Using manifest content analysis in purchasing and supply management research

Kevin J. Dooley

Department of Supply Chain Management, Arizona State University, United States

ARTICLE INFO

ABSTRACT

Much of the data relevant to study modern organizations is textual and qualitative in nature. With advances in computerized text analysis that enable researchers to collect and analyze large amounts of textual data, there are opportunities to address new research questions or old questions in new ways. This essay describes the use of manifest or computerized content analysis to study research questions in purchasing and supply management. The essay explores why manifest content analysis is needed to study current problems in purchasing and supply management, and discusses issues of methodological rigor, especially in the context of large data sets.

© 2016 Elsevier Ltd. All rights reserved.

1. Introduction

The modern business world is awash in textual data. From casual conversations in hallways to formal discussions in team meetings, and from social and printed media to so-called big data, understanding the textual data that organizations, institutions, and markets create can enrich the study of any organizational phenomenon. Researchers use content analysis methods, the "systematic reading of a body of texts, images, and symbolic matter" (Krippendorf, 2012, p. 10), in order to understand such data. The purpose of content analysis is to reduce the complexity of qualitative, textual data so that it can be more easily and reliably understood, and identify patterns in such data, typically in an inductive (i.e., theory-building) manner.

There are two approaches to perform content analysis, latent and manifest. In latent content analysis, a human researcher reads the relevant text(s) and then responds to the research question at hand with a textual response—the interpretation and encoding of the text being analyzed takes place within the mind of the researcher. In manifest content analysis, explicit mechanical rules are used to create metrics and other analytics that are then interpreted by the researcher. Latent content analysis tends to have higher validity than manifest methods because there is more "human in the loop", but suffer from reliability problems because of human error and fatigue in encoding. Manifest content analysis has high reliability (perfect reliability if done with computer), but can suffer from validity problems because of reducing sentences, paragraphs, and texts to a "bucket" of words. While most academic research using content analyzes have used latent content analysis

methods, advances in technology and methods, as well as the need to process large amounts of data, suggest that future research will largely be dependent upon manifest content analysis.

Purchasing and supply management researchers will benefit greatly from adopting manifest content analysis methods in order to study modern problems—qualitative data has simply become too voluminous to do otherwise. For example, there is increased interest in purchasing and supply management to study disaster relief and humanitarian logistics (Altay and Pal, 2014; Yoo et al., 2016). Hurricane Sandy, which devastated the east coast of the U.S. in 2012, is an example of such an event. Twitter announced that in just five days during and after the storm, over twenty million tweets occurred (Olanoff, 2012). The task of obtaining, processing, sorting, and understanding such a volume of data can only be done with the help of a computer.

The purpose of this essay is two-fold. First, I discuss the nature of modern purchasing and supply management phenomena and why we need to more broadly adopt manifest content analysis methods. Second, I discuss some common methodological issues in using manifest content analysis, including the need to use multiple data sources, multiple units of text, and higher-order analytics. I will conclude with comments about researching purchasing and supply management phenomenon with big data in real-time.

2. Manifest content analysis essential to purchasing and supply management research

Traditional empirically driven business research, including purchasing and supply management research, largely uses structured data such as quantitative econometric data or survey response data

E-mail address: Kevin.Dooley@asu.edu

to create or test theoretical propositions. Within an organizational context, however, the vast majority of data is semi-structured or unstructured. For example, a group of fifty people in an office might create several dozen pages worth of data in the form of spreadsheets in a single day, but Corman et al. (2002) estimated that about 3500 pages of text would be needed to transcribe their conversations. By concentrating on structured quantitative data to address our research questions we have been quite limiting in the type of data that has been used to create knowledge.

Case studies are the most common way in which purchasing and supply management research incorporates semi-structured or unstructured qualitative data, although even case studies are still somewhat of a niche method in the discipline (Barratt, Choi and Li, 2011). While case studies typically use latent content analysis methods to analyze texts such as interview or focus group transcripts, they don't typically refer to the methods used as "content analysis"; that term is more typically used in context of manifest (computerized) content analysis. Comparatively, it would appear case studies are more common than formal (manifest) content analysis. A search of the Arizona State University library online database identified over 25,000 items matching the search phrase <"case study" and "supply chain management"> from 2006 to 2015, and over 15,000 matching <qualitative and "supply chain management">, but only 1900 matching <"content analysis" and "supply chain management">.

Purchasing and supply management phenomena create large amounts of textual data from human communication – the discipline is largely relational both inside and outside the organization – but there are also enormous volumes of transactional data being generated that create unique challenges and opportunities because of its semi-structured nature (Waller and Fawcett, 2013). Whereas structured data defines the range of data that can be observed (e.g., "port" can be "Los Angeles" or "Long Beach"), semi-structured data indicates the variable ("port") but does not pre-identify a set of possible values. Such semi-structured data exist in invoices and purchase orders, claims and error reports, customer surveys, and web logs.

3. Methodological issues in manifest content analysis

3.1. Reliability and validity of manifest content analysis

The reliability of manifest content analysis is usually quite high. As long as the analytical coding rules that are used are explicitly specified, then repeated application of the same rules to an identical input text should yield identical results. For example, if your coding rule is to denote the presence of the word "quality", then a tally of the number of times that word occurs will likely be reliable across different raters, and will be completely reliable if a computer is used. Manifest methods however can suffer from validity challenges. For example, the word "network" can signify different meanings depending on its context, e.g., social network versus computer network versus supply network.

For that reason, manifest methods are often combined with steps involving latent interpretation. In using media sources to study how stock prices are impacted by supply chain events, Hendricks and Singhal (2003) use a manifest approach (computer search engine) to identify candidate events, and then used a latent approach (reading through the news stories) to ensure that the candidate stories were valid relative to the scope of the research question, and to assess whether the article identified a single responsible source or not. In examining the supply chain management themes within corporate social responsibility reports, Tate et al. (2010) use manifest methods to identify the most important words and themes in each report, and latent assessment to check the validity of the words highlighted in each factor.

3.2. Selecting texts

The process of manifest content analysis involves selecting data sources, analyzing the data, and interpreting results. The quality of this process largely depends on the quality and quantity of data selected and how it is pre-processed prior to analysis. When selecting possible texts, only texts relevant to the research question should be included. As mentioned above, this may require a latent filtering of texts.

Text selection must consider the research questions and design at hand. For example, stories about a particular business innovation may be published at roughly the same time in different media and press outlets. If the main interest was in obtaining a history of the innovation, then one might consider only sampling a single source, if one deemed it to be relatively complete and objective. In doing so one would reduce unwanted variation in content due to different editorial systems, and would eliminate the problem of redundant information. On the other hand, if one wanted to measure the media impact that news about the innovation induced, then one would want to sample a large number of sources to see how broadly the news disseminated. Finally, if one was interested in how different types of institutions discussed and framed news about the innovation, then a stratified sample comparing (e.g.) technical and investment sources may be desirable. In general, unless the research design suggests otherwise, using multiple sources will increase sample size and improve triangulation and thus external validity.

After selecting appropriate texts the next step is to pre-process, or "clean" the texts prior to analysis. While human coders can ignore irrelevant text within a document, computers cannot. Thus before computerized processing text documents must be edited appropriately. This may involve deleting such things as headers and footers, publishing and copyright information, so-called boilerplate text (i.e., standard text that is the same in all documents) and tables and figures that may not be processed correctly. More sophisticated pre-processing can further improve the quality of outcomes. For example, treating "SCM" and "supply chain management" as the same phrase, or token, in a text can enhance validity.

As an empirical method, results from manifest content analysis are more generalizable and accurate if multiple sources are used. First, multiple text documents should be treated independently rather than as a single text. Each text can be considered a sample, so we need to have an adequate sample size in order to generate degrees of freedom for subsequent statistical analyzes. Also, when we combine texts, we lose the ability to distinguish what makes them similar or different, which is where some of the most valuable insights may come from. A common mistake I have seen is for researchers to create a single document from a download of news articles about a particular topic or company. In this case, each news article should be treated and processed as separate texts, and then analyzed collectively.

3.3. Analyzing texts

As discussed, manifest content analysis is most commonly done using computer software. Most text analysis software programs equate a word's frequency as a measure of its importance (Jurafsky and Martin, 2000), but other approaches such as network text analysis (Corman et al., 2002) or latent semantic analysis are also used (Landauer et al., 1998). The web site http://www.content-analysis.de/software/qualitative-analysis provides information on different software packages that are commonly used by content analysis researchers.

The power of manifest content analysis is not fully realized without higher-order analytics. If we let $X=(x_1, x_2, \ldots x_j)$ be a measure of the importance of words 1 through j in a text, then the

second and third order analytics F(X), and G(F(X)) based on some statistical transformations F, and G are likely to provide much more insight, and remove noise, than the raw data in X. Returning to Tate et al. (2010), Centering Resonance Analysis, a manifest network text analysis method (Corman et al., 2002) was used to identify the most important words in each report (X), and exploratory factory analysis of those data (F(X)) identified collections of words that had similar co-variance patterns. These collections of words, or themes, were labeled using human coders (latent content analysis). Because each reporting company could be identified with an industry sector (a type of structured data), they could use statistical analyzes (G(F(X))) to test whether the magnitude of each theme was different across different industry sectors. Descriptive statistics about the content of each text document only inform the researcher about what the content is. Analytics detect patterns of similarity and differences in the content amongst multiple texts, and link attributes of the document or its author (e.g., date of publication, gender or functional role of author, industry sector of author) to the content—they help inform why the content is what it is.

In summary, manifest content analysis that is non-rigorous will tend to use a single text document, or a single source without reason, or a single type of text document. Text selection and data cleaning may not be adequate leading to validity problems, and the use of descriptive statistics alone leads to trivial insights. Rigorous manifest content analysis uses multiple types of text, multiple sources for any type of text, and samples to obtain multiple units of text, ideally over time so changes can be observed. Texts have been validated as relevant and cleaned of extraneous information, and analytical statistics are employed to create deep insight.

4. Conclusion

In this essay I have discussed the need for more broad use of manifest content analysis in purchasing and supply management research, and some of the common methodological issues that need attention in such studies. One broad area where manifest content analysis methods will be significantly needed is with so-called "big data". Big data is already becoming a dominant force in supply chain operations (Simpson et al., 2015), and much of it is qualitative in nature. If business creates and uses such data for planning and decision making then researchers must be able to process and analyze it to address research questions that are relevant and timely. As academic researchers are called to make more direct impact on practice and policy (Hoffman et al., 2015), developing capabilities to analyze quantitative big data in (near) real-time may represent the next Holy Grail for empirical researchers.

The other broad area that can benefit significantly from manifest content analysis methods is behavioral operations management (Katsikopoulos and Gigerenzer, 2013). While there is significantly more activity in applying organizational behavior theories to the study of purchasing and supply management (Touboulic and Walker, 2015), there are many fewer studies that specifically examine communication itself. Communication is the lifeblood of any relation between two people or organizations, and so studying communication directly (e.g., contracts, conversations, email streams) can help us understand existing behavior better and make suggestions for improvement. For example, performing content analysis on the conversations between a buyer and supplier during a contract negotiation can help identify negotiating patterns that each side uses as well as the way they use word

choice and sentence construction to frame their rhetorical arguments (e.g., Faes et al., 2010). Manifest content analysis can also be used to validate or triangulate experiments where communication takes place. For example, in a study of how supply managers responded to framing in decision making, Kull et al. (2014) used text analysis of participant survey responses to open-ended questions in order to validate the proposed causal mechanisms being tested in the experiment.

As Karl Weick (1995) once said, "How can I know what I think until I see what I say". If we want to understand what purchasing and supply managers think and what others think about their issues, we first should examine what they and others say.

References

Altay, N., Pal, R., 2014. Information diffusion among agents: implications for humanitarian operations. Prod. Oper. Manag. 23, 1015–1027.

Barratt, M., Choi, T.Y., Li, M., 2011. Qualitative case studies in operations management: trends, research outcomes, and future research implications. J. Oper. Manag. 29 (4), 329–342.

Corman, S., Kuhn, T., McPhee, R., Dooley, K., 2002. Studying complex discursive systems: centering resonance analysis of organizational communication. Hum. Commun. Res. 28 (2), 157–206.

Faes, W., Swinnen, G., Snellinx, R., 2010. Gender influences on purchasing negotiation objectives, outcomes and communication patterns. J. Purch. Supply Manag. 16, 88–98.

Hendricks, K.B., Singhal, V.R., 2003. The effect of supply chain glitches on shareholder value. J. Oper. Manag. 21, 501–522.

Hoffman, A., Ashworth, K., Dwelle, C., Goldberg, P., Henderson, A., Merlin, L., Muzyrya, Y., Simon, N., Taylor, V., Weisheit, C., Wilson, S., 2015. Academic Engagement in Public and Political Discourse. University of Michigan Library,, Ann Arbor.

Jurafsky, D., Martin, J.H., 2000. Speech and language Processing: An Introduction to Natural Language Processing Computational Linguistics, and Speech Recognition. Prentice Hall, Upper Saddle River, NJ.

Katsikopoulos, K., Gigerenzer, G., 2013. Behavioral operations management: a blind spot and a research program. J. Supply Chain Manag. 49, 3–7.

Krippendorf, K., 2012. Content Analysis: An Introduction to its Methodology, 3rd edition. Sage, Thousand Oaks, CA.

Kull, T., Oke, A., Dooley, K., 2014. Supplier selection behavior under uncertainty: contextual and cognitive effects on risk perception and choice. Decis. Sci. 45, 467–505.

Landauer, T.K., Foltz, P.W., Laham, D., 1998. An introduction to latent semantic analysis. Discourse Process. 25, 259–284.

Olanoff, B., 2012. Twitter releases numbers related to Hurricane Sandy: More than 20M tweets sent during its peak. Tech Crunch, 11/2/2012.

Simpson, D., Meredith, J., Boyer, K., Dilts, D., Ellram, L., Leong, K., 2015. Professional, research, and publishing trends in operations and supply management. J. Supply Chain Manag. 57, 87–100.

Tate, W., Ellram, L., Kirchoff, J., 2010. Corporate social responsibility reports: a thematic analysis related to supply chain management. J. Supply Chain Manag. 46, 19–44.

Touboulic, A., Walker, H., 2015. Love me, love me not: a nuanced view on collaboration in sustainable supply chains. J. Purch. Supply Manag. 21, 178–191.

Waller, M.A., Fawcett, S.E., 2013. Data science, predictive analytics, and big data: a revolution that will transform supply chain design and management. J. Bus. Logist. 34 (2), 77–84.

Weick, K., 1995. Sensemaking in Organizations. Sage, Thousand Oaks, CA.

Yoo, E., Rand, W., Eftekhar, M., Rabinovich, R., 2016. Evaluating information diffusion speed and its determinants in social media networks during humanitarian crises. J. Oper. Manag. 45, 123–133. http://dx.doi.org/10.1016/j.jom.2016.05.007.

Dr. Kevin J. Dooley is a Distinguished Professor Of Supply Chain Management in the W.P. Carey School of Business at Arizona State University. He is also a Senior Sustainability Scientist in the Julie Ann Wrigley Global Institute of Sustainability, and Chief Scientist of The Sustainability Consortium. He is a world-known expert in sustainable supply chain management, complexity science, and research methods. He has published more than 100 research articles and co-authored an award-winning book *Organizational Change and Innovation Processes.* He is on the editorial boards of the *Journal of Supply Chain Management* and *Elementa: Science of the Anthropecene.*