric evaluation of behavior. Nunnally, Stephenson's student [Brown, 2001], notes that Q-sorting forces a distribution on respondents, limiting their ability to show an absolute level of importance on any given topic and thereby compromising any inferential statistics drawn from the data [Nunnally, 1967]. Kerlinger, also Stephenson's student [Brown, 2001], comments:

One can rarely generalize to populations from Q samples. Indeed, one usually does not wish to do so. Rather, one tests theories on small sets of individuals carefully chosen for their

“known” or presumed possession of some significant characteristic or characteristics. One explores unknown and unfamiliar areas and variables for their identity, their interrelations, and their functioning. [Kerlinger 1973, p.598]

Within Nunnally or Kerlinger’s psychometric realm, one can understand that to test individual differences scientifically initially requires a scientific understanding of one or more specific individuals. Understanding those individuals in context proceeds from a scientific study of their behavior. Thus, Q-method is separate from drawing inferences from a sample to a population.

SMALL SAMPLES AND NON-RANDOM SELECTION

Q-sorting is often used with small samples that are not randomly selected [Brown, 1980]. A common mantra about survey methodology says, “the smaller the sample size the less its precision” and is supported by researchers suggesting at least 50-100 observations as an adequate survey sample size ([Pinsonneault and Kraemer 1993, p.92; deVaus, 1995, p.73]. Questions of sample size relate to statistical power. In the case of factor analysis, they typically indicate a measure of factor stability, which is used to predict the replicability of a factor structure on data collected using the same instrument in a sample from the same population. Q-methodological generalizations do not achieve this goal. Instead, they relate to “specimen” and “type” [Brown, 1980, p. 67].

The logic of specimen and type generalization runs like this: *if* you observe type A, you can predict its behavior within given contexts, and so on for types B, C and D. Type A does exist and does have specific behavioral patterns, but one cannot be certain of how many of a type exist where, only that a given type exists in a given condition. This condition is the Q-study. The behavioral patterns are the Q-samples arranged by a given respondent, and each factor found in factor analysis represents a type.

Measuring operant subjectivity through intensive analysis leads to the discovery of types through the observation of specimens. In 1969 Skinner explained intensive analysis and commented as follows, “Operant methods make their use of Grand Numbers; instead of studying a thousand rats for one hour each, or a hundred rats for ten hours each, the investigator is likely to study one rat for a thousand hours” [Brown 1980, p. 112]. By focusing analysis on the subjectivity of an individual the principle of representing a proportion of a population through an *objective* representative, random sampling becomes moot. Such proportional explorations are suited to traditional large-number, random-selection statistical techniques [Brown, 1980].

V. CONCLUSION

This article takes a brief look at Q-methodology and one of its techniques, Q-sorting, a simple and effective way to study subjectivity. The references serve as pointers for MIS researchers interested in exploring the world of Q further. The steps of Q-sort can easily be followed, namely:

1. Q-Study Design
 - a. Represent the topic with Q-samples
 - b. Decide the distribution
2. Q-Sort Administration
 - a. Ensure self-reference
 - b. Force the distribution
 - c. Randomize Q-sample initial ordering
 - d. Use a standardized format for Q-samples
3. Q-Sort Data Analysis
 - a. Factor analyze to produce groupings
 - b. Apply induction or abduction to produce insights

MIS researchers often attempt to explore group attitudes and opinions including technological and sociological aspects. The flexibility of the Q-sort in being Web-enabled, capable of measuring response to statements as well as Web pages, pictures, or smells, and highly effective for in-depth study of subjectivity makes it a potentially useful technique for their needs.

Editor's Note: This paper was fully refereed. It is an expansion of a presentation at the conference of the Southern Association for Information Systems, Savannah GA, March 2-3, 2001. The article was received on June 16, 2001 and was published on February 13, 2002. It was with the authors approximately 3 months for one revision.

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Communications of the Association for Information Systems

ISSN: 1529-3181

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