
A Methodology for Analyzing Web-Based Qualitative Data

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ABSTRACT: The volume of qualitative data (QD) available via the Internet is growing at an increasing pace and firms are anxious to extract and understand users' thought processes, wants and needs, attitudes, and purchase intentions contained therein. An information systems (IS) methodology to meaningfully analyze this vast resource of QD could provide useful information, knowledge, or wisdom firms could use for a number of purposes including new product development and quality improvement, target marketing, accurate "user-focused" profiling, and future sales prediction. In this paper, we present an IS methodology for analysis of Internet-based QD consisting of three steps: elicitation; reduction through IS-facilitated selection, coding, and

clustering; and visualization to provide at-a-glance understanding. Outcomes include information (relationships), knowledge (patterns), and wisdom (principles) explained through visualizations and drill-down capabilities.

First we present the generic methodology and then discuss an example employing it to analyze free-form comments from potential consumers who viewed soon-to-be-released film trailers provided that illustrates how the methodology and tools can provide rich and meaningful affective, cognitive, contextual, and evaluative information, knowledge, and wisdom. The example revealed that qualitative data analysis (QDA) accurately reflected film popularity. A finding is that QDA also provided a predictive measure of relative magnitude of film popularity between the most popular film and the least popular one, based on actual first week box office sales. The methodology and tools used in this preliminary study illustrate that value can be derived from analysis of Internet-based QD and suggest that further research in this area is warranted.

KEY WORDS AND PHRASES: attitudes and purchase intentions, clustering, coding, elicitation, future sales predictions, information systems (IS), qualitative data analysis (QDA) methodology, reduction, selection, visualization.

THE VOLUME OF QUALITATIVE DATA (QD) AVAILABLE via the Internet is growing exponentially [41, 61]. In response, firms are anxious to find better ways to understand user thought processes, wants and needs, attitudes, and purchase intentions [9]. "The Internet's potential to supplement more traditional methods of listening to the customer makes it worthy of exploration as a preliminary step in the development of theory and practice" [23]. Methods for measuring Internet marketing campaign responses are often inaccurate or misleading [69.] As a science, understanding online behavior is in its infancy and *quantitative* data need to be supported and supplemented by *qualitative* observations [69].

New Internet-based data sources generate immense quantities of QD; however, much of it may be useless without methods to collect, analyze, process, and make sense out of it [61, 66]. Today's information flow overwhelms firms' collection and analysis systems and most information is lost or wasted [61]. Organizations are now efficient at collecting Internet-based data and transforming it into information; however, many companies seldom acquire critically important information [61], and when they do, they often neglect to establish processes or design and build systems to convert it into useful knowledge [29, 61] or wisdom [52] for decision-making, marketing, or customer relationship management (CRM). Awareness of which data to collect and how to analyze it to create meaningful information, knowledge, and wisdom are key challenges firms must address to derive significant value-added from these new QD sources.

This paper presents an information systems (IS) methodology for analysis of Internet-based QD consisting of three steps: elicitation; reduction through IS-facilitated selec-

tion, coding, and clustering; and visualization to provide at a glance understanding to produce meaningful information, knowledge and wisdom firms can use for a number of purposes including new product development and quality improvement, accurate “user-focused” profiling, and future sales prediction.

Research Motivation

THREE MAIN FACTORS MOTIVATE THE DEVELOPMENT of an IS methodology for analysis of Internet-based QD. First is the aforementioned growing volume of QD overwhelming firms processing capabilities and yet containing valuable information. Second is the nature and attractiveness of QD and the need for open-ended questions to provide rich information from the commenter’s perspective. Third are challenges and limitations of traditional QD analysis (QDA). The latter two motivations are discussed in this section. Then in the next section we present a review of previous IS Internet-based QDA research.

The Attractiveness of Qualitative Data for Consumer Research

Information obtained through qualitative techniques, “subjective, in-depth understandings of consumers, and the nature or structure of the consumers’ attitudes, feelings, and motivations” defines and distinguishes them from quantitative methods [7]. The very “richness” of QD has led to qualitative methods, such as open-ended surveys or self-administered questionnaires, individual interviews, focus group interviews, and nominal group interviews, often being used to examine consumer attitudes [7].

Free-form answers to nondirective questions reveal points of view and feelings normally inaccessible through direct questions and provide better insights into attitudes and intentions than predefined questions, which are often leading or biased [11, 24]. Anecdotal evidence that companies are starting to use Internet discussions as a source of information about customer desires [23] and the growing application of qualitative data analysis (QDA) in the analysis of focus group data in market research [21] further illustrates the attractiveness of QD for consumer research. Content analysis literature [38, 39, 59] illustrates that researchers can learn a great deal from even a simple QD word analysis. Finally, eliciting QD as free-form comments may help to overcome the threats to validity of experimenter expectancy and respondent bias [10] inherent in traditional data collection methods.

This discussion illustrates the value of QD and that free-form QD has a great deal to offer those seeking to extract information, knowledge, and wisdom from it. QD appears valuable on the surface, however, once collected it must be effectively analyzed to yield meaningful information, knowledge, or wisdom. QDA is not as straightforward as quantitative statistical analysis. Next we describe the challenges associated with traditional and computer-supported QDA to illustrate the need for an IS-based methodology.

Qualitative Data Analysis Challenges

QD is comprised of words and cannot be directly analyzed without researchers organizing the words for comparison, contrast, and analysis to discover relationships, patterns, and principles within them [48, 55]. Those employing traditional QDA strategies face a “cruel trade-off” between QD richness and monotonous analysis tasks [20]. “As recently as the mid-1980s, most qualitative researchers were carrying out the mechanics of their analyses by hand: typing up field notes and interviews, photocopying them, marking them up with markers or pencils, cutting and pasting the marked segments onto file cards, sorting and shuffling the cards, and typing up their analyses” [68]. Coding is the most cited process bottleneck and is time-consuming, laborious, and error prone, especially when there are many cases [34, 48]. These problems are compounded when one has to iterate through data to do a thorough multiple perspective analysis [34].

Four major perceived constraints that have traditionally limited use of qualitative approaches include [54]:

1. volume of data,
2. complexity of analysis,
3. detail of classification record, and
4. flexibility and momentum of analysis.

Before computer statistical programs arrived in the 1960s, quantitative researchers suffered from the same difficulties, as evidenced by the fact that quantitative studies in sociology were all but restricted to small data sets and simple analytical strategies [53]. In 1946, two-thirds of all sociology journal publications with statistical results presented only totals, percentages, and simple cross tabulations [53]. Clearly, this situation has changed dramatically. Computer-supported QDA may offer a potential avenue to overcome challenges associated with traditional QDA; however, it does not come without its own challenges.

Computer-supported QDA is not a new idea [22, 53] and programs appeared in the early 1980s [17, 60]. The last two decades have seen the emergence of many programs designed for QDA [16, 30, 43], however, how they can be used is reported more often in the social sciences than in business or IS literature [63, 68]. Surveys of QDA software and features assessments have been carried out [22, 49, 63] and some have experimented with commercial products designed for other uses, such as word processors, databases, data indexing systems, and hypertext systems, but with little success [16, 51, 68]. Many QDA tools are excellent for specific research functions in the social sciences, case studies, and ethnographies; however, they are not designed to deal with analysis of Internet-based QD for business purposes [5, 57].

QDA software has a number of associated limitations and problems including, but not limited to: designer imposed biases [20, 68] decontextualization [16, 49], and poor usability and inefficiency [57, 62, 68]. Most QDA software was developed in social science academic programs, and many started as projects to support specific doctoral student needs [22]. Researchers [49, 68] have argued, convincingly, that no

one QDA program supports the entire qualitative research (QR) life cycle, rather there are categories of software designed to support specific functions within the process [20, 63, 68].

This brief look at QDA software systems illustrates that there are some inherent problems with current IS support for this part of the QR process. It illustrates that no one system supports all QDA for various types of research and that although newer versions of systems like ATLAS/ti and NUD*IST offer powerful features for ethnographic and case study field work, they may not be well suited to business and IS research of Internet-based QD. This points to a need to design, develop, and evaluate methodologies and tools grounded in IS principles that will support analyses to answer business-based research questions about electronic commerce, consumer behavior, and CRM.

These challenges motivated us to design and develop a generic methodology and tools for QDA research based on sound IS principles that will ensure both an efficient and effective process and meaningful results; and then to evaluate them through an applied example in consumer research. With this in mind we next discuss previous qualitative-based QDA research in IS.

Previous Information Systems QDA Research

WE FOUND LITTLE QUALITATIVE IS RESEARCH to extract information, knowledge, and wisdom concerning concepts like attitudes and purchase intentions; however, we did find a number of relevant studies that explored QD through customer comments and other measures for various purposes. One study explored attitudes, two focused on Internet conversations, one discusses unsolicited free-form comments, and one explored attitudes and intentions and their effects on Internet shopping behavior. We summarize this literature in terms of its relevance to our methodology development and identify gaps in the research that we seek to fill.

Fisher et al. [27] developed fuzzy indices to measure purchasing attitudes in older consumers. They sought to uncover “what information can the analysis of fuzziness index provide that an analysis of traditional Likert-type scale raw score does not provide?” They found age did not correlate with fuzziness index, however, socioeconomic indicators did: such that higher income, educated, white, members of the AARP tended to give more fuzzy endorsements than those in other demographic groups. Their results illustrate that factors other than traditional Likert-type scale raw scores can provide rich sources of information on consumer attitudes; however, the fuzziness scale was derived from two survey instruments, rather than from QD from the consumers and the technique they used is tied to the specific measure of the fuzziness index and not applicable to other sources of QD or theoretical constructs.

Finch and Luebbe [24] monitored all hobby-related mailing list discussions over two, three-month periods and found product-oriented messages comprised a small, but meaningful portion of conversations. They found Internet conversations contain useful data for quality improvement processes that are frequently used to by U.S. and

Japanese firms to improve existing products and services by identifying, prioritizing, and eliminating problems associated with quality [24]. They used passive surveying, similar to the “murmurs” [15] technique some Japanese firms use to observe customers using a product or listen to them discussing it. This process can reveal customers’ likes and dislikes about a firm’s products and the products with which they compete. Examples of conversational queries and responses that were specific enough to guide product design or improvement of existing products through quality improvement efforts are given below.

I’m thinking about buying a new _____. I can’t decide between a brand X model 100 and a Brand Z model 727. Can anyone help? [24]

Responses were frequent and often contained enough information to provide significant direction in making purchase decisions [24].

They also found subject areas from this group of messages showed strong potential for use in identifying customer wants and needs. Following is an example of such a comment [24].

How can I identify the size of a fly line that came without any indication of its weight? I know that weights are determined by the last 30 feet of the line, but what weight indicates what line size? [24]

Another example relates to clothing worn under waders. The following query resulted in a number of responses that, while not immediately obvious from the query, elicited responses that provided information directly applicable to customer wants and needs. One example response is given.

Query: “When you fish wearing waders, what do you wear underneath?” [24]

Response: “Actually, Bob, I haven’t worn waders for a few years either (a change in physique). My preference was for fleece pants (sweats). They help a bit with the cold water too. If you can find a pair with stirrups, even better (keeps the pant leg from riding up as you pull on the waders)—especially with neoprenes, which are quite form-fitting.” [24]

In responses to the query, a common issue was the need for a way to keep pant legs from riding up or bunching up when wearing waders, which was not what was being requested in the original request for information.

This study has implications for our methodology because it illustrates that Internet conversation text can yield meaningful information about consumers’ wants, needs, and attitudes toward products. As in the Fisher et al. [27] study, Finch and Lubbe [24] focused on a specific set of constructs related to quality and did not develop a generic IS-based methodology for QDA.

Finch [23] explored Internet conversations as a source of customer involvement and product quality information. He monitored the entire Usenet Group network over one year for a specific company name and categorized over 1,600 messages on objective and subjective criteria. Score, newsgroup, type, product, product mentioned,

compare, and company compared were objective criteria. Purpose, evaluation, and tone were useful subjective criteria. Example messages with meaningful information follow.

Here is an example Evaluative Type 1 (an original message that was not posted in response to another message) message that uses comparison.

Hi! I am about to buy a power miter saw and a table saw for misc. projects. I am not a pro, but I want to buy something that is going to last me some time. All things being equal, would anyone care to rank brands by quality, such as: B_____ D_____ ToolTek M_____ N_____. For instance, I assumed that D_____ was junk, but when I read this group, it seems that I was wrong. Anyone here to set me straight? [23]

Evaluative messages with comparisons included names of 56 companies other than Tooltek [23].

Within the “purpose” construct, messages were identified as “evaluative,” “for sale,” “useful information,” “flame,” “humor,” or “other” [23]. Here is an example of an evaluative purpose message.

RE: ToolTek table saw. I own one. The only drawback seems to be that you should keep a square handy to check the fence for square to blade after you have moved it. Other than that it is very good for its price range. [23]

They also categorized messages by “tone” as positive, negative, or neutral. Here is an example positive tone message.

I have a ToolTek benchtop jointer about US\$300 that is great. I work in my kitchen and it is almost dustless when hooked up to a shop vac. [23]

This study illustrates that comments can be meaningfully classified according to their tone (negative, positive, or neutral) and other criteria such as evaluation and purpose. It also reveals that such analyses can identify important variables, discount others, and identify apparent relationships among constructs that help in understanding the information. This study goes further toward developing a set of more generic measures and categories for QDA; however, this is only one aspect required to develop a generic methodology for analysis of Internet-based QD and again focuses on the narrow aspect of product quality. What is still missing is an IS-based methodology for analysis of Internet-based QD that can be used with any set of theoretical constructs of interest to business researchers or practitioners.

Tabor [62] found that 66 percent (1,824) of respondents to an electronic satisfaction survey added free-form comments that, when analyzed, supplemented scaled measures and revealed a number of interesting issues beyond the surveys’ scope. This illustrates that a high percentage of customers may have thoughts and feelings they wish to communicate that are not covered by questions in a traditional survey and suggests that allowing free-form comments may get at more consumer-focused attitudes. The study focused on the Consumer Decision Model (CDM) [35] to develop categories for content analysis and does not develop an IS methodology for QDA.

Limayem et al. [45] investigated factors affecting online shopping and developed a model explaining the impact of different factors on online shopping intentions and behavior based on the Theory of Planned Behavior [3]. They tested the model through a longitudinal study of 705 consumers with two surveys and found that attitude had the strongest effect on intention compared to other variables and that intentions significantly influenced online shopping behavior. The qualitative aspect of the research was done through “belief elicitation” via focus groups to develop a list of formative items for closed-ended surveys. Whereas items developed in such a way may be salient and relevant to the sample from which they are drawn, as the researchers assert, the responses to these items from the entire population may still suffer from experimenter expectancy and respondent bias. The researchers were careful to only select reflective items that had been validated in previous research; however, this does not provide evidence that these two threats to validity are minimized, let alone eliminated. In fact, 65 percent of the variance in the study remained unexplained, revealing that whereas their model has some explanatory power, it is significantly limited. Finally, the methodology does not provide a way to analyze QD, but relies on traditional survey methods and, as with the other studies in this review, the methodology is not broadly applicable to other areas because it is tightly tied to the Theory of Planned Behavior and thus limited to studies of constructs within that domain.

This literature review reveals that whereas exploratory studies are appearing in the IS literature that demonstrate comments contain useful data that can be classified and analyzed to yield meaningful information, knowledge, and wisdom, an overall step-by-step IS methodology for analysis of QD has not been developed. Neither have specific tools to aid in the process been developed or described in the IS literature. With this gap in mind, we next present our IS QDA methodology and then present an example to illustrate how the methodology can be applied to get at truly “customer-focused” attitudes and intentions.

An Information Systems Methodology to Analyze Internet-Based Qualitative Data

THE REVIEW OF PREVIOUS LITERATURE ON IS QDA research reveals that effort has not been put forth to develop an IS-based methodology or tools for the important task of analyzing the growing volume of QD available on the Internet. Whereas some work has been done to describe the overall QR process and QDA in the social sciences literature, it is not specific enough to develop a step-by-step methodology or IS-based tools to support the steps. Weitzman offers an overview of the entire QR process as follows: “In general, researchers begin with a set of research questions and move toward reaching conclusions. Data are collected in order to answer the research questions, and in qualitative studies the data are often voluminous. The researcher then faces the task of somehow reducing the data into a form in which it can be examined for patterns and relationships” [68]. Although this provides a useful explanation of the entire QR process, it includes steps more generally associated with eth-

nographic or case study research, rather than analysis of Internet QD for business or electronic commerce purposes. The focus of this research is on QDA, which is a critical component of the overall QR process [48, 68], and on data reduction, the actual step in which raw QD is converted into useful information that can be meaningfully examined and visualized [48, 68]. It is in this critical step of reduction that IS has the greatest potential to improve the QR process. Miles and Huberman [47, 48] offer a view of QDA as consisting of three major steps: data collection, data reduction, and data display. Further, they explain that reduction consists of selection, coding, and clustering. This is a useful high-level abstraction of the QDA process and the reduction subprocess, however, it cannot be implemented without more specifics as to how to provide IS support for each of the various steps.

Following Miles and Huberman's [47, 48] outline of the steps in the QDA process, our methodology consists of three major steps: elicitation; reduction through IS-facilitated selection, coding, and clustering; and visualization to provide at a glance understanding. Figure 1 presents our IS methodology for analyzing QD in terms of inputs, process, IS support, and outputs for the overall methodology and for each step. We describe each step in detail in the remainder of this section and also explain how IS tools can facilitate the process.

Step 1: Elicitation

Elicitation is collecting or recording what is seen, heard, spoken, or written in words [48]. Traditionally, elicitation involves interviews, ethnographic observations and field notes, and focus groups [48], similar to consumer techniques described earlier [7]. The act of elicitation is considered to be an important component of the research in qualitative studies [31, 48]. QD input can be obtained as primary data through direct elicitation via online or e-mail open-ended surveys, online group support systems, or any other means. QD input can also be collected as secondary data from indirect sources, such as Internet discussions [23, 24] or any other online or offline source of QD. The output of elicitation is formatted comments that can be analyzed through reduction in step 2. Formatting is typically not a very difficult task and may be as simple as placing blank lines or some other token between the comments to keep them separate. Many tools for collection of QD will already provide a mechanism to separate the comments within the overall text.

Step 2: Reduction

Reduction is a critical step in the methodology and involves selecting, focusing, simplifying, abstracting, and transforming raw data to make it useful [48]. Codes and categories are derived from general theory, the researcher's hypotheses, key relevant concepts, or from the data itself (as in grounded theory [31]). Figure 1 depicts the important subprocess of reduction as involving three steps each of which is described in detail.

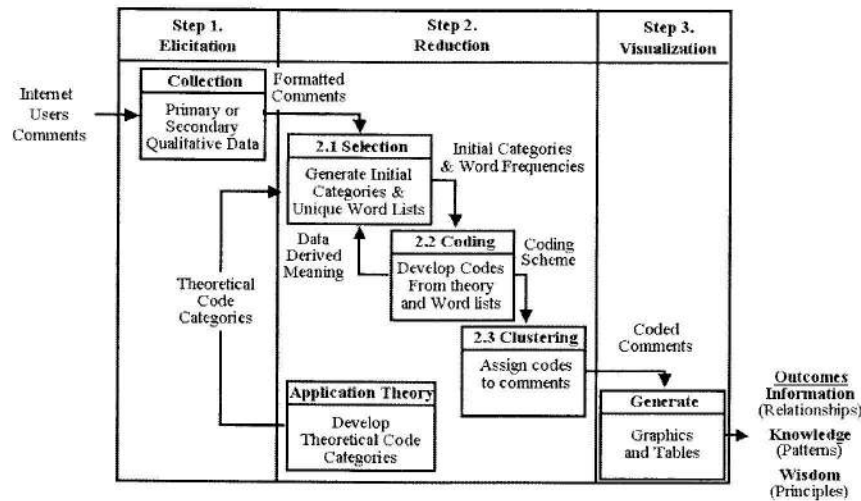


Figure 1. An IS Methodology to Analyze Internet-Based QD

Step 2.1: Selection

Selection involves deciding on initial categories and developing category schemes and unique word lists [31, 38, 48]. Initial categories are shaped by preestablished research questions and derived from application theory, yet researchers and practitioners should remain open to adding new meanings from the data [30, 48]. Figure 1 illustrates this as the flow of “data derived meaning” back to step 2.1 (selection) from step 2.2 (coding). Unique word lists and word list frequencies can be developed via the technique employed by Jehn and Doucet [38] using the WORDs program developed by Johnson [39]. WORDs is a software tool for unique word identification that eliminates extraneous words, such as “a,” “and,” and “the,” through a stop word list, and allows the set of unique words to be viewed sorted by frequency of occurrence or alphabetically [39]. Similar programs for unique word identification could also be used for this purpose. The outputs of selection are an initial set of categories and word frequencies, which serve as inputs to step 2.2 (coding).

Step 2.2: Coding

Coding is the process of grouping the observations into the classes defined in selection to establish specific sets of codes for the categories developed in selection, derived from application theory, or based upon word frequencies [38, 48]. To avoid researcher bias during this step, at least three external judges with experience in the application research area should perform the code development. The judges should generate a list of codes corresponding to the initial categories from their experience

and to come to agreement as to the items on the list and develop an initial set of codes for each category. Next the judges review the word frequency lists individually and add any codes to the list they thought were needed to fully classify the words. Again, the judges compare their amended lists and come to consensus on a shared list of codes. The judges then individually review the actual QD comments in context and again add to their lists any missing codes. Finally, the judges again combine their lists to form a single final coding list they all agree defines the nature of theoretical constructs underlying each category contained within the word lists and the comments. The outcome of coding is an unbiased coding scheme that is based on application theory and the structure of the QD itself in terms of both word frequencies and in context reviews through grounded theory.

Step 2.3: Clustering

Clustering involves deciding which data to code and how to code them [48]. Coding can be done manually with paper comment sets separate from paper coding sheets; however, experience with pilot tests of this method revealed that coders had problems maintaining their place in the comment lists and on the coding sheets, as they had to move back and forth between the two and onto additional pages. This suggested to us that an IS-facilitated coding tool may be useful. Observations of manual coding suggested that placing the comments and the coding sheet on the same screen (page) may minimize perceptual and physical loading associated with switching between them. Two manual coders developed methods to assist with these problems. One used a paper clip to keep track of their place in the comment list, whereas the second marked off comments with a check mark after they had coded each comment. Both solutions suggest the need for a method to keep track of the current location in the comment set list and the coding sheet. Another serious problem with the manual coding sheet was the need for coders to trace down columns and across rows to ensure that they had assigned the correct comment to the correct code. This observation suggests that having the list scroll down and the headings remain stationary could help to alleviate this problem. Reviews of other QDA software tools revealed that many require multiple passes through the data for different categories and coding schemes [30, 34] therefore we thought that presenting all categories and coding schemes at the same time would enable coders to perform all coding for one comment at the same time and ensure that multiple passes were not required. Finally, comments were isolated on the page one at a time to focus the attention of the user on the specific comment being coded in context. Pilot tests with the tool illustrated that these design features helped minimize inefficiency and poor usability seen in other computer-based QDA coding applications. Later in the section on the example application of the methodology, we will present a screen capture of the prototype coding tool with live data from a coding task. The output of the step 2.2 (coding) is the set of coded comments that can be used to generate graphical or textual visualizations of the data based on the categories and the codes assigned to the comments.

Step 3: Visualization

Visualization involves preparing organized, compressed assemblies of the coded comments from step 2 (reduction) that permit conclusion drawing and action [48]. Common data display methods include extended text, matrices, graphs, and charts. Visualizations organize data into accessible compact forms in which analysts can identify patterns [48]. The outcomes of the step 3 are not the visualizations themselves, but rather the relationships, patterns, and principles that are revealed through meaningful visual presentations of the data. Later in the section on the example application of the methodology we will present example visualizations that are automatically generated from the coded comments.

We specifically developed our QDA methodology to analyze Internet-based QDA for business and IS research. With this understanding of our generic QDA methodology, in the next section we present an example application in the domain of consumer attitudes and purchase intentions and provide screen captures and explanations of the IS tools we designed and developed or employed to facilitate the process.

An Example Application of the IS QDA Methodology

TO EMPLOY THE IS QDA METHODOLOGY we described in the previous section, researchers or practitioners must have a clear focus on the constructs they wish to measure and the theory underlying those constructs. Research questions and theoretical code categories must be defined before data collection begins and to facilitate customization of the prototype coding tool for clustering. Moreover, they must define a specific set of procedures for elicitation.

Example Research Questions

In this example, we are interested in answering two research questions: “Can QDA of free-form consumer comments to multimedia stimuli over the Internet produce meaningful consumer attitude and purchase intention data that can be visualized in a manner that adds value to understanding consumer wants and needs?” and “If QDA of free-form consumer comments results in purchase intention data, is this data a good predictor of future sales?” These questions are of interest because well-validated consumer behavior models posit that attitudes may lead to purchase intentions and in turn purchase intentions may lead to purchase behavior. Moreover, future sales predictions can help firms allocate resources for advertising campaigns, select target markets, adjust production and marketing plans accordingly, and estimate demand for new products. Analyzing qualitative consumer data is difficult and time-consuming and few have attempted to extract attitudes and purchase intentions from Internet-based free-form consumer comments. This is an important area for exploratory research and practice in marketing and IS.

Product Stimuli

To answer our two research questions we needed to select a specific product about which to collect data. After researching purchase decision processes and several possible product types we decided to use trailers for soon-to-be-released movies for several reasons. First, the decision about whether to see a movie or not is one that involves routinized problem-solving, requires little information prior to the purchase, and is usually made quickly. This is evidenced by the fact that people make decisions about whether to attend a movie or not on a regular basis and that the cost is relatively low compared to many other consumer products that may be purchased over the Internet. Second, this is a large, economically important industry with a long tradition of evaluation of consumer attitudes toward films based on their reactions [12, 40, 64]. However, there has been little study into understanding what people like about individual movies or developing methods to quantify their attitudes and intentions, which is surprising considering one-fifth of the population goes to the movies at least once a month [1]. A final reason for selecting film trailers is that the demographics of the readily available population of college students between 18 and 24 show that they are the most avid moviegoers [1].

During our search for a product, we also learned that there are in fact many movie-rating Web sites, such as All Movie, Apollo Guide, and Efilecritic; however, they all employ very different Likert-type semantic anchor scales that employ anywhere from five to 100 different rating codes. Results of a survey of ten of these sites revealed that the ratings do not reflect the actual popularity of movies based in box office sales. There are several possible explanations for this result. One is that the sheer volume of responses tends to average out across movies. Another is the problem of respondent bias and different interpretations of the scales by potential consumers. Our search for a product with which to explore an example of our QDA methodology reveals an interesting and unexplored niche for research that cuts across film, marketing, and IS; that is, employing free-form comments to discern attitudes and intentions and to predict future sales among several films.

We searched the Dark Horizons Web site (www.darkhorizons.com) that links to nearly every available movie trailer for unreleased films and films for suitable trailers. We focused on movies that had release dates shortly after our study would conclude, to ensure that none of the participants could have seen the films prior to the study and so that we could compare our scoring results with actual first week box office sales. We selected four trailers that provide variety in terms of a number of common film factors including: genre, music, actors, setting, and so on. The selected trailers were: *Muppets from Space*; *Mystery, Alaska*; *The Mummy*; and *A Midsummer Night's Dream*.

Participant Selection

Study participants consisted of 54 students in an introduction to management information systems (MIS) class at a major U.S. university. Females comprised 48 percent of

the sample, males 50 percent, and 2 percent did not report gender. Age ranged over 32 years, from 18 to 49, with a mean of 22, median of 20, and mode of 19, with 84 percent between the ages of 18 and 24. This sample is part of the population of most avid moviegoers that purchases 66 percent of movie theater tickets [1]. The sample represented 28 different majors including nursing, psychology, retail, German, fine arts, as well as MIS and business. Based on these demographics we felt that this was a meaningfully representative sample for an initial exploratory example of our methodology.

Example Theoretical Background

The theoretical foundations of this example lie in aspects of attitude structure, purchase intentions, and consumer behavior. Affective experience leads to attitudes that impact consumer decision processes and this effect may be magnified for Web consumers [62]. Purchase intentions may play a significant role in predicting future sales and are a critical component of consumer decision models [35]. Consumer behavior models explain the decision process leading to a purchase for a consumer and a sale for a firm [18, 36]. Each of these three areas is discussed in this section in relation to our example.

Attitudes: Definition and Structure

Crespi defines attitudes as “relatively fixed ways individuals have of acting toward certain aspects in the world in which they live, which are characteristic to themselves and related to an underlying structure that accounts for consistency reflected through characteristic behaviors” [11]. More recently, Littlejohn defined an attitude as “an accumulation of information about an object, person, situation or experience . . . a predisposition to act in a positive or negative way toward some object” [46]. Table 1 identifies four dimensions of the underlying structure of an individual’s attitude that map well into consumer decision models [11].

These dimensions meaningfully describe attitude structure contained in consumer comments and are supported in the IS and marketing literatures. Trauth and Jessup [65], in an analysis of GSS sessions, found evidence of three types of information that could be extracted from comments using interpretive methods: cognitive, affective, and behavioral. This illustrates that IS researchers have found similar categories in textual comments. Each dimension is briefly described along with supporting literature.

Cognition level ranges from well-informed to totally uninformed [11]. The Engel-Kollat-Blackwell (EKB) [18] and Howard-Sheth [35] models include “cognitive” constructs like attention, memory, perception, and comprehension, which reflect awareness and knowledge. Research illustrates that the consumer’s level of product knowledge may affect their information and decision-making behavior [8, 28].

Context concerns internal (needs, values, feelings) and external (situational characteristics) factors that define stimuli significance for an individual [11]. The EKB [18]

Table 1. Four Dimensions of Attitudes Derived from Literature and Theory

Dimension	Description
Cognition	Awareness and knowledge
Context	Values and norms that establish the context of reaction
Evaluation	Positive or negative direction of reaction
Affect	Intensity of feeling and involvement

and Howard-Sheth [35] models include contextual constructs such as values, lifestyle, personality, motivation, family, reference groups, and culture reflecting the context of a reaction to a stimulus. The EKB model classifies variables that influence a consumer's decision process into three categories: individual characteristics, situational influences, and social influences, all of which are related to context.

Evaluation refers to the relative positivity or negativity of a reaction to an object in light of cognition and context and may be viewed on a continuum from "most positive" to "most negative" with a center neutral point [11]. This is referred to as attitude "valence" and is a key part of attitude models [3, 25, 46].

Affect reflects intensity of feelings about an object, or how important the needs, values, and feelings are to the consumer [11, 18, 62]. Russell [58] asserts that the dimensions of pleasure and arousal can describe people's internal emotional state and that affect is a mediating variable driving stimuli, cognitive processes, and behavioral responses. Crespi [11] notes that in some instances even though people have very limited knowledge of an object, they may still hold very strong attitudes toward it.

These four dimensions comprise the initial list of theoretical categories that serves as an input to step 2.1 (selection) in our QDA methodology. Each of them provides detailed and specific information about how and why a person has certain feelings and thoughts toward a stimulus. This detailed attitude information could be used to develop highly specific and precise attitude profiles toward specific stimuli and in general.

Purchase Intentions

Dissatisfaction with predictive accuracy of purchase behavior based on socioeconomic and demographic variables lead researchers to experiment with purchase intentions and attitudes as predictors [14, 30]. In short-term cross-sectional studies, purchase intentions usually more accurately predicted purchase behavior than attitudes [2, 42]. Consumer researchers commonly use purchase intentions to forecast sales [4]. This widespread use may be because purchase intentions are inexpensively obtained and easily understood by managers [4]. "The single best predictor of an individual's behavior will be a measure of his intention to perform that behavior" [26]. Social psychological models linking attitudes to behavior provide theoretical support for using purchase intentions to predict consumer behavior [50]. There is extensive empirical support for the use of intentions in marketing, dating back to U.S.

government studies of financial position and demographic characteristics of U.S. households carried out in the 1940s [50]. Many marketing studies have measured the relationship between consumers' stated purchase intention and their subsequent behavior and most found positive associations [19, 33, 50].

One relevant finding is that the predictive validity of stated purchase intention in terms of subsequent behavior varies by product type [33, 37] such that studies of nondurable goods [32, 67] found positive associations between stated consumer intention and actual purchase behavior; whereas those of durable goods [32, 67] found weak positive relationships between stated intention and purchase behavior. This finding is interesting for IS researchers and practitioners that study intangible products such as intellectual capital, because relationships between stated intention and purchase behavior were stronger for nondurable goods than for durable ones, and this may also hold true for "intangible" goods.

Consumer Behavior

Fishbein's [25] Theory of Reasoned Action propositions that behavior results from intentions; intentions, in turn, are functions of attitudes to the stimulus in question and subjective norms. This is consistent with well-known consumer decision-making behavior models such as the EKB [18] and Howard-Sheth [35] models. These consumer behavior models illustrate the connection between attitudes, intentions, and purchase behavior.

We expand the attitude construct of these well-validated models to include the additional elements identified earlier, which may be contained in free-form comments. The EKB model presents a view that consumptive perception depends on three sets of variables: individual characteristics (motives, values, lifestyle, personality, etc.); social influences (culture, reference group, family, etc.); and situational influences. The Howard-Sheth [35] model puts more emphasis on stimuli display; however, it also recognizes social influences as affecting the consumer's perception. However, Tabor [62] asserted that Internet consumers often shop in isolation and therefore affective experience aspects may play a more significant role in purchase decision processes than the other dimensions. Logically, isolated Internet consumers would be less affected by social influences than those shopping with others in physical environments.

It stands to reason that understanding these attitude subcomponents would be useful for building accurate consumer attitude profiles that are based on consumer-stated interests, and that these attitudes would lead to accurate stated purchase intentions, which would lead to accurate predictions of future sales for the product sets and specific products mentioned in free-form comments. With this theoretical background in mind, we will explain an example application of the IS methodology for QDA.

Figure 2 illustrates the process for the example of the IS QDA methodology in terms of inputs, process, outputs, and the IS support employed for the various steps as screen captures or results tables. All of the graphical and tabular figures within Figure 2 are presented in enlarged format in the discussion of the germane step.

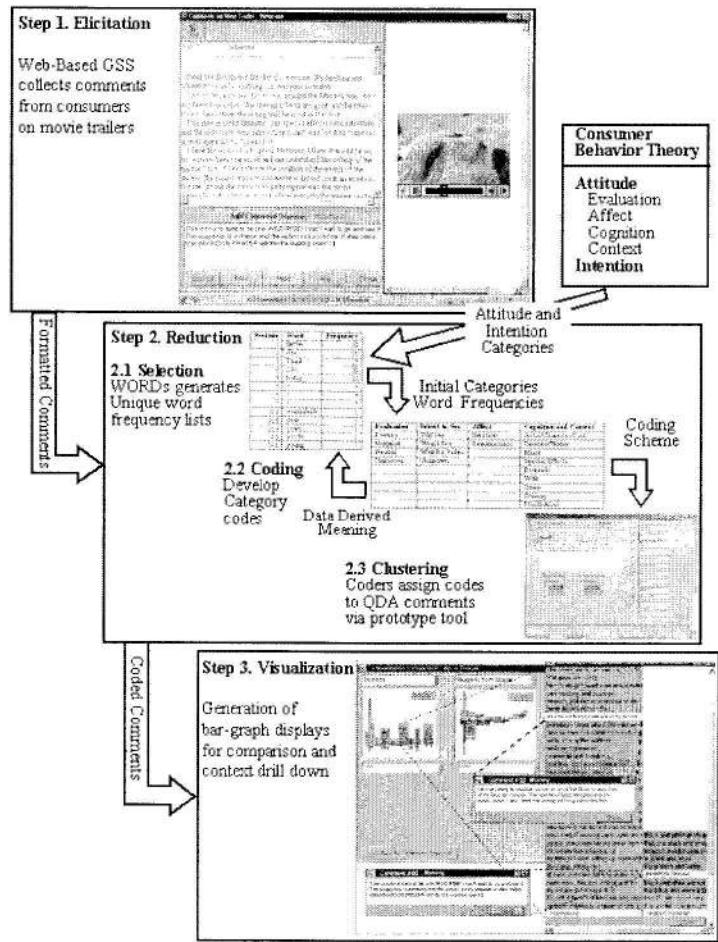


Figure 2. An Example Application of the IS QDA Methodology

Step 1: Elicitation

Prior to elicitation, researchers or practitioners employing the QDA methodology must develop a set of data-collection procedures. In this example, primary QD was gathered from potential consumers as free-form comments with no cues provided. To control potential confounds due to different technology or download and playback speeds, all participants came to a multimedia lab where files were installed locally. The lab was reserved for this study over a nine-day period and participants could watch and evaluate the film trailers when it was convenient for them during this time period. Each participant signed up for a time and then checked in when they entered the lab to ensure only single responses. Moreover, participants wore headphones to eliminate the possibility of distraction from background noise. The movie trailers were shown in blocked random order to potential consumers such that one-fourth of

them saw a specific trailer first, one-fourth saw that same trailer second, one-fourth saw it third, and one-fourth saw it last.

Fundamental to our example is Internet collection of free-form comments from potential customers about a set of products. GS_{Web}, a Web-based group support system, developed at the University of Arizona [56], was modified for elicitation to enable potential consumers to view multimedia objects and comment on them in their own words. Figure 3 shows the GS_{Web} screen through which participants entered comments.

The screen has two areas: a comment area to the left, and a reference object area to the right, wherein any type of multimedia hyperlink can serve as a stimulus to the participants. The interface is streamlined to provide only controls needed to add comments and thus focuses effort on the task of evaluating the reference object, which in this case is the trailer for the movie *The Mummy*. Participants logged into the system with a provided user ID and password and filled out a brief demographic survey before the task. The output of elicitation consisted of 217 comments the participants made about the movie trailers, which serve as the input to step 2 (reduction).

Step 2: Reduction

Figure 2 shows that inputs to this step are the formatted consumer comments and the theoretical attitude and intention categories from consumer behavior theory. Each of the three methodology sub-steps of selection, coding, and clustering is described in terms of inputs, process, outputs, and IS support.

In step 2.1 (selection) we ran all the comments through the WORDs program using the original stop word list of 125 words and then we reviewed the full list of unique words to identify additional stop words. Five additional words, all forms of the stop word personal pronoun "I" (I'M, I'd, I'll, I'm, I've), were added to the stop word list. The outputs of selection are the initial set of categories and the word frequencies, which serve as inputs to step 2.2 (coding).

Step 2.2 (coding) involved identifying codes among the words in the lists and the comments. Based on attitude structure, the full set of general unique words, and the comments themselves (as in grounded theory [31]), we created codes for the four high-level categories: evaluation, affect, intention, and cognition and context. To avoid researcher bias, we had three external judges with experience in attitude research do the category development. The judges were told to generate a list of codes corresponding to the categories about movie trailers from their experience and to come to agreement as to the items on the list. The initial process resulted in a short list of codes. After this, they were asked to review the four word frequency lists individually and add any codes to the list they thought were needed to fully classify the words. Table 2 shows the first five words and the last five words from the comment set for the Muppets from space trailer and illustrates how words like "see," appearing 51 times, led to the codes "will see" and "won't see" and the more explicit category name intent-to-see, which replaced the general intention. Moreover, the code "wait for video" was also added based on the common occurrence of the word video and the fact that the population is twice as likely to rent a video in a week than the average American [1].

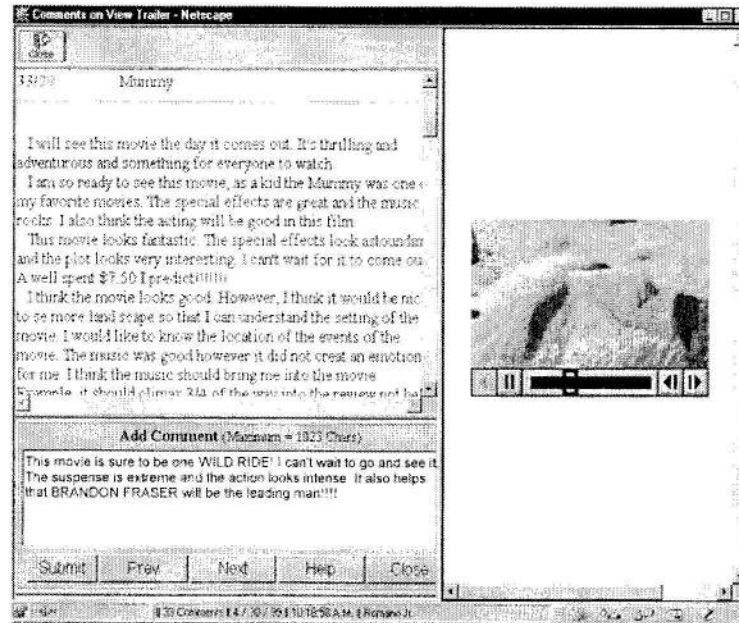


Figure 3. Screen Capture of IS Support for Step 1 (Elicitation)

Table 2. Sample WORDs Output: Frequency Order Word List for Trailer *Muppets from Space*

Position	Word	Frequency
1	Movie	59
2	See	51
3	Think	27
4	Like	20
5	Looks	18
*	*	*
*	*	*
*	*	*
312	Worthwhile	1
313	Year	1
314	Years	1
315	You're	1
316	Young	1

Next, the judges compared their amended lists and came to consensus on a shared list of codes. The judges then individually reviewed the actual comments in context and again added to their lists any missing codes. Finally, the judges again combined

Table 3. Coding Scheme from Step 2 (Reduction); Developed in Step 2.2 (Coding)

Evaluation	Intent-to-see	Affect	Cognition and context
Positive	Will see	Emotion	Actor/character/cast
Negative	Won't see	Reminiscence	Director/writer
Neutral	Wait for video		Music
Unknown	Unknown		Special effects
			Reminds
			With
			Genre
			Scenery
			Plot/subject

their lists to form a single final coding scheme they all agreed defined the nature of the attitudes contained within the word lists and the comments. Table 3 shows coding scheme output from step 2.2 (coding), which serves as input to step 2.3 (clustering).

In step 2.3 (clustering), three coders used the prototype QDA-coding application shown in Figure 4 to code all the comments for all four trailers. The application was designed to minimize the problems we observed during initial manual coding and the previously identified challenges associated with QDA software. The outputs from step 2 (reduction) are the coded comments for each of the four movie trailers.

Inter-rater reliability (IRR) was calculated for the data sets from three raters. The intent-to-see classification had an average IRR of 88 percent for all four movies. The evaluation classification had an average IRR of 95 percent for all four movies. Identification of the selected elements for affect, cognition, and context had an average IRR for all four movies of 83 percent. All of these reliabilities are above accepted minimums for QD and show a high degree of consistency across raters.

Example Coded Comments

The text of the comments themselves specifically provide detailed insights into all four of the attitude components and intent-to-see. Table 4 lists attitude dimensions and example comments from step 1 (elicitation) and Table 5 lists intent-to-see categories and example comments from step 1 (elicitation), with specific words in bold-face to illustrate the dimension expressed in the comment. The sample comments illustrate that most comments received more than one attitude code.

Step 3: Visualization

In this step tabular and graphical visualizations are generated to illustrate relationships, patterns, and principles within the coded comment sets. Visualizations were generated for both qualitative and quantitative measures.

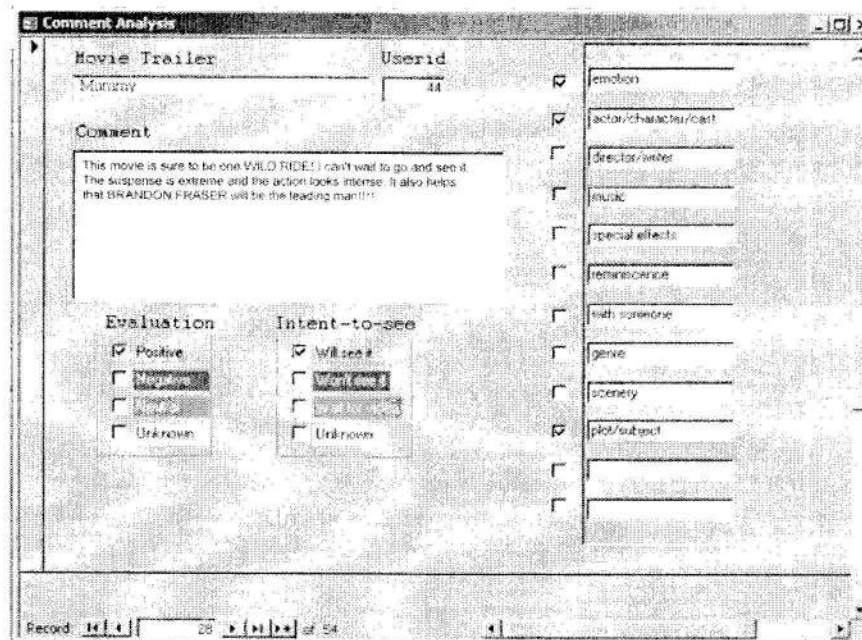


Figure 4. Screen Capture of IS Support for Step 2.3 (Clustering)

Qualitative Visualizations

A unique aspect of our tool is the ability to compare visualizations. Figure 5 presents visualizations for *Muppets from Space* and *The Mummy* that clearly illustrates one movie is more popular among the participants than the other overall and in terms of all but one of the specific attitude dimensions. Comments that express the same attitude key word association are grouped together in vertical bars to form a histogram-like visualization. Key word names are listed along an evaluation line (the horizontal axis) and positive comments are shown above the line and negative and neutral comments below. The height (or depth for negative values) of a bar represents the number of comments assigned to that key word. Comments classified as unknown are placed in a separate box and not associated with the evaluation line, but are shown in a gray box in the lower right-hand corner of Figure 5. The prototype tool supports automatic generation of such visualizations and comparisons.

Figure 6 presents a more detailed visualization comparison interface and illustrates various levels of abstraction from the full graphic of all attitude components to the text of specific comments. The dotted lines and reverse video indicate the location that was clicked on to open specific comment text windows in the foreground. The user can scroll up and down through all the comments for a specific code, or left and right across different codes to see the actual text of each comment.

These visualizations represent affective key word association magnitudes and directionalities and provide at-a-glance understanding. Further, they provide contextualization

Table 4. Attitude Dimensions and Example Comments from Step 1 (Elicitation)

Attitude dimensions	Sample Comments
Awareness and knowledge	<p>I love Shakespeare so this is a must see for me. I also enjoy the actors (Kevin Kline, Michelle Pfeiffer, and Calista Flockhart). The set for the trailer looked very well done. I can't wait!!</p> <p>I would go to see this movie. I like underdog movies, plus I like the actors Colm Meaney and Burt Reynolds. I think it's great to see Burt Reynolds back on the screen too. The scenery looks beautiful and I like the experience of cold weather as long as I don't have to be there. Also, I like ice-skating.</p> <p>This looks great! I definitely want to see it. I like the scenery, it looks exciting and interesting. I like Gregory Peck, too.</p>
Context	<p>This is a definite date movie! I think that if I was taking a date to a movie then this would be it. This plot looks good and could make you laugh, cry, and all the rest.</p> <p>This movie looks really cute. I think it is something that I would like to see, but I would wait until it was on video. I would like to watch it with my mom because she would get a kick out of it. It seems like a nice clean movie for families with kids of all ages.</p> <p>I really want to see this movie, it looks like an Indiana Jones flick and a Stargate movie tied into one. I will definitely look for this one in the theater.</p>
Affect	<p>Boring! I hate the Muppets. Only if I had a kid would I go and see this movie.</p> <p>I would probably go see this movie. I like sports movies and I'm a big fan of hockey. I also like Burt Reynolds.</p> <p>I have always loved the Muppets, and there has not been a new Muppet movie in a while, so even though I am 20 years old, I would probably go see it, probably with my little cousins or something.</p>
Intensity	<p>This movie looks fantastic. The special effects look astounding and the plot looks very interesting. I can't wait for it to come out. A well-spent \$7.50 I predict!!!!!!</p> <p>Say I, I cannot stand any more Shakespeare dialog. It is most annoying. I like Shakespeare's plots, but the dialog I can't stand.</p> <p>This movie is sure to be one wild ride! I can't wait to go and see it. The suspense is extreme and the action looks intense. It also helps that Brendan Fraser will be the leading man!!!!</p>

Note: Boldface words illustrate the dimension expressed in the comment.

Table 5. Intent-to-See Categories and Example Comments from Step 1 (Elicitation)

Intent-to-see category	Example comments
Intention-to-see	<p>This is one that I will probably most definitely see. I have read the book several times so it should be interesting. Holds an amazing cast of actors.</p> <p>I am definitely going to see this movie. I have seen this preview before and it looks like an absolute must see!!!!</p> <p>I will see this movie the day it comes out. It's thrilling and adventurous and something for everyone to watch.</p>
Intention- <i>not</i> -to-see	<p>I would not personally spend money to see this movie, but I'm sure many people will. It has a very specific market, and I am sure the younger generations will be pleased with it. The special effects and the new setting should attract the masses.</p> <p>No, no, no. This movie is nothing original and it is way too sci-fi and cheesy for me to see it. The plot does not interest me, nor does the trailer catch my eye.</p> <p>I am not really into the whole old English thing, or the cheesy love thing either. This looks like a movie that my roommate would rent and I would watch because it was on, but I wouldn't go out of my way to see this movie.</p>
Wait for video	<p>I'm a huge Muppet fan, so I would love to see this movie, but I probably wouldn't spend \$8 on it. I would probably wait until this movie came out on video and rent it. I grew up with Jim Henson's Muppets and was always a big fan, particularly of the old grumpy men in the balcony.</p> <p>Read the play. I like the story and probably would definitely see it, but not at the movies. Wouldn't be worth \$8 plus all the expensive popcorn in the world. I don't think any movie is. Wait till it's on video. Calista Flockhart in Shakespeare? Yikes!</p> <p>This movie I would like to see, however I don't think I would pay the money for it and if I did I would be with a group of friends or on a date. This is more of a rental than a theater movie for me.</p>

Note: Boldface words illustrate the dimension expressed in the comment.

by allowing users to drill down to the actual comment text and to scroll through all the comments for a given code and evaluative direction and see the comment text in a window.

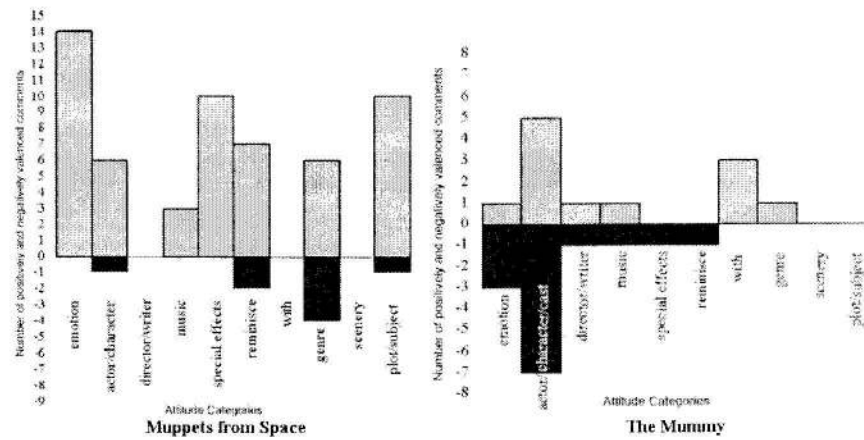


Figure 5. IT Support for Step 3 (Visualization): Attitudes for *Muppets from Space* and *The Mummy*

Quantitative Visualizations

Four quantitative measures were calculated for each movie from the coded comments: the number and percentage of positive comments and the number and percentage of comments that stated an intent-to-see or not-to-see the movie. These scores provide a measure of relative popularity and purchase intention to compare to the first week box office sales. We compared QDA intent-to-see results with actual first week box office sales, as we thought that word-of-mouth and other advertising would have more of an effect on attendance than the movie trailer after the first week.

Table 6 indicates that QDA results for intent-to-see produced the same rank order as the first week box office sales, whereas QDA results for positive comments only matched with first week box office sales for the most popular and least popular movies, but not for the two in between, and this is highlighted by asterisks within the table next to these values. This is not surprising considering that other consumer studies have found that intentions are better predictors of future sales than attitudes. These results illustrate that QDA for intention-to-see can provide an accurate prediction of future sales in terms of order of popularity.

One interesting result is that the intent-to-see values for the most popular movie and the least popular movie are very similar in terms of the magnitude of the difference between them to the actual first week box office sales. Figure 7 graphically compares the two results to illustrate this result more clearly. First week box office sales revealed that *The Mummy* earned almost 14 times more than *Mystery, Alaska*, whereas the QDA intent-to-see results showed an 11-to-1 difference. This finding is interesting in that it may mean that not only relative order of popularity can be predicted, but also relative magnitude as well. This interesting finding warrants further investigation.

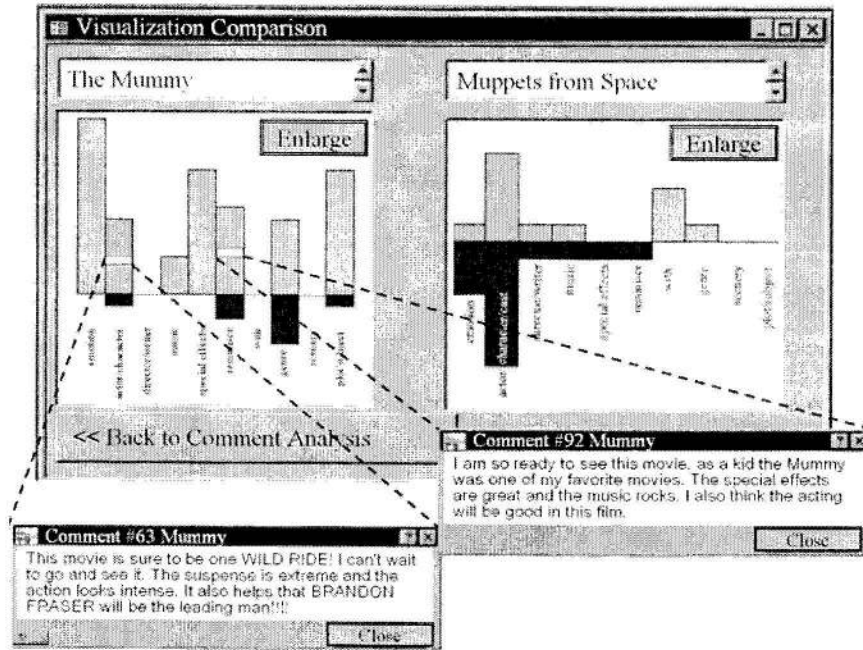


Figure 6. IT Support for Step 3 (Visualization) with Detailed Comment Viewing

Table 6. First Week Box Office Sales Compared to QDA Positive Comment and Intent-to-See Number and Percentages

Rank order/ movie	First week box office sales	Number/ percentage of positive comments	Number/ percentage of intent-to-see comments
<i>The Mummy</i>	\$43,369,635	48 / 88%	44 / 81%
<i>Muppets from Space</i>	\$6,686,522	*43 / 80%	33 / 61%
<i>A Midsummer Night's Dream</i>	\$4,285,620	*45 / 84%	28 / 54%
<i>Mystery, Alaska</i>	\$3,102,191	40 / 73%	4 / 7%

* QDA positive comment results did not match first week box office sales (ranks are reversed).

The results of our example application indicate that the answer to the first research question is “yes.” Clearly, the customer-stated comments about product stimuli did provide a clear indication of the attitudes, wants, needs, and purchase intentions of the consumers in the study. The results also lend some support to the answer to the second question being “yes”; however, since only the most popular and least popular movies had similar ratios between the actual sales and the QDA intent-to-see measure its validity is hard to assess. It does lead us to consider that this finding warrants

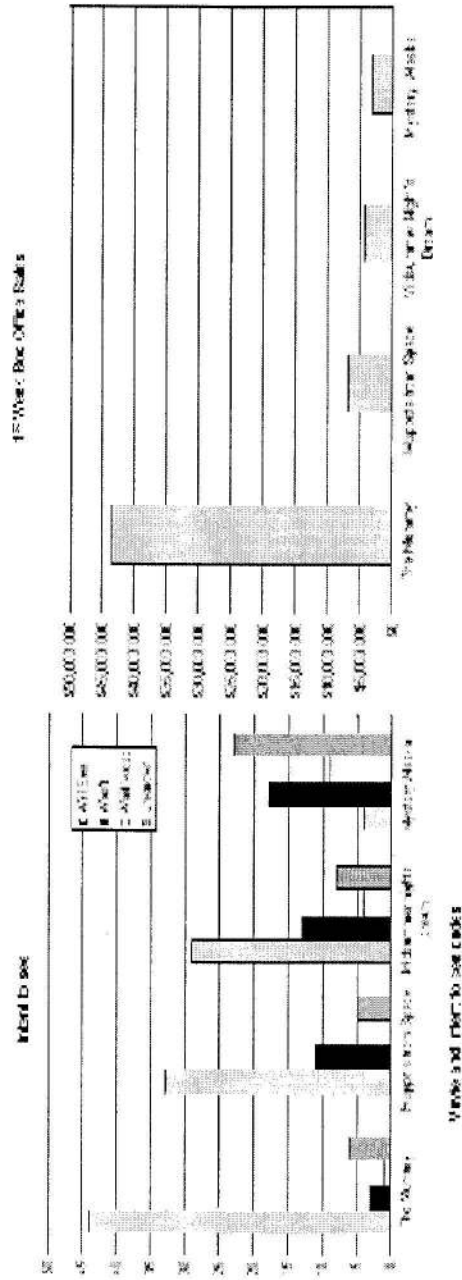


Figure 7. IT Support for Step 3 (Visualizations) of Intention-to-See and First Week Box Office Sales for All Movies

further study with larger samples and follow on studies to see if participants actually carry out their intentions and purchase a ticket to a movie.

This example has illustrated how our IS QDA methodology and tools can enable researchers or marketing professionals to efficiently and effectively elicit, analyze, quantify, and understand through visualization Internet-based QD in the form of consumer comments. The data collection tool, GS_{web} , enables potential customers, or users of services and software, to express attitudes and intentions toward products in their own words, rather than through predefined questions or other potentially biased techniques. The comment analysis support system provides rich attitude information than may not be obtained from traditional quantitative and closed-ended survey methods and it produces visualizations to provide at-a-glance understanding. The methodology overcomes drawbacks often associated with QDA and offers marketers and IS researchers a means to measure attitudes and purchase intentions from free-form comments.

Lessons Learned

THE MAJOR CONTRIBUTION OF THIS PAPER is an IS methodology for analysis of Internet-based QD consisting of three steps: elicitation; reduction through IS-facilitated selection, coding, and clustering; and visualization to provide at-a-glance understanding to produce meaningful information, knowledge, and wisdom firms can use for a number of purposes including new product development and quality improvement, accurate “user-focused” profiling, and future sales prediction. The methodology and tools developed may enable researchers or marketing professionals to efficiently and effectively elicit, analyze, quantify, and understand through visualization comments reflecting attitudes and purchase intentions.

While designing the methodology, prototype tools, and implementing a preliminary study, we observed a number of important lessons learned about computer-supported QDA from an IS perspective that are presented in this section. Table 7 lists our observations in two categories: those about the methodology and those for practitioners, and then we discuss each.

Methodology Lessons Learned

Both A Priori and Data-Generated (Grounded Theory) Categories are Important for Reduction

One important lesson that we learned is that both a priori and data-generated categories are important in helping to uncover the information, knowledge, and wisdom that is contained in QD comments. Without an initial theory and set of categories it would have been much more difficult to select a product stimuli that would have elicited data that could have been meaningfully coded. At the same time “data derived meaning” was equally important as it revealed specific codes that we might otherwise have overlooked, such as the fact that many participants mentioned they would wait to see a film until it was released as a video. There needs to be a balance between experimenter

Table 7. Lessons Learned

 Methodology Lessons Learned

- Both a priori and data-generated (grounded theory) categories are important for reduction
- IS-facilitated reduction may be much more efficient than manual reduction
- Word frequency lists can assist in selection and coding
- Consumer decision processes and product costs play a role for intentions

 Practitioner Lessons Learned

- Results provide a “big picture” understanding and answers to many questions
 - Setup and implementation time and cost are less than with other methods
 - Web browsers enable reach to the masses and richness in consumer-focused data
 - Open-ended responses unconstrain participants to explain “why” they think and feel as they do
 - Comfortable home environment may lead to more consumer-focused responses
-

expectancy through overreliance on a priori theory and total dependence on data-derived meaning that may not provide any generalizability of the results.

IS-Facilitated Reduction May Be Much More Efficient Than Manual Reduction

An unexpected and important lesson learned is that IS-facilitated reduction (coding and clustering) was on average 60 percent more efficient than manual coding. We did not find any studies in the literature that compared manual reduction to IS-facilitated reduction or any that compared various IS-facilitated tools or techniques on the basis of efficiency. This leads us to consider experimental comparisons of IS-facilitated and manual reduction in future research. We also think that such future research should measure physical and mental time-on task separately, as Lim et al. [44] did, to determine more explicitly which particular system aspects lead to performance enhancement. Another way to get at which aspects lead to improved performance may be to measure participants’ perceptions of ease-of-use and usefulness with a well validated instrument such as the Technology Acceptance Model [13] to compare several QDA systems.

Word Frequency Lists Can Assist in Selection and Coding

We learned that generation of unique word lists and word list frequencies can be very useful for developing categories and codes from large amounts of QD. Simple word frequency lists helped us to identify categories and codes more quickly than if we had to read through the entire data set. This illustrates that content is important and should be analyzed thoroughly. One possible future avenue for research in this area is to look at word pairings or phrases of three or four words that commonly occur across a QD data set. For example, phrases such as “would go see” and “will not see” were com-

mon across our data sets, but it was hard to identify them quickly or determine their frequency without multiple passes through the data and separate recording of frequencies. This may not be easy to completely automate because such phrases can be worded many different ways but have the same meaning. Part of this lesson is that content can add validity to the framing of the domain. It is important to keep in mind that word frequency lists must be used in conjunction with the actual data to ensure that context is taken into account when developing categories and codes.

Consumer Decision Processes and Product Costs Play a Role for Intentions

In our example, we selected a product that was low cost, involves routinized problem-solving, requires little information prior to the purchase, and is usually made quickly; however, there are many products and service people buy over the Internet that do not meet these criteria. The complexity of the decision process in terms of the frequency with which it is made, the amount of information required prior to making a decision and the cost may all play a role in mediating whether a consumer will state a purchase intention through free-form comments on the Internet and its nature and content. It may well be that higher cost products involving more complex decision processes that require significantly more information prior to purchase may require enhancements and extensions to this methodology in order to collect data that can be meaningfully analyzed. There is a clear opportunity for future research with other product sets and decision-making processes.

Practitioner Lessons Learned

Results Provide “Big Picture” Understanding and Answers to Many Questions

This data-collection technique provides a much bigger picture of the domain of interest than other techniques, all of which give truncated views. Focus groups are limited in number and surveys are closed-ended, so neither of them enables this big picture perspective to be developed. By employing our methodology, the fear of too much data to analyze can be overcome and data collection can be expanded 100- or 1,000-fold to get a much more representative set of data for analysis. Analysis of large quantities of data will enable validation of gut feelings or intuition from the consumers’ perspective and will lead to answers to many more questions than other techniques.

Setup and Implementation Time and Cost are Less Than with Other Methods

This method is inexpensive in terms of both time and cost compared to other methods and yet it yields significantly richer and larger amounts of data for analysis. Instrumentation and preparation time and cost are significantly less for this open-ended technique than for either surveys or focus groups. There is no need for an expensive focus group leader, who may in fact lead the group toward his or her own biased perspective.

Web Browsers Enable Reach to the Masses and Richness in Consumer-Focused Data

By using the freely available Web browsers, our technique enables marketers to reach the masses and to present rich multimedia stimuli that result in rich consumer-focused responses. Marketers and researchers can employ Web browsers to present multimedia content to large populations of potential consumers and thereby fully utilize today's high bandwidth information technology (IT) infrastructure.

Open-Ended Responses Unconstrain Participants to Explain "Why" They Think and Feel as They Do

Asking open-ended questions removed the boundaries that are put in place by closed-ended surveys so that unanticipated responses are not missed. Free-form comments do not constrain the respondents in any way and the answers are likely to reveal why people think and feel the way they do. Answers to why questions are important, and this technique allows consumers to explain the reasons underlying their feelings, attitudes, and thoughts.

Comfortable, Natural Home Environment May Lead to More Consumer-Focused Responses

Although our preliminary study was performed in a lab setting we believe that if people are allowed to participate in future studies from home this may lead to more consumer-focused answers. The home environment is more casual and comfortable to the consumer, not to mention it may well be where they will actually use the product they are evaluating. Participating from home also removes any time or peer pressure that may be experienced in the artificial environment of a focus group. So it makes sense that consumers are likely to give more contextually meaningful answers at home than in a special room they have traveled to in order to participate in a focus group. Although surveys can be anonymous, they are closed-ended, and thus may constrain the respondents answers and not allow them to express their full feelings, thoughts, and attitudes as open-ended questions do.

Implications for IS Researchers and Practitioners

WE THINK THAT THIS RESEARCH HAS IMPLICATIONS for both IS researchers and practitioners in marketing and other disciplines. First, because it presents a generic methodology for IS-based analysis of Internet QD that can be applied to almost any domain of interest to extract information, knowledge, and wisdom that firms can employ for a number of strategic, tactical, and operational initiatives in the areas of CRM, product development and quality improvement, and relationship marketing. Second, the example we provided illustrates that by following the methodology rich, meaningful

information can be derived from Internet-based free-form consumer comments. Third, such data may have predictive capability in terms of future sales. Clearly, researchers and firms that employ closed-ended surveys to determine attitudes and purchase intentions to predict future sales may want to consider extending their repertoire to include such an IS-based QDA methodology that can augment and perhaps outperform quantitative methods in some respects.

Future Research Directions

BASED ON WHAT WE LEARNED FROM THIS initial study, there are a number of interesting ways to extend the research stream from our example application of the methodology. We could perform a field study that would enable consumers to view the movie trailers from their home or work environment and thus see if differences in technology and download speeds affect the results. We would like to gather data from a larger more representative sample in a follow-up study and track participants' actual behavior to determine if their expressed intention-to-see a film results in an actual ticket purchase. One serendipitous finding was that many participants described their previous behavior in relation to intention-to-see a movie, and this could have implications for research and practice, as psychological [6] and consumer behavior literature [3, 18, 35] both suggest that past behavior is an important predictor of future behavior. Participants also frequently mentioned the influence of others on their decision-making processes, and some consumer studies have explored this as well. Another area for future research involves allowing consumers to carry on discussions through queries and responses, as Finch and Leubbe [24] and Finch [23] did in their studies, to see if interaction with others changes intention-to-see, leads to more detailed information, or provides some other unanticipated results. Both interactivity and the influence of others are areas that should be further explored within the context of this research stream. The rich QD that we were able to gather could be used to develop user profiles and models for comparison with those generated from indirect data such as click streams and other sources of consumer information. Finally, we could explore the use the demographic data gathered to assist in market segmentation or for additional stratified analyses. We think that this is a rich area for continued future research.

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