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Compatibility between Text Mining and Qualitative Research in the Perspectives of Grounded Theory, Content Analysis, and Reliability

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The objective of this article is to illustrate that text mining and qualitative research are epistemologically compatible. First, like many qualitative research approaches, such as grounded theory, text mining encourages open-mindedness and discourages preconceptions. Contrary to the popular belief that text mining is a linear and fully automated procedure, the text miner might add, delete, and revise the initial categories in an iterative fashion. Second, text mining is similar to content analysis, which also aims to extract common themes and threads by counting words. Although both of them utilize computer algorithms, text mining is characterized by its capability of processing natural languages. Last, the criteria of sound text mining adhere to those in qualitative research in terms of consistency and replicability. *Key Words: Text Mining, Content Analysis, Exploratory Data Analysis, Natural Language Processing, Computational Linguistics, Grounded Theory, Reliability, and Validity*

Problem and Purpose

With advances in computing technology, text mining has become an emerging research method in various fields, including bioinformatics (Cohen & Hersh, 2005; Kano et al., 2009; Kostoff, Block, Stump, & Pfeil, 2004; Kostoff, Morse, & Oncu, 2007; Koussounadis, Redfern, & Jones, 2009; Vellay, Latimer, & Paillard, 2009; Winnenburg, Wachter, Plake, Doms, & Schroeder, 2008; Yao, Evans, & Rzhetsky, 2009; Zaremba et al., 2009), business (Consoli, 2009; Miller, 2005; Singh, Hu, & Roehl, 2007; Spangler et al., 2009), engineering (Kostoff, Bedford, del Río, Cortes, & Karypis, 2004; Kostoff & DeMarco, 2001; Kostoff et al., 2006; Kostoff, Karpouzian, & Malpohl, 2005), and education (Chen, Kinshuk, Wei, Chen, 2008; Huang, Chen, Luo, Chen, & Chuang, 2008; Lin, Hsieh, & Chuang, 2009). The preceding applications have a strong quantitative focus in the sense that the outcome variables can be clearly defined; nonetheless, some researchers have applied text mining into qualitative research projects, and view text mining as a viable qualitative research method (Camillo, Tosi, & Traldi, 2005; Hong, 2009; Janasik, Honkela, & Bruun, 2009).

The purpose of this article is to demonstrate that text mining and qualitative research are epistemologically compatible. First, like many qualitative research approaches, including grounded theory, text mining encourages open-mindedness and discourages preconceptions (Vilkinas, 2008). Second, text mining is similar to content analysis, which is qualitative in essence (Lin et al., 2009). Last, the criteria of good text mining adhere to those in qualitative research in terms of reliability and validity (Krippendorff, 2004).

What is Qualitative?

One may argue that text mining and qualitative methods are vastly different in nature because the former, which employs algorithms for counting words, is inherently a quantitative method. In response to this assertion, Krippendorff (2004) argued that text analysis is indeed qualitative. In his view, reading texts and counting words, regardless of whether it is performed by a human or a computer, does not remove the qualitative nature of the texts. As a matter of fact, today many qualitative researchers employ computer software modules as an aid.

According to Janasik et al. (2009), the seemingly qualitative method of gathering data, such as observation, participation, document analysis, and interviews does not necessarily make a study qualitative. The qualitative attribute of a study resides not in the data collection method, but in the data type and in the method with which the data are analyzed. In their view, in a qualitative study the data should not be converted to numeric values, and mathematical and statistical tools should not be used in the analysis. Rather, the data are processed through systematization, categorization, and interpretation. The first part of the definition (data type as qualitative) is the same as that suggested by Krippendorff (2004), but the second part (the absence of mathematical and statistical tools) is debatable. It is doubtful whether this type of "purity" in methods is an essential feature of qualitative research.

Consider the metaphor of photography. Some film-based photographers complained that digital photographers distort the authenticity of the captured images by digital manipulation, and thus digital photography is computer graphics rather than true photography. However, they overlook the fact that adding filters on the lenses and darkroom manipulation, such as burning and dodging, are also considered manipulation. There is no "purity" in any photographic process. By the same token, purity in the analytical process cannot be a criterion for demarcating quantitative and qualitative approaches. For example, when a quantitative researcher employs exploratory data analysis (EDA) and data visualization (DV) to detect a pattern, there is no "cut-off" value or numeric standard to determine what constitutes a pattern. In this case, he or she must make a qualitative-based decision. It would be absurd to exclude EDA and DV from the realm of quantitative methodology just because qualitative elements are involved in the analytical process. Therefore, it is the conviction of the authors that the qualitative attribute of a research study should be associated with the data type. Although text mining involves counting words and appears to be a quantitative method, its data type is still qualitative. And in essence there are common grounds between text mining and other qualitative methods, such as grounded theory, which will be discussed next.

Text mining and Grounded Theory

Openness to Surprising Results

Text mining is typically defined as a process of extracting useful information from document collections through the identification and exploration of interesting patterns (Feldman & Sanger, 2007). Similarly, grounded theory was developed to explore the data with an open mind. Grounded theorists intend to identify categories, concepts, and constructs that explain a process, an action, or interaction about a substantive topic (Glaser, 1978, 1992; Glaser & Strauss, 1967). In alignment with grounded theory, in which preconceptions must be put aside, text mining requires open-mindedness of the miners in order to let the categories emerge from the data. Classical grounded theorists assert that a theory must be grounded on the data. Following this logic, Glaser asserted, "There is a need not to review any of the literature in the substantive area under study" (p. 31) However, it is impossible for any researcher, no matter how open the researcher is, to maintain "purity" or to be "uncontaminated" by any preconceptions. So-called "forcing," which results from certain unconscious preconceptions, can occur when the researcher imposes certain tacit structures on the phenomenon under study and then the researcher fits the data into the existing interpretive framework (Janasik et al., 2009).

As a remedy, initially text miners conduct the coding using automated algorithms and it restrains the researcher from making any premature decisions in the research process. It does not necessarily mean that text mining is truly "open-minded" or is superior to grounded theory. Development of the text mining algorithms necessitates some preconceptions about the proper classification method, but the user of the text mining software module is blind to these preconceptions of the programmer.

Coding as an Iterative Process

More importantly, both grounded theory and text mining utilize an *iterative* process. In the former, initial categories extracted from the data must be constantly compared against new data (Glaser & Strauss, 1967), and thus the researcher is open to the possibility that previous categories might be collapsed and revised, and new categories might be added. By the same token, a text mining algorithm is designed to learn from the data by revising the categories. However, if this learning and revision is performed by automated algorithms alone, how could it be related to openness of the researchers? It is important to point out that text mining is not characterized by complete automation. Kostoff et al. (2007) explicitly stated that text mining is not a substitute for the judgment of the researchers, and should serve as a supplement. Human judgment, especially qualified-based judgment, must be made at different points of the process. The text miner might re-classify some entries into different categories or delete some redundant categories when the software makes an obvious mistake. In addition, Hong (2009) asserted in order to unearth hidden insight, rare but meaningful data must be scrutinized for pattern recognition. The text miner must make a qualitative judgment to set the key words and decide on the constraints. Based upon the input from the human miner, the computer system extracts small but meaningful data and then passes the output to pattern recognition. Therefore, the miner must interact with the pattern generated from the system, and also set more rigorous constraints and keywords to narrow down the search space. This iterative process continues until an optimal solution is obtained. In this sense, the openness in text mining is just like that of grounded theory in terms of employing an iterative process to look for new and unexpected categories.

Text Mining and Content Analysis

As mentioned in the previous section, text mining aims at pattern recognition and does not test pre-formulated hypotheses or assume the existence of pre-established taxonomies. In this sense, text mining should be in alignment with exploratory data analysis (Hearst, 1999). In terms of the exploratory character, text mining is closely related to content analysis (CA), which is a method of gathering, analyzing, and categorizing the content associated with psychological constructs without preconceptions. The data-driven categories are called inferred categories, which mean that they are inferred or emerge from the data (Vilkinas, 2008).

Strategies and Examples of Content Analysis

Different researchers might implement CA differently. Based on the framework of qualitative analytical procedures developed by Miles and Huberman (1994), Romanowski (2009) outlined the common strategies of qualitative content analysis as follows: (a) The researcher carefully examine the textual data and takes notes; (b) The researcher performs data reduction by selecting, focusing, and condensing the data in the way that could best answer the research questions; (c) The researcher organizes, arranges and displays the condensed data. Based on the display, the researcher identifies themes, patterns, connections, and omissions that could help answer the research questions. Further, quotations might be listed for supporting the themes and inter-connections among the themes. If necessary, categories could be added, deleted, and revised to maximize mutual exclusivity and exhaustiveness; and (d) The researcher revisits the data many times in order to verify, test, or confirm the themes and patterns identified.

While Romanowski (2009) outlined the basic principle, a study conducted by Tsai (2009) illustrates how CA is implemented to investigate the experiences of occupational injury and illness among Chinese immigrant restaurant workers in the US. After conducting twenty-one interviews and three focus groups, the researcher read each transcript word by word and highlighted the texts that appeared to capture the injury or illness experiences. Additionally, notes were taken as reflections about the raw data. After all of the highlighted texts with codes were entered into a qualitative data management software module, the coded data were re-organized and displayed in print for within- and between-interviews comparisons. While examining the retrieved data segments, the researcher revised some codes or quotations. After going through an iterative process of recoding, the researcher integrated the final set of codes into meaningful categories based on how the codes were inter-connected. It was found that occupational illnesses among Chinese workers are closely tied to certain cultural concepts, such as the belief that illness is a consequence of broken harmony and balance.

History of Content Analysis

Historically, CA can be seen as a precursor to today's text mining. While initially used in classifying religious hymns in 18th century Sweden (Smith, 2000), CA has its social science origins in both political science and psychology. In political science, CA was heavily used in propaganda analysis (Lasswell et al., 1949), whereas in psychology it was associated with data analysis for personality tests (Russell & Stiles, 1979; Smith). While psychologists do not refer to this process as CA, the emphasis in examining the verbal text from these tests relies on analysis of the text to identify common themes, associations, and imagery, in which their importance is ranked by their frequency in contexts.

Early development of personality psychology heavily relied on text analysis. To identify personal dispositions that are unique to individuals, Allport, the father of modern personality psychology, and his colleague Odbert (1936) counted 17,953 descriptive words in *Webster's New International Dictionary* in order to extract descriptions of personality characteristics (Feist & Feist, 2006). In addition, psychology has historically used CA to explore small group communication (Bales, 1950) and dream interpretation (Hall & Van de Castle, 1966). As early as 1966, computers were also used to assist in CA. Stone, Dunphy, Smith, and Ogilvie (1966) created a computer program to provide basic statistics on word usage and categories for the words used, allowing for a basic, computer-based analysis of the inputted text.

More recently, as computing power has increased, CA has been used to examine a variety of texts and settings, including unidentified written works to determine authorship (Smith, 2000), to distinguish between stories of women who were and were not victims of sexual abuse (Arkhurst, 1994), to investigate the psychological status of psychiatric patients (Oxman, Rosenberg, Schnurr, & Tucker, 1985), and to create a personality portrait of President Nixon based on his inauguration speech (Winter & Carlson, 1988). Based on a complex system of text analysis initially developed for use in analyzing results from psychological personality tests, researchers examining Nixon's inaugural speech applied CA to the language used to create a personality profile of his achievement, affiliation-intimacy, and power motives. This profile was validated by six aides that worked closely with Nixon and used to explain the paradoxes in his behavior (such as comments made early in his life regarding honesty compared to his involvement in the Watergate scandal). In the last example, CA was used as a tool to write "psycho-history."

Interestingly, although CA and text mining possess many commonalities, researchers in the two fields rarely make references to each other. If a literature review is conducted using both keywords, one can find only a few articles that link CA to text mining (e.g., Lee & Hu, 2004; Lin et al., 2009). Lin et al. found that although CA is a popular method to study student discussion in course management systems, it is too labor-intensive for instructors. To save time and resources, they developed a text mining system to facilitate the automatic coding process. In their view, TM is a suitable replacement of CA.

Role of Natural Language Processing in Text Mining

Content analysis is not necessarily totally manual and labor-intensive. Before the emergence of text mining, use of statistical methods, aided by the availability of increasingly powerful computers, had applied to content analysis. This trend resulted in a form of text analysis that provides novel information about a passage, allowing more advanced theories and hypotheses to be drawn from the text (Manning & Schütze, 1999).

Well-known examples of software modules for text-based CA are *WordStat* (Provalis Research, 2006), *HYPEresearch* (Researchware, 2008), *MAXQDA* (VERBI Software, 2007), and *Nvivo* (QSR International, 2007). Although both CA and text mining utilize computer algorithms, there is one major difference between the software packages for CA and those for text mining. At the present time, most CA-oriented software packages, as cited above, use statistics-based algorithms for counting words. On the other hand, natural language processing (NLP) plays an important role in text mining. While strict CA provides descriptive information, text mining using NLP can uncover patterns and provide predictive information, based on a more sophisticated understanding of language.

Natural language processing is a subfield of artificial intelligence (AI) and computational linguistics (CL), which focus on the automatic analysis of human language with use of algorithms that can handle "fuzzy" structures (Gelbukh, 2007; Jurafsky & Martin, 2000; Kao & Poteet, 2007; Mehler & Köhler, 2007). Based on AI and CL theories, NLP aids text mining in information retrieval (Singhal, 2001) and automatic summarization (Mani, 2001). Natural language processing aims to address the complexity and multiple connotations of natural languages. In varying contexts, a single word can mean different things. For example, "books" in the phrase "he books tickets" is different from the same word in "he reads books." Relying on a computer to conduct text analysis could be dangerous if the software is not well-written. As a remedy, text mining employs NLP in an attempt to "understand" the data as though a human coder read the text. The NLP movement is inspired by Chomsky's (1957) notion that there are universal syntactic structures that are common to all languages. Based on this notion, linguists and computer scientists believed that ruled-based algorithms could be developed to process languages. As a result, research in linguistics and the philosophy of language set the agenda for explorations in NLP. Besides the school of universal syntactic structures, NLP researchers also explore the viability of data-driven NLP, which are example-based rather than rule-based (Dale & Moisl, 2000).

Data Sources of Content Analysis and Text Mining

There is another major difference between CA and text mining: data sources. Historically, most CA studies have been concerned with sociological or psychological constructs while recent text mining applications span across many fields. However, it is by no means an inherent characteristic of CA. Not only are the techniques of CA not restricted to analyzing social sciences data, but also the data sources of CA are broader than those of text mining. Content analysis can be conducted on written text, transcribed speech, verbal interactions, visual images, nonverbal behaviors, sound events, or any other message type. For example, one of the seminal works of CA is film analysis during the 1920s and 1930s. At that time some Americans were concerned with obscene movie content and its effects on young people. As the research center of the film content analysis, Ohio State University sent coders to take notes in theaters while watching movies for later classification of the sex and crime scenes of the movies (Neuendorf, 2002). Another masterpiece of CA was accomplished by British Intelligence during World War II. A group connected with the BBC systematically analyzed propaganda from radio broadcasts aired by the Axis of Power. Based on this analysis, the Allied Forces were able to forecast the deployment of German troops and the launch of V2 rockets (Krippendorff, 2004; Neuendorf). All these "non-text" data sources must be counted and analyzed by human coders. Even today no automated text mining software module is smart enough to "watch" a movie or "listen" to a radio broadcast.

In summary, the history of CA and the examples of CA studies cited above indicate that text mining, by objective and essence, is similar to CA. Traditionally, it is perceived that CA is based on human coding while TM utilizes computerized coding. Today this demarcation is blurred. In the flowchart of content analysis illustrated by Neuendorf (2002), the researcher could choose either the human coding approach or the computer coding approach. However, in most cases the researcher might employ both. As mentioned before, a good text miner does not completely hand over the judgment to the automated computer system; rather, he or she might override the computer-coded results by adding, deleting, collapsing, and renaming certain categories. In this sense, a text miner is a content analyzer, and vice versa.

Reliability and Validity in Text Mining and a Qualitative Approach

Controversy of Reliability and Validity in Qualitative Research

Krippendorff (2004) asserted that the most crucial form of reliability in text analysis is replicability, which means that a convergent result can be yielded from different coders at different points of time and under different circumstances. For him, reliability is a means rather than an end, because the purpose of obtaining reliable data is to make valid inferences. Simply stated, there is no point in counting unless the frequencies could lead to inferences regarding the subject matter. In short, Krippendorff contended that "validating evidence …is the ultimate justification of content analysis" (p. 30). Text miners also view reliability as a central issue of text analysis. For example, SPSS Inc. (2006), publisher of *Text Analysis for Surveys*, highlighted the benefit of computer-aided text analysis by saying "reliability of results increases dramatically, since extraction and categorization are always performed in a consistent and repeatable manner" (p. 3). Although the preceding assertions are well-intended, it might be disputable in the context of the qualitative paradigm. By definition "inference" is an act of expanding the conclusion from a smaller subset to a broader set (e.g., from the sample statistics to the population parameter), but most qualitative studies do not aim to make "valid inferences." While the meanings of reliability and validity are standardized in quantitative research (e.g., internal consistency, temporal stability, form equivalence, inter-rater reliability, content validity, criterion validity, and construct validity), the usage of reliability and validity in qualitative research are diverse and controversial. As a result, one might wonder what type of reliability could be used as the criterion for assessing a text mining study. It is the conviction of the authors that text mining, which emphasizes reliability in the form of consistency and replicability, is highly compatible with the qualitative paradigm.

Originally, the concepts of "reliability" and "validity" were introduced by quantitative methodologists in an attempt to preserve the scientific merits of research studies. While certain qualitative researchers accept these criteria (Morse, 1999), some hold skeptical attitudes toward these concepts (Altheide & Johnson, 1998; Guba & Lincoln, 1985, 1989; Lincoln & Guba, 1985). A qualitative project is typically regarded as a *contextualized* study, and thus generalizability and reliability in terms of replicability are not accepted as standards of rigorous research by some qualitative researchers. In addition, many qualitative researchers question the use of reliability and validity in qualitative research on the ground that these are "positivist" or "logical-positivist" concepts, which are based upon the recognition of an "objective reality" and the goal of seeking causal relationships (Golafshani, 2003; Guba & Lincoln, 1989), and that a quantitative approach would "fragment and delimit phenomena" (Golafshani, p. 598). An argument that is commonly used to question the conventional sense of reliability is that absolute objectivity, which is based upon the premise of an objective reality, is delusional (Niemann et al., 2000). Under careful scrutiny, one can see that negating a notion by saying that the ideal state (absolute objectivity) can never be achieved is not a good strategy at all. Simply put, we cannot absolutely cure all diseases, but it does not mean that medical researchers who devote efforts to finding better cures are delusional, or that it is better to leave germs and bacteria unchecked, for they continue to exist anyway.

Positivism as a Straw-Man

Further, the anti-positivist argument is nothing more than attacking a straw-man, because positivists did not subscribe to the preceding views. For example, although positivist Schlick (1959) stated that reality refers to experience, Schlick (1925/1974) did not maintain that there is a direct path from sense experience to genuine knowledge because immediate contact with the given is both fleeting and subjective. Contrary to popular belief, some logical positivists are anti-realists. Even those logical positivists who accept a realist position do not regard the aim of science as finding the objective truth corresponding to the objective reality. Instead, they view inquiry as a convention for conveniences. The most well known brand of conventionalism is Carnap's linguistic conventionalism (Carnap, 1937). In addition, the meaning of causation has been approached by different schools of thought. One of these approaches believes that causation involves a producing or forcing phenomenon (If X is a cause of Y, a change of X produces or forces a change in Y; Blalock, 1964). However, this view is incompatible with logical positivism's perspective that "cause," as an invisible force or a theoretical entity, cannot be observed or measured. In brief, according to "verificationism" proposed by logical positivists, statements that cannot be verified had no content. In this view, causal statements are non-verifiable statements (Schuldenfrei, 1972; Yu, 2006). In short, questioning the value of reliability and validity for their alleged association with positivism is problematic.

Alternate Terms do not Introduce New Information

While Lincoln and Guba (1985) asserted that the conventional benchmarks based on reliability and validity do not fit into the assumption of multiple constructed realities in qualitative research, different alternatives have been proposed, such as trustworthiness, rigor, quality (Golafshani, 2003), credibility, neutrality, confirmability, dependability, applicability, transferability (Lincoln & Guba, 1985), complexity, and consensus (Hall & Stevens, 1991), However, Long and Johnson (2000) found that there is nothing to be gained from the use of alternative terms. Actually, they are often shown to be the same as the traditional terms of reliability and validity. For example, Guba and Lincoln (1989) defined "dependability" as the stability of data over time (p. 242). Indeed, the very essence of dependability is the same as that of reliability: "to ensure that data collection is undertaken in a consistent manner free from undue variation which unknowingly exerts an effect on the nature of the data" (Long & Johnson, p. 31). In short, it is not a novel conceptualization at all. Rather than putting aside the issues of reliability and validity or renaming them, qualitative researchers should take them into account in terms of their original meanings

Text Mining Improves Consistency and Replicability

A high degree of subjectivity in coding open-ended responses has drawn researchers' attention to the issue of inter-rater reliability in qualitative research (Armstrong, Gosling, Weinman, & Martaeu, 1997; Moret, Reuzel, van der Wilt, & Grin, 2007; Thompson, McCaughan, Cullum, Sheldon, & Raynor, 2004). Some critics expressed concerns that qualitative data analysis fails to provide replicable and generalizable conclusions (Carey, Morgan, & Oxtoby, 1996). Moret et al. are concerned with whether qualitative researchers involved in the same project can converge into the same interpretive framework. As a remedy, they conducted an inter-rater agreement analysis in the fashion of estimating reliability. However, some proponents assert that inter-rater reliability is applicable to semi-structured data only, in which all respondents answer the same question in the same format, but interpreting unstructured responses to interactive interviews should be conducted by the interviewers who know the messages the subjects intended to convey through their responses. Conversely, study results based upon member checks of coding would be *decontextualized* and abstracted from individual participants (Morse, 1997; Morse, Barratt, Mayan, Olson, & Spiers, 2002).

It is important to point out that Morse et al., (2002) did not intend to reject the concepts of reliability and validity altogether. On the contrary, they see value in qualitative research but question the indispensability of inter-rater reliability. At the beginning of their article, Morse et al., explicitly state, "Without rigor, research is worthless, becomes fiction, and loses its utility" (p. 11). On another occasion, Morse (1999) asserted, "Rigorous research must be reliable and valid" (p. 717). Understandably, different coders might interpret the data differently whereas some coders are more familiar with the participants and the content. However, aside from inter-rater reliability and replicability, reliability can be characterized by consistency and test-retest reliability. Assuming that the person most familiar with the data performs the coding, is it reasonable to expect that a consistent scheme is evenly applied to all data by the same coder? In addition, if the same person goes back to the data set one more time, it is expected that similar classified results would be generated, unless the coder re-conceptualizes the research question or gains new insight after the first round of coding. The aforementioned scenarios have a quantitative equivalence in internal consistency and test-retest reliability. They are not about replicability between coders or generalizability in other contexts; rather, they refer to the quality of data interpretation *within* the same coder. However, a human coder is subject to many uncontrollable factors, such as fatigue, boredom, varying emotional states, and carelessness. Undoubtedly, text mining algorithms can produce more consistent and verifiable results than a human coder. If Morse (1999) and Morse et al. (2002) accept the notion of reliability and validity as using rigorous standards to verify research results, then a high degree of compatibility between text mining and rigorous qualitative research truly exists.

Conclusion

In summary, text mining, as a data-driven research tool that allows categories to emerge from the data, shares the same goal with certain qualitative methods, such as grounded theory and content analysis. Both content analysis and text mining employ computer algorithms for counting words, but text mining goes further by interpreting the contexts of the words using natural language processing. However, it doesn't necessarily imply that text mining is superior to content analysis. Text mining is confined to textual analysis whereas the scope of content analysis expands to audio and video. Last, if a well-written algorithm is used and the researcher is well-trained enough to make discernment on the categories, text mining could maintain a high degree of consistency, and this aspect of reliability is fully compatible with the criteria of sound qualitative research.

In 2006 a conference entitled *Bridging quantitative and qualitative methods for social sciences using text mining techniques*" was held by the National Centre for Text Mining in England and many promising ideas were proposed (Ananiadou, 2006; Frantzi, 2006: Gibbs, 2006; Gillam, 2006; Lewins, 2006; Nasukawa, 2006; Wilson, 2006). However, most contributors for building this "bridge" are European and these "building blocks" are much less visible in the American methodological community. At the time of this writing, when the keywords "text mining and qualitative" are used for searching scholarly articles in major research databases, such as *Academic Search Premier* (EBSCOhost), *ERIC*, and *PsycINFO*, no entries are returned. In *Electronic Journals Service* there is just one article. Nevertheless, the objective and the criteria for rigorous research of text mining are fully compatible with that of qualitative research, and thus it is the hope of the authors that more attention will be paid to text mining by qualitative researchers.

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