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Maximizing NVivo Utilities to Analyze Open-Ended Responses

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Abstract

Open-ended responses are widely used to explore and understand participants' experiences and perspectives in a variety of fields. As one of the most powerful computer-assisted qualitative data analysis software, NVivo allows researchers to analyze open-ended responses to survey and/or interview questions, as well as other text data like reflective writing, image, and videos. The purpose of this paper is to describe and demonstrate how the NVivo word frequency, text search, and matrix coding features can be used to analyze qualitative data from a longitudinal evaluation project. The authors show how the matrix coding feature maximizes NVivo utilities in an analysis of open-ended responses and highlights differences across and within participants' groups. The authors explain this approach by presenting a step by step overview: data cleaning and case coding; data import; word frequency analysis; text coding and reference extracting; and matrix coding and inductive analysis. Using this approach, the Clinical Translational Science Institute (CTSI) evaluation team acquired deeper insight into the participants' experiences and perspectives about CTSI programs and received insights that may lead to improvement. From a methodological perspective, this approach capitalizes on NVivo's features to mine qualitative data. The methodology described in this paper is applicable to other educational or program evaluations. Also, it is appropriate for analyzing large samples or longitudinal qualitative data in marketing and management.

Keywords

NVivo, Matrix Coding, Qualitative Method, Open-Ended Responses, Large Sample Size Data

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Open-ended responses are widely used to explore and understand participants' experiences and perspectives in a variety of fields. As one of the most powerful computer-assisted qualitative data analysis software, NVivo allows researchers to analyze open-ended responses to survey and/or interview questions, as well as other text data like reflective writing, image, and videos. The purpose of this paper is to describe and demonstrate how the NVivo word frequency, text search, and matrix coding features can be used to analyze qualitative data from a longitudinal evaluation project. The authors show how the matrix coding feature maximizes NVivo utilities in an analysis of open-ended responses and highlights differences across and within participants' groups. The authors explain this approach by presenting a step by step overview: data cleaning and case coding; data import; word frequency analysis; text coding and reference extracting; and matrix coding and inductive analysis. Using this approach, the Clinical Translational Science Institute (CTSI) evaluation team acquired deeper insight into the participants' experiences and perspectives about CTSI programs and received insights that may lead to improvement. From a methodological perspective, this approach capitalizes on NVivo's features to mine qualitative data. The methodology described in this paper is applicable to other educational or program evaluations. Also, it is appropriate for analyzing large samples or longitudinal qualitative data in marketing and management. Keywords: NVivo, Matrix Coding, Qualitative Method, Open-Ended Responses, Large Sample Size Data

Introduction

Open-ended survey responses and/or interview questions are widely used to explore and understand participants' experiences and perspectives in a variety of fields, such as program evaluation, marketing, and management (Creswell, 2012; Vitouladiti, 2014). By analyzing the text embedded in open-ended question responses, researchers can acquire further information and obtain deeper insight into participant beliefs and experiences (Creswell, 2012). In education, collecting open-ended responses is helpful in the assessment of program effectiveness, educational product (e.g., textbooks, assessments) development, and measurement (Fitzpatrick, Sanders, & Worthen, 2011).

To analyze open-ended responses, researchers use qualitative methods to code, organize information and logically group the data into categories or themes, and to gain an innate understanding. Prior to the introduction of computer assisted qualitative data analysis software (CAQDAS), coding was completed manually, often by using two or more research analysts. An often-cited criticism of qualitative research is that researchers' personal viewpoints may unduly impact the ways in which they analyze data (Castellan, 2010; Creswell, 2012). However, CAQDAS reduces the potential for bias when only human coders are used. According to Woods, Macklin, and Lewis (2016), using CAQDAS may diminish this type of bias. The use of CAQDAS enhances confidence in the conclusions drawn because access and retrieval of data, which allows for visualization of the data, is more easily accomplished than with manual methods (Woods, Macklin, & Lewis, 2016). For example, researchers recently

described how reading, sifting and sorting, grouping similar responses together, and developing categories, could be used to calculate the frequency of occurrences across assigned categories (i.e., using a A QUAN→qual sequential method; Behar-Horenstein & Feng, 2017). Use of the CAQDAS increased our confidence in the rigor of the analysis (Davidson & Skinner, 2010; Welsh, 2002).

As one of the most used CAQDAS, NVivo allows researchers to analyze text, image, and videos within the same research project (QSR International Pty Ltd, n.d.). The intrinsic value of NVivo lies in its capacity to code and categorize various data formats. Similar to other CAQDAS, using NVivo can minimize researcher bias. However, the disadvantages ascribed to qualitative data analysis is that it does not always include evidence needed to support observability and measurability. Using particular programmatic functions overcomes these limitations. For example, the word count function permits the measurement and logical arrangement of qualitative data. Such an approach can be useful in analyzing qualitative data from reflective writing, interview, and open-ended responses of survey, etc. NVivo also provides a matrix coding feature that allows researchers to compare qualitative data across and within categories. Within educational program evaluation, NVivo's word count and taxonomic coding for text data has been reported (Behar-Horenstein & Feng, 2017; Behar-Horenstein, Feng, Isaac, & Lee, 2017; Wagland et al., 2017). However, studies utilizing matrix coding have not been reported. Considering that NVivo is one of the most used CAQDAS, the purpose of this paper was to describe and demonstrate the application of its word frequency, text search, and matrix coding utilities in an analysis of qualitative data from a longitudinal evaluation project. The researchers demonstrate how matrix coding assists in the exploration of potential differences across and within different participants' groups.

The original survey from which data for this study was taken was conducted at a research-intensive university to evaluate the effectiveness of its Clinical Translational Science Institute (CTSI) programs. The purposes of this survey were to assess the use of and impact of the university's CTSI programs on the research environment.

To assess the success and impact of the CTSI programs the CTSI Evaluation and Tracking Committee has annually surveyed academic health science center and other college faculty at the main and satellite campuses since 2011. A longitudinal dataset was created based on the survey data. Although the CTSI Evaluation and Tracking Committee analyzed quantitative data and reported related findings annually, to date, the open-ended responses have been not systematically analyzed. Beginning in 2017, researchers from the CTSI Educational Development and Evaluation team analyzed the open-ended responses from 2011-2016 annual surveys (Behar-Horenstein & Feng, 2018).

Overall, 1,845 faculty participated in the annual CTSI survey while 1,096 answered at least one of the eight open-ended questions. Participants' demographic information included: CTSI-ID (a unique number used to track their use of CTSI resources and services), CTSI user status (yes/no), laboratory status, clinical status (clinical and non-clinical faculty), campus location, and college group. In this study, we explain the methods that were used to thematically analyze participant responses to three survey questions: 1. What changes can you suggest (if any) that would encourage collaboration? 2. Please share any additional suggestions or comments that can help the CTSI better meet your needs, and 3. Other comments and their comparisons across the main campus health, main campus others and satellite campus.

Research Approach

NVivo Pro 11.4 served as the data analysis tool. As a well-developed software utilized in managing text, video, and observational data, NVivo, is especially helpful for logically

organizing the longitudinal data and exploring the insights of a data sample (QSR International Pty Ltd, n.d.).

The major focus of this approach was to use NVivo's matrix coding feature to search for patterns and insights in the responses among different demographic groups. The approach to matrix coding includes five steps: data cleaning and case coding; data import; word frequency analysis; text coding and reference extracting; matrix coding and follow-up inductive analysis.

Step One: Data Cleaning and Case Coding

Before analyzing the data, the first step was to clean the data and code the cases. Each case was coded by CTSI-ID as case identification. Case classification was coded based on participants' demographical attributes: (a) CTSI user status (1=CTSI users; 0=non-users), (b) laboratory status (1=laboratory faculty; 0=non-laboratory faculty), (c) clinical status (1=clinical faculty; 0=non-clinical faculty), (d) campus location (1=main campus; 0=satellite campus), and attributes of campus location and college group (1=Main Campus Health Science; 2=Main Campus Others; 0=Satellite Campus-Medicine).

The original data was separated into unique Excel spreadsheets; each one was matched to an open-ended question. Within each Excel spreadsheet, each row contained the participant's open-ended text response and demographic information for each case (See **Panel 1**).

ID	Respond	CTSI	JAX	LAB	CLINICAL	College	Set1_2014	Set1_2015	Set1_2016
247	RESP-000	1.00	0.00	0.00	1.00	2	More sharing of resources across departments and		more cross-talk
248	RESP-000	1.00	0.00	1.00	1.00	2	Less regualtory paperwork and training to allow for		"Critical mass" of researchers with a common mission; more visibility
269	RESP-000	1.00	0.00	1.00	0.00	1			Cross department seminars
286	RESP-000	0.00	0.00	1.00	0.00	7	Web site grouped by research specialty lisiting	Easy access to finding other with similar	Social gatherings
289	RESP-000	1.00	0.00	0.00	1.00	0	easy to find info on research of others		
302	RESP-000	0.00	0.00	1.00	0.00	2			Local symposiums about a specific topic (e.g., brain trauma) to gather
309	RESP-000	1.00	0.00	1.00	0.00	12	Not sure. Struggled with this problem at other	More seed grants for collaborative research.	
324	RESP-000	1.00	0.00	1.00	1.00	0	the RVUs sytem of reimbursement rewards		
326	RESP-000	1.00	0.00	1.00	0.00	3	Ac entral web site that can be searched, e.g. like the	evening series of "in house" seminar	I suggest a site where all active investigators have a page with key
347	RESP-000	1.00	0.00	1.00	1.00	2			I think there needs to a database of some sort of database that
366	RESP-000	1.00	0.00	1.00	1.00	2		index of resources, experts	

Panel 1. Original Data in Excel

Step Two: Data Import

The next step was to import the open-ended responses and participant demographic data into NVivo. Using the data import feature of NVivo, the cases in Excel spreadsheet were easily read and imported into NVivo (See **Panel 2**).

RowID	CTSI	JAX	LAB	Clinical	College	CollegeGro...	set1_2014	set1_2015	set1_2016
87	1	0	1	0	7	2			
88	1	0	1	1	2	1	A "clearinghouse" to pair interests. For example, I have ideas about medical devices, but have no idea of who to contact in engineering to discuss. I also have ideas for computer modeling, but have no idea what department can help me. I would like a syste where people say, "what if..." or "that is possible..." and not "it cannot be done" or other barriers to moving forward.		There are competing interests/emphasis depending on a person's department and or clinical mission. For example, many departments place a huge emphasis on clinical work load whereas others allow researchers to research and promote collaboration. I have a hrd time collaborating due to my clinical work load.
89	1	0	1	1	2	1	more awareness of what others are doing..	getting to know what other people is doing.	
90	1	0	1	1	2	1	be provided time to seek out collaborations and pursue research		
91	1	0	1	0	2	1			
92	1	0	0	1	2	1	CTSI to help network/connect with other institutional researchers	Give faculty more protected time to do research	provide protected time to faculty for research and more effective research mentoring for junior faculty

Panel 2. Import Data into NVivo

Step Three: Word Frequency Analysis

The third step was to use NVivo's word count feature to calculate the most frequently occurring words of five or more letters. The most frequently used words were viewed as a proxy that represented participants' perspectives. Supporting this approach was the assumption that important and significant words would be used more frequently (Carley, 1993). Word count has also been cited for its advantages in (a) identifying patterns more easily, (b) verifying a hypothesis and (c) maintaining analytic integrity (Jackson & Trochim, 2002). Researchers assert that analyzing word frequency improves analytic rigor, and decreases their bias regarding overweighting (Halpern, 1984; Lincoln, & Guba, 1985; Onwuegbuzie, & Leech, 2007; Sandelowski, 2001). However, the use of the word count function is not without its critics. Word count can result in decontextualization to the point where particular words lack meaning. For example, words such as "him, "was", "I" do not increase the researcher's understanding of a phenomenon. Thus, we only used words of five or more letters (for example, we excluded words like "we", "the", "is", etc.; these words were frequently used but could not contribute to the analysis) in the word frequency analysis to avoid involving meaningless articles, pronouns, and prepositions.

To analyze the word frequency, researchers used one of NVivo's features, the "word frequency query". First, the open-ended responses of each question were run through the word frequency query using words with stemmed variants (e.g., "research, researches, researcher, researchers" were counted as "research") their weighted percentages were calculated (see **Panel 3**).

The most frequently occurring words, with a weighted percentage of more than .5%, served as nodes or coded words in NVivo. A weighted total percent of the contents was provided for each question, which reflects the words that were highly representative words of participants' responses. For question 1, 15 coded words (e.g. researches, collaborators, faculty) emerged from 349 participant responses, which represented 18.2% of the data. For question 2, 14 coded words emerged from 184 responses, which represented 12.3% of the data. For question 3, 13 coded words emerged from 425 responses, which represented 12.3% of the data.

	word	length	count	weighted percentage (%)	stemmed words
1					
2	researches	10	259	4.58	research, 'research', researcher, researchers, researches
3	collaborators	13	154	2.72	collaborate, collaborating, collaboration, collaborations, collaborative, collaborator, collaborators, collaborators'
4	faculty	7	74	1.31	faculties, faculty
5	funds	5	64	1.13	funded, funding, funds
6	departments	11	59	1.04	department, departments
7	college	7	55	0.97	college, colleges
8	clinical	8	46	0.81	clinical, clinics
9	grants	6	44	0.78	grant, grants
10	support	7	44	0.78	support, supported, supporting, supportive
11	campus	6	43	0.76	campus, campuses
12	opportunities	13	43	0.76	opportunities, opportunity
13	interests	9	42	0.74	interest, interested, interests
14	university	10	37	0.65	universities, university
15	people	6	33	0.58	people
16	projects	8	33	0.58	project, projects
17	seminars	8	28	0.49	seminar, seminars
18	meetings	8	27	0.48	meeting, meetings
19	across	6	26	0.46	across
20	investigators	13	25	0.44	investigation, investigator, investigators
21	encourage	9	25	0.44	encourage, encouraged, encouragement, encourages, encouraging
22	expertise	9	24	0.42	expertise
23	groups	6	24	0.42	group, grouped, groups

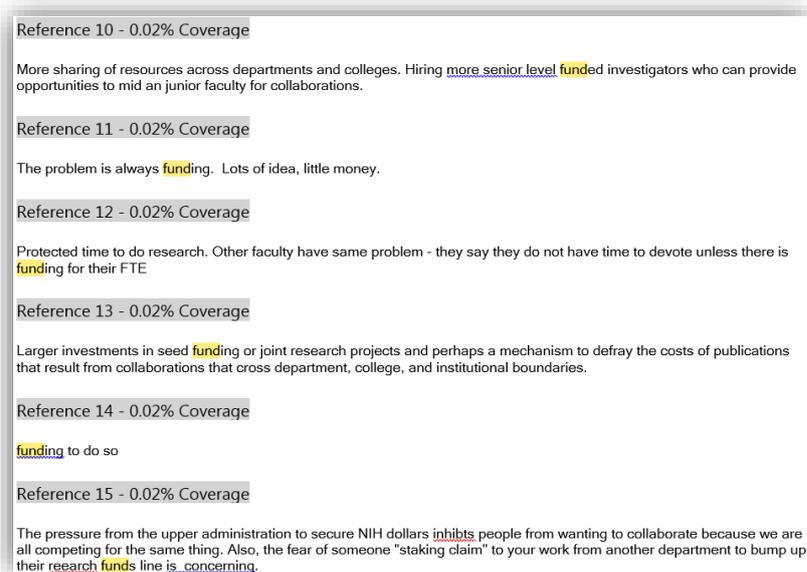Panel 3. Using NVivo Query to Identify the Most Frequently Used Words in Data

Step Four: Text Coding and Reference Extracting

Next, while employing the text search query feature, we used the most frequently occurring words (with the stemmed variants) to code the responses content (all sentences or paragraphs for each case within each question). In NVivo, those words are referred to as "nodes" (QSR International Pty Ltd, n.d.). Content that included the most frequently occurring words were identified as references of the nodes. The text coding summary, provided by NVivo, shows the number of references for each node (see **Panel 4**).

1-projects	1	27
1-people	1	28
1-university	1	29
1-interests	1	38
1-opportunities	1	41
1-campus	1	37
1-support	1	36
1-grants	1	38
1-clinical	1	30
1-college	1	41
1-departments	1	50
1-funds	1	51
1-faculty	1	56
1-collaborators	1	123
1-researches	1	177

Panel 4. Most Frequently Used Words as Nodes to Code the Data

Next, we used NVivo's reference extract feature to tag and extract the response content (the "reference") within highlighted nodes (see **Panel 5**).

Reference 10 - 0.02% Coverage

More sharing of resources across departments and colleges. Hiring more senior level funded investigators who can provide opportunities to mid an junior faculty for collaborations.

Reference 11 - 0.02% Coverage

The problem is always funding. Lots of idea, little money.

Reference 12 - 0.02% Coverage

Protected time to do research. Other faculty have same problem - they say they do not have time to devote unless there is funding for their FTE

Reference 13 - 0.02% Coverage

Larger investments in seed funding or joint research projects and perhaps a mechanism to defray the costs of publications that result from collaborations that cross department, college, and institutional boundaries.

Reference 14 - 0.02% Coverage

funding to do so

Reference 15 - 0.02% Coverage

The pressure from the upper administration to secure NIH dollars inhibts people from wanting to collaborate because we are all competing for the same thing. Also, the fear of someone "staking claim" to your work from another department to bump up their reearch funds line is concerning.

Panel 5. Coded References

## Step Five: Matrix Coding and Inductive Analysis

The fifth step is matrix coding. The use of this feature allowed comparisons across and between different demographic categories (case classification attributions) with the participant responses.

Four matrices were produced for each open-ended question: 1. nodes (the most frequently occurring words) by CTSI user status; 2. nodes by laboratory status; 3. nodes by clinical status (clinical/ non-clinical faculty); 4. nodes by the combined data of campus location and college group (Main Campus Health Science; Main Campus Others; Satellite Campus-Medicine). Within each matrix, the first column shows the nodes. The first row shows the case classification attribution and each cell of the matrix represents the number of responses (also the number of cases) which mentioned the nodes (the most frequently occurring words) (see **Panel 6**).

1-Clinical_matrix ✖ 1-Clinical_matrix [Results\\1-o	A : caseID:Clinical = 0	B : caseID:Clinical = 1
1 : 1-campus	14	23
2 : 1-clinical	5	25
3 : 1-collaborators	59	64
4 : 1-college	27	14
5 : 1-departments	26	24
6 : 1-faculty	31	25
7 : 1-funds	24	27
8 : 1-grants	21	17
9 : 1-interests	22	16
10 : 1-opportunities	21	20
11 : 1-people	14	14
12 : 1-projects	12	15
13 : 1-researches	71	106
14 : 1-support	17	19
15 : 1-university	15	14

Panel 6. Matrix of Nodes by Each Category (Attribution)

To view the results, researchers double clicked the number in each matrix. Clicking on the number resulted in a display of the coded references, which were then used for further analyses and reporting purposes (see **Panel 7**). While reviewing the results of matrix coding, we used inductive analysis to explore participants' subjective perspectives (Saldaña, 2015). Based on the coding results, researchers identified themes and provided conceptual definitions of the themes. Using participant responses to three questions [What changes can you suggest (if any) that would encourage collaboration? Please share any additional suggestions or comments that can help the CTSI better meet your needs, and Other comments] this process resulted in the identification of themes across the main campus health, main campus others and satellite campus.
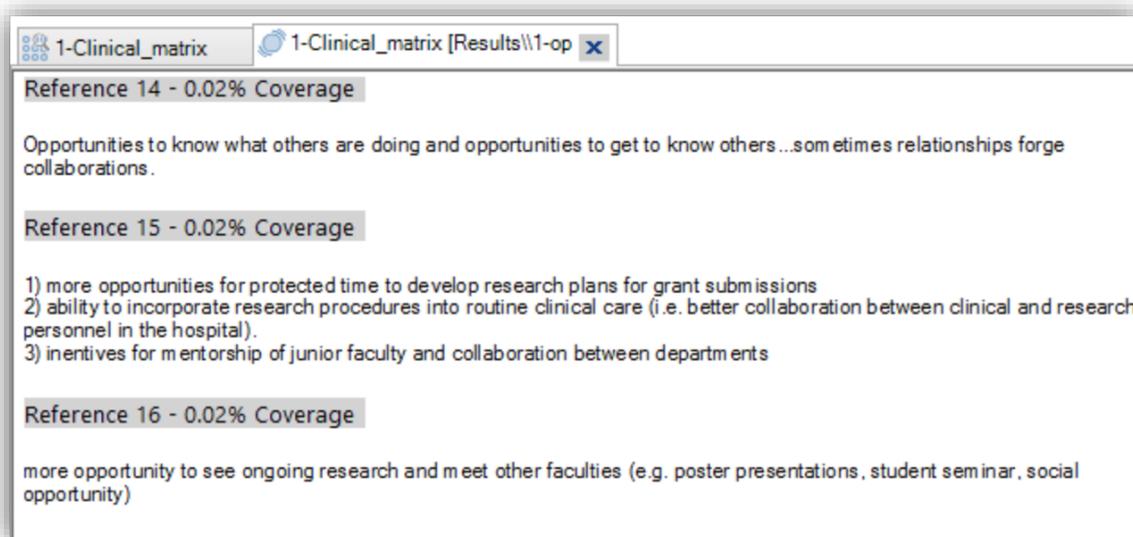
Panel 7. Matrix Content

Researcher's Perspectives

The research team included one faculty member and a Ph.D. graduate in educational leadership. The first author is an experienced qualitative and educational researcher from the College of Education who studies outcomes that accrue from pedagogical interventions, and explores changes in faculty beliefs related to teaching, educational research, and assessment practices. Her research initiatives encompass faculty development, cultural competency, and the assessment of behavioral, cognitive, and attitudinal change. The second author has expertise in qualitative and quantitative analyses as well as in NVivo. The researchers' interest in this study emanated from their observation that open-ended surveys comments had not been previously analyzed and their belief that this dataset potentially contained rich information.

Implications

Using this approach, the CTSI evaluation team acquired otherwise inscrutable insight into the participants' experiences and perspectives about CTSI programs. Based on the findings, the CTSI evaluation team utilized different demographic group viewpoints and strategically enhanced program delivery. Identifying commonly shared viewpoints provided guidance towards improving specific CTSI programs (Behar-Horenstein & Feng, 2018; Behar-Horenstein & Zhang, 2019).

This approach to data analysis produced contextually rich understandings that exceed the type of information which may be acquired from a sole reliance on the close-ended survey data. From a methodological perspective, this approach amplifies NVivo's features to mine qualitative data and to produce novel findings. Indeed, it highlights the value of NVivo features and qualitative research methods to provide findings that had not been previously explored and remained unknown.

The methodological approach described in this paper is applicable to other educational or program evaluation studies, in which open-ended text responses are collected among demographic groups. For the evaluator who wants to explore specific perspectives and provide targeted improvement strategies, this approach may be appropriate. Besides comparing demographic groups, this approach can also be used to analyze categorical data and identify similarities and differences among, for example experimental vs. control group participants. We encourage researchers to use this approach in future studies.

This approach is also appropriate for analyzing large sample or longitudinal qualitative data in marketing and management fields. In marketing, this approach can assist in people product analysis. An analysis of comments from participant survey can provide precise product improvement strategies to different customer groups.

Overall, large sample size or longitudinal qualitative data can be difficult to analyze. With the help of NVivo features, qualitative data can be logically and measurably managed. Specifically, using NVivo's matrix coding feature, open-ended responses could be analyzed among different group, help researchers better understand the participants' viewpoints, discover the specific perspectives for different groups, and offer targeted suggestions and strategies that maximize the effectiveness of program evaluation.

References

Behar-Horenstein, L. S., & Feng, X. (2017). Enhancing cultural competence among dental students through active teaching and experiential learning. *The Qualitative Report, 22*(4), 1169-1185. Retrieved from https://nsuworks.nova.edu/tqr/vol22/iss4/14

Behar-Horenstein, L. S., Feng, X., Isaac, C. A., & Lee, B. (2017). Dental student's expression of cultural competence. *Journal of Ethnographic & Qualitative Research, 11*(3), 171-188.

Behar-Horenstein, L. S., & Feng, X. (2018). What open-ended comments reveal: An analysis of a clinical translational science institute's annual surveys. *The Qualitative Report, 23*(8), 2003-2018. Retrieved from https://nsuworks.nova.edu/tqr/vol23/iss8/15

Behar-Horenstein, L. S., & Zhang, H. (2019). Assessing participant group affiliation and attitudes towards CTSI services. *The Qualitative Report 24*(2), 262-275. Retrieved from https://nsuworks.nova.edu/tqr/vol24/iss2/5

Carley, K. (1993). Coding choices for textual analysis: A comparison of content analysis and map analysis. *Sociological Methodology*, *23*, 75-126.

Castellan, C. M. (2010). Quantitative and qualitative research: A view for clarity. *International Journal of Education*, *2*(2), 1-14. Retrieved from http://www.macrothink.org/journal/index.php/ije/article/viewFile/446/361

Creswell, J. W. (2012). *Educational research: Planning, conducting, and evaluating quantitative and qualitative research* (4th ed.). Boston, MA: Pearson.

Davidson, L., & Skinner, H. (2010). I spy with my little eye: A comparison of manual versus computer-aided analysis of data gathered by projective techniques. *Qualitative Market Research: An International Journal, 13,* 441-459.

Fitzpatrick, J. L., Sanders, J. R., & Worthen, B. R. (2011). *Program evaluation: Alternative approaches and practical guidelines* (4th ed.). Upper Saddle River, NJ: Pearson

Education.

Halpern, E. S. (1984). *Auditing naturalistic inquiries: The development and application of a model* (Doctoral thesis). Indiana University. Retrieved from https://elibrary.ru/item.asp?id=7390072.

Jackson, K. M., & Trochim, W. M. (2002). Concept mapping as an alternative approach for the analysis of open-ended survey responses. *Organizational Research Methods*, 5(4), 307-336.

Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry.* Thousand Oaks, CA: Sage.

Onwuegbuzie, A. J., & Leech, N. L. (2007). Validity and qualitative research: An oxymoron? *Quality & Quantity*, 41(2), 233-249.

QSR International Pty Ltd. (n.d.). *What is NVivo?* Retrieved from https://www.qsrinternational.com/.

Saldaña J. (2015). *The coding manual for qualitative researchers* (3rd ed.). Thousand Oaks, CA: Sage.

Sandelowski, M. (2001). Real qualitative researchers don't count: The use of numbers in qualitative research. *Research in Nursing & Health, 24,* 230-240.

Vitouladiti, O. (2014). Content analysis as a research tool for marketing, management and development strategies in tourism. *Procedia Economics and Finance, 9,* 278-287.

Wagland, R., Bracher, M., Drosdowsky, A., Richardson, A., Symons, J., Mileshkin, L., & Schofield, P. (2017). Differences in experiences of care between patients diagnosed with metastatic cancer of known and unknown primaries: Mixed-method findings from the 2013 cancer patient experience survey in England. *BMJ Open*, 7(9), e017881.

Welsh, E. (2002). Dealing with data: Using NVivo in the qualitative data analysis process. *Forum, Qualitative Social Research, 3*. Retrieved from http://www.qualitative-research.net/fqs/fqs-eng.htm

Woods, M., Macklin, R., & Lewis, G. K. (2016). Researcher reflexivity: Exploring the impacts of CAQDAS use. *International Journal of Social Research Methodology, 19*(4), 385-403.

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