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SAMPLE CASE STUDY

Using Digital Content Analysis for Online Research: Online News Media Depictions of Older Adults

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Abstract

This case study describes how I used the method of digital content analysis in a research project aimed at understanding how online news media articles depict and represent older adults in a New Zealand context. The focus in this case study is on the methodological practice of collecting and analysing data using a digital content analysis method. Furthermore, this case study discusses the main differences between traditional print-based content analysis and contemporary online digital content analysis. Specifically, through my research experiences of online news media depictions of older adults, I highlight the advantages, challenges, and implications I encountered when using this methodological approach. Finally, I provide recommendations on how to design a research project if you were to use digital content analysis in future research.

Learning Outcomes

By the end of this case, students should be able to:

- Understand the concepts of traditional content analysis and digital content analysis
- Understand the principles of collecting data for digital content analysis
- Design and conduct research using digital content analysis
- Evaluate the limitations of digital content analysis

Project Background

We know that our world's population is ageing: virtually every country in the world is experiencing growth in the number and proportion of older people in their population. Alongside climate change and the COVID-19 pandemic, population ageing is one of the most significant human developments this century (Ayalon et al., 2020; Harper, 2019). Given the growing proportion of older adults within our societies, more needs to be done to strengthen intergenerational relations between younger and older adults as we go forward (Amundsen, 2020; Li et al., 2021; Sedick & Roos, 2011). Too often, older people experience harmful negative attitudes or behaviours toward them based on their age. One example of ageist discrimination is the language used to label or describe groups of people, particularly groups of older adults (Amundsen, 2021).

This project set out to investigate how the term “the elderly” portrays older adults and to understand what stereotypes of “the elderly” are being used (reproduced or challenged) by online news media articles. Stereotypes are an important element in the study of media depictions because they are a key filter through which groups learn about each other (Ross, 2019). Furthermore, Robinson et al.’s (2007) “cultivation theory” suggests that, as stereotypes recur in media content, people tend to naturalise their messages which has the effect of cultivating perceptions. Recurrent exposure to stereotypes may cultivate how people perceive themselves and various other subgroups within society, for instance, perceiving who belongs to the dominant, mainstream “in-group” (e.g., nonelderly), and who belongs to the marginalised, minority “out-group” (e.g., the elderly).

Project Overview and Outcomes

This research involved the digital content analysis of online news media articles published in a New Zealand context over a period of 18 months before, during, and since the COVID-19 pandemic in 2019 and 2020. In all, 6,690 phrases with the term “the elderly” comprised the dataset. Two research questions drove this study:

1. What stereotypes of “the elderly” are being used (reproduced or challenged) by online news media articles in New Zealand?
2. How is language such as “the elderly” being used in online news media articles in New Zealand to shape identities and experiences of older adults?

Findings revealed that 74% of the phrases using the term “the elderly” conveyed negative stereotypes about this group of older adults, while just 14% of the data conveyed positive stereotypes and 12% carried both negative and positive stereotypes. Online news articles socially constructed being elderly as a bleak lifespan stage characterised by vulnerability, decline, disability, dependency, loneliness, and social isolation. Despite news story topics traversing significant issues for older adults such as housing, transportation, crime, finances, health, well-being, and COVID-19 effects, by contrast, “the elderly” were depicted in a marginalised, inadequate way. The proposition that older adults might be healthy, self-reliant, and capable of autonomous living was largely absent. Stories reporting the voices of older adults themselves were rare. The findings also do not ignore that stereotypes contain elements of actuality. For example, it is undeniable that health issues become more prevalent with age or that functional abilities change over time. (Although recent research of Parr-Brownlie et al., 2020, suggests that ill-health and disability in old age are more a product of life-long inequalities.)

Implications arising from this research suggest that further professional development and media training about less ageist language would be beneficial. Evidence from this study suggests that phrases referencing older adults must be carefully selected or risk homogenising and marginalising older adults in terms of their health, capabilities, dispositions, desires, and social needs. New Zealand online newspapers have more to do to meet their responsibilities of supporting a societal journey to age equality. The research concluded that the ageist term “the elderly” is a form of prejudice shaping public perceptions which tend to diminish and negatively stereotype older adults. Recommendations were made to replace the term “the elderly” with more respectful language such as advocated by the United Nations, such as “older adults”, “older person(s)”, or “older people”.

Section Summary

- The purpose of this project was to explore how news media articles depict older adults in New Zealand online newspaper articles through use of the term “the elderly”.
- The project used a digital content analysis method to analyse 6,690 online news media phrases for 18 months before, during, and since the COVID-19 pandemic in 2019 and 2020.
- Recommendations resulting from the research evidence suggested that the term “the elderly” be replaced by more respectful language in the media, such as “older adults”, “older person(s)”, or “older people”.

Content Analysis Method

Content analysis is a well-used traditional method in research projects examining print newspaper content and was appropriate for its capacity to identify patterns in communication. Typically, print-based content analysis research projects collect data from a range of sources including newspapers, magazines, advertisements (Robinson & Callister, 2008), documents, books, speeches, interviews, and even photographs and films (Krippendorff, 2018).

Content analysis can *quantitatively* focus on counting, measuring, or quantifying, (e.g., how many times does “the elderly” appear each month?) or *qualitatively* focus on understanding and interpreting meaning (e.g., what stereotypes are associated with the term “the elderly” in the context of stories about older adults and drivers licenses?). For instance, if I wanted to quantitatively research the significance of crime committed upon older adults, I could analyse news stories about older adults for the frequency of terms such as “crime”, “scams”, “abuse”, and “victim” and use statistical analysis to find similarities or differences over time, or between publication sources. Yet, if I wanted to qualitatively research the issue of crime for older adults, I could locate the word “crime” in news stories about older adults, and identify what other words or phrases appear close by, such as “victim”, “vulnerable”, “stupid”, “easy target”, “perpetrator”, or “hero”. Analysing the meanings of these relationships would provide a deeper understanding of how older people are positioned in relation to stories about crime.

Sometimes content analysis will employ yet a third *mixed method* approach by using a combination of quantitative (numerical) and qualitative (textual) data analysis (White & Marsh, 2006). No matter which of the three approaches to content analysis is adopted, steps using this method are systematically the same. First, the researcher must determine data collection criteria for what will be included and excluded for the research. Second, data must be collected. Third, the collected dataset of words, phrases, themes, or ideas found within the text must be coded and categorised. And finally, the coded and categorised data must be analysed (Krippendorff, 2018).

Content analysis can be used for numerous research goals, such as: discovering correlations and patterns in how particular concepts or ideas are communicated; identifying bias in communication; knowing the intentions of an institution, group, or individual; and illuminating differences and similarities in communication in various contexts. Content analysis has been widely used as a systematic examination of communication to study media, however, the adapted version of qualitative digital content analysis (sometimes called *computer assisted computer analysis* or CATA) is a relatively new approach that has arisen due to online environments. Since my investigation sought to understand use of "the elderly" in online news media by collecting data digitally, potential existed to go beyond a traditional, print-based approach of content analysis and make use of a digital content analysis method. However, it is also worth noting here that my study did not involve interactive media (Skalski et al., 2017) such as Facebook, Twitter, Instagram, and Snapchat. Digital content analysis would be suitable for studies concerning social media platforms as well, however, some steps may be slightly different than what I outline in this case.

Section Summary

- Content analysis can be conducted quantitatively (numerical) or qualitatively (textual) or in a mixed methods study (both numerical and textual).
- All three approaches generally follow the same five broad steps of determining data selection criteria, collecting the data, coding and categorising the data, and lastly analysing the data.
- Content analysis has historically been used in studies of print-based newspapers; however, since this research concerned online news media, I decided to use a digital content analysis method.

Content Analysis Advantages

One of the advantages of content analysis is that it can be done as soon as the researcher is ready. Ethical approval was not necessary to conduct my study (which saved time) as the information used for data collection and analysis is widely available in public arenas. Despite this, I took careful steps to minimise identifiability of any individuals named in news stories in subsequent publications of the findings.

In my study, a digital content analysis method also appeared advantageous for its capacity for large-scale data collection, low-cost, and potential to generate strongly generalisable findings given the large-scale dataset. Compelling reasons for using digital content analysis were the ability to systematically and reliably process large-scale text collections at high speed, without massive funding support.

A third major benefit of digital content analysis was the unobtrusive, noninvasive system of data collection. For instance, direct involvement of participants was not required, nor was administering a survey, nor conducting interviews. The data collection process is systematic, transparent, and easily able to be replicated by other researchers. I made sure to clearly document the details of the procedure because this aspect contributed to strong reliability of the process.

I found another value of digital content analysis was the extreme flexibility because carrying out data collection and analysis could be done at any time, in any place where I had access to appropriate computer and internet sources, and again, all at a fairly low cost.

Lastly, I also knew that, if done well, contemporary digital content analysis offered a potentially fast automated method for consolidating large amounts of data into manageable concepts by systematically coding patterns within content. I thought this would be tremendously time-saving. Unfortunately, there can be snags with automation which I discuss later in this case study.

Section Summary

- Ethical consent was not required for the digital content analysis method in this case, as the data collected is publicly available and not confidential.
- There were many advantages of this method such as ability to process large-scale text collections at high speed, low cost, and minimal funding.
- It was important to clearly document the steps of the data collection and analysis process in order to strengthen reliability and for other researchers to be able to replicate the process.

Method in Action Part 1: Data Selection Process

I collected and analysed online news stories published in New Zealand. Stories for this study were located from publicly available archives as well as the online digital database *Newztext* accessible through my university and local public libraries. Search criteria included keywords of "the elderly" or "elderly" and news items published between 01 January 2019 and 30 June 2020 in New Zealand. Initially, the goal was to analyse twelve months of publications (2019) but following the COVID-19 outbreak, data collection continued into 2020 for a further 6 months. Terms such as "older adult" or "older person" or "senior citizen" were excluded since the research aims focused specifically on use of the language "elderly".

Sources included major New Zealand media groups, Fairfax Metropolitan and Provincial Newspapers (10), Herald (10) and Other (7), including Daily Newswires. These media outlets were investigated because they comprise the main (though not quite all) online text-based news outlets in New Zealand, and represent a wide range of news publications nationally, regionally, across geographically diverse regions. Using database commands, any duplicate terms retrieved by Newztext database were removed (and manually spot-checked to ensure accuracy); remaining data were transferred into the project Excel spreadsheet ready for coding, categorising, and analysis.

I used a Microsoft Excel spreadsheet to store the information gathered from the Newztext data base. A different worksheet was used for each month (N = 18 worksheets). Each worksheet had a column listing information such as the article date, source of article, headline of article, phrase(s) containing the search term, and any other relevant information such as key story topic. Essentially, a large amount of data could be easily mined from the database and systematically placed in our project spreadsheet. Collecting the data from the Newztext database was fairly quick and straightforward once the data selection criteria were established. In all, after removing duplicates, a total of 6,690 phrases containing "the elderly" comprised the data collection set.

Section Summary

- Once the selection and search criteria were established (these were guided by the focus of the research questions), data collection was able to be done easily in a systematic and fairly quick manner.
- The Newztext database was used to locate data by using the search criteria of "the elderly" and the relevant sources and dates for the period under investigation.
- Results were manually copied from the Newztext database and pasted into the project Excel spreadsheet with one month per worksheet. Excel was used to sort the data into relevant columns (e.g., article date, newspaper source, phrase with the search term).

Method in Action Part 2: Data Coding, Categorising, and Analysis Process

Step 1: Select Data

I planned to follow five steps to conduct content analysis. So far, I had completed step one which was to select the content to be analysed. Specifically, I had decided on the medium (online newspapers), the genre (news articles), the criteria for inclusion (phrases containing the term "the elderly"), and the parameters of the date range and location (01 January 2019 to 30 June 2020, in New Zealand), as described above.

Step 2: Determine Analysis Level

Next, I needed to decide on the levels of analysis (sometimes referred to as the units of meanings) – first codes, then categories. Every phrase that used the words "the elderly" or "elderly" needed to be individually coded and also grouped into a relevant stereotype category.

Step 3: Develop Coding Rules

The third step I took was to develop a set of rules for coding, which was particularly important to ensure reliability and transparency. I developed sets of codes and categories to guide the analysis based on information found in the literature review. Recording the rules for the categories and coding helped to make the process more transparent and more easily able to be accurately repeated, and therefore enhanced the overall research reliability. For each code and category, I outlined rules for what would and would not be included to ensure consistency. For example, for the stereotype category "vulnerable" I decided specific coded data related to vulnerable would be grouped in this category (e.g., frail, weak, dependent, physically disabled, slow, etc.).

Step 4: Code and Categorise Data

The dataset was too large to manually code everything, therefore, it was when I arrived here, at step four, that I parted with a traditional, print-based manual process of coding and turned to digital content analysis using automation for coding. Increased accessibility of online news media articles has dramatically expanded the volume of digital text available for research. Traditional methods of hand-coding textual datasets become impractical in order to understand and interpret such large datasets (DiMaggio et al., 2013). This was the case for my research in which the dataset comprised 6,690 items. Content analysis, done entirely "by hand", is often time-consuming, and unreliability is a persistent problem (Krippendorff, 2018).

I was unsure of how accurate computer coding would be so I needed to establish a "human" check. Grimmer and Stewart's (2013) supervised method of digital content analysis procedure seemed the best place to start. Human coders are still needed in order to preliminarily define categories and codes. Their method involves creating a coding scheme and then manually coding a subsample of the data set being analysed, called a representative training or validation set.

For my training set, I selected a data sample using just the first two months (January and February 2019) of 660 phrases (out of the entire 6,690 phrases). It was important to categorise and code the text according to the rules established for inclusion and exclusion. This part of the process was challenging, messy, and required some of the coding and categorizing rules to be changed in relation to the data encountered. I was back and forth between the data and the list of codes and categories until at last, my final list of codes, categories, and the coding rules were all redefined, and all 660 phrases were coded and categorised. After this tedious stage, I was looking forward to having the computer digitally code and categorise the remaining data, thereby circumventing the tedium involved in manual data handling and eliminating potential problems of unreliable coding.

During that stage, I began to wonder if an unsupervised method (Grimmer & Stewart, 2013) may have been more time efficient as it can be used when categories or coding are not able to be clearly defined before the analysis begins. In contrast to the supervised method, you do not need to set up codes and categories in advance. You don't need to train the algorithm as it will learn on its own – the automation will calculate categories and codes in response to the data encountered. This could be advantageous for identifying unknown ideas or themes you have not observed on your own.

However, by using the training set, natural language processing (NLP) software could be instructed to learn how particular words correspond to each category and then automatically analyse the remainder of the data set. Even better, manually coded data from the training or validation set could then be compared to the automatic coding output to find out how well the computer replicated (or deviated from) the human coding. (This is not too different from intercoder reliability checks used to validate the consistency and reliability of human coders in traditional print-based content analysis). Complexity of language makes it challenging for automated digital content analysis to replace careful, close reading of texts (Grimmer & Stewart, 2013), therefore validation is essential when applying automated analysis.

Unfortunately, I began to encounter difficulties when it came to validating the automatically coded data with the manually coded training set. Disastrously, the computer had coded the same sample set as I had, but we had both come up with very different results according to our percentage (dis)agreement figures (0.64 and our target was above 0.90). I had to go back to my coding rules and make changes, but I could not make very many without compromising the nature of what I was seeking to investigate. Next, I asked an independent researcher familiar with big data software to run the algorithm as I did not have the necessary software or knowledge. Big data describes datasets that are too complex for traditional analysis methods and by definition implies that data are too voluminous and complicated for humans so must employ computer power for analysis (Skalski et al., 2017).

The independent researcher returned to his NLP software processor and made changes: some were clerical and relatively easy to accomplish, while others called for human intelligence that would have been difficult to specify in advance. We ran the algorithm again, but with not very much difference to the initial output. We repeated this process numerous times, until ultimately, we were just able to arrive at an acceptable match between the human and computer coded training dataset. This had proven to be very time-consuming, occurring over some months before reaching this point and I was still unsure of the validity of the dataset.

Eventually, to validate and complete the research process, I enlisted the help of two research assistants, and trained them individually to serve as independent coders. Each coder was asked to begin coding the same data sample from the months of January and February 2019; all discrepancies were discussed with me so that the coders were consistently following the coding rules. The coders continued their work and completed a “spot check” of the rest of the automated data coding until we were satisfied that the process had been reliable and valid.

Step 5: Analyse Data

Finally, after all 6,690 phrases had been automatically coded and categorised, I could analyse the results in order to understand existing patterns and draw conclusions related to the questions I set out to investigate. I used Lewis-Beck, Bryman and Liao's (2004) cross-tabular analysis to identify correlations and trends, and I was also able to infer meaning about the creators and context of the texts. The findings in my study revealed that words and phrases related to "the elderly" being vulnerable appeared more frequently than any other stereotype (41%). From the results, I could conclude that online news media articles present "the elderly" using negative stereotypes more than positive stereotypes and infer that this might have an effect on cultivating readers' (self) perceptions of the ageing process.

Section Summary

- I followed five steps in the digital content process: selecting the data, determining the analysis level, developing the coding rules, coding and categorising the data, and analysing the data.
- In step four of coding and categorising the data, I departed from traditional, manual coding typical of content analysis and sought an automated process of coding.
- I used a supervised digital content analysis method in order to create a representative training or validation data subsample set.
- I encountered difficulties matching the human coding and the automated coding and had to iteratively review the data coding stage of the process, which was very time-consuming.

Practical Lessons Learned

Like traditional print-based content analysis, digital content analysis presented me with three main drawbacks that I had to navigate during this research process concerning subjectivity, time- and labour-intensity, and being reductive. Whether traditional or digital approaches are used, clearly, an issue for content analysis methods is that some degree of subjective interpretation is part of the method, and this can have an impact on the reliability and validity of the research conclusions. Furthermore, in my case, although I set out to employ a time-saving method, in the end the time and manual labour input was not much different between conducting a traditional or automated digital content analysis. Lastly, simply focusing on one phrase, "the elderly" tended to be overly reductive, ignoring contextual and ambiguous meanings; this is a known issue of content analysis methods.

Over and above these issues, attempting an automated digital content analysis method threw up unexpected pitfalls as it required extensive (and problem-specific) validation. Ultimately, it was difficult to substitute careful human thought and close reading. I became unsure of how the software could really help. The promise of automating the more laborious, time-consuming, and clerical aspects of processing textual data proved to be illusive in practice, making the coding and categorising decisions difficult to retrace.

Krippendorff (2018) proposes that in contrast to people, computers are deterministic; they are powerless to process text reliably since they lack any sense of what they do, their users, or what the character strings they process may mean to human readers. Furthermore, they are unable to sense cultural contexts within which we interpret text. Saying that computers "read" texts or data is really a metaphor for what people do with texts. It would pay you to reflect on this as a researcher considering the digital content analysis method and not be misled into thinking that computers can read text like humans. Programming software to imitate the way people so easily comprehend, infer, and understand text is still a surprisingly challenging, downright difficult, endeavour.

Section Summary

- I encountered three main drawbacks of using digital content analysis which concerned subjectivity, time- and labour-intensity, and being reductive.
- The main snag of using an automated digital content analysis process came down to the coding criteria and ability of software to "read" the data in the same way that a human would.
- A well-structured research design using simple variables is recommended to minimise the risk of losing relevant meanings of the original text and achieving semantic validity.

Conclusion

In this case study, I aimed to include enough detail of my findings about online news media depictions of older adults to illustrate how I used the digital content analysis method. In all, the promise of digital content analysis holds possibilities for future advances, yet there are presently some major unresolved methodological concerns, as I shared with you in my research experience.

Would I recommend using this method, or on reflection, would I make a different choice in the future? Yes, I would suggest this method for readers, however, I would encourage you to note the cautions I have raised. In my case, the supposed advantages of saving time through automation were offset by the laborious task of human validation of the outputs to reach a high percentage agreement. Further, training the software to be able to accurately code and categorise text in the same way as a person is not yet a straightforward process. Researchers using digital content analysis would be wise to pay attention to reporting their validation measurements and processes (e.g., intercoder reliability or representative training sets). Like other content analysis scholars (Aaldering & Vliegenthart, 2016; Krippendorff, 2018), I advocate the importance of validation when using automated, digital content analysis methods.

If I were to conduct another study using digital content analysis, something I would more carefully consider is when to define the codes and categories. Options include doing so deductively before the data collection process begins (i.e., based on a review of literature), or back-and-forth as I ended up doing in this research project, or fully automated in an inductively unsupervised digital collection method. It would be up to you to determine which option best suits your research context.

Clearly, digital content analysis triggers a methodological shift from traditional content analysis. Traditionally, content analysis presented difficulties of achieving reliable coding for large amounts of text at a practical pace. The methodological emphasis of digital content analysis has now shifted onto how to protect relevant readings of the texts. In traditional print-based content analysis, semantically valid reading occurs instinctively as human coders do not easily violate their tacit understanding (Krippendorff, 2018). Yet, use of computers for digital content analysis may still be hampered by the difficulty of achieving semantic validity. Despite this, you can mitigate the risk of preserving relevant meanings of the original text by well-structuring your research design contexts and keeping variables simple, as I did by just using one term, "the elderly".

One final word concerns what you could learn from my experience to apply in your own research. Although ethical consent is not required to conduct digital content analysis, there are still ethical implications and challenges in collecting and analysing large-scale datasets that might not be manageable by humans. Research findings must be consistent and dependable to contribute to knowledge creation. To address this, I would recommend any digital content analysis researcher to take notice of the principles of a representative training or validate a subsample set. Embracing a hybrid approach to blend the advantages of automated capacities with human sensitivities in a complementary way seems the most salient point to keep in mind to reliably and validly use the method of digital content analysis.

Discussion Questions

1. What do you think are the key differences between traditional content analysis and digital content analysis?
2. In what situation would you design a research project using digital content analysis as a method?
3. What do you see as some of the key advantages and disadvantages of using digital content analysis?
4. What advice about things to be aware of would you give any researcher setting out to use digital content analysis?
5. What ethical considerations do you think are important about digital content analysis methods?

Multiple Choice Quiz Questions

1. The main difference between traditional content analysis and digital content analysis is:
    a. **The automated process of coding and categorising data [CORRECT]**

    b. The automated process of collecting data
    c. The automated process of analysing the results
2. The most important principle of collecting data for digital content analysis is:
    a. To decide on the medium (e.g., newspapers, speeches, websites)
    b. **To decide on the criteria for inclusion (e.g., newspaper articles that use the phrase “the elderly”) [CORRECT]**
    c. To decide on the parameters of date ranges, location, and sources (e.g., between January to June 2020, in New Zealand, Fairfax publications)
3. If you were to design a research project using digital content analysis as a method, you would be wise to follow these five steps. Which is the correct order?
    a. 1) collect data; 2) develop a set of rules for coding; 3) define units and categories for levels of analysis; 4) analyse the results; 5) code the data according to the rules
    b. 1) collect data; 2) analyse the results; 3) develop a set of rules for coding; 4) code the data according to the rules; 5) define units and categories for levels of analysis
    c. **1) collect data; 2) define units and categories for levels of analysis; 3) develop a set of rules for coding; 4) code the data according to the rules; 5) analyse the results [CORRECT]**
4. Two challenges for researchers using digital content analysis are:
    a. **Subjectivity and validation [CORRECT]**
    b. Inaccessibility and high cost
    c. Automation and small-scale datasets
5. Digital content analysis could be used for numerous research goals as listed below. Which answer is the *least* suited to a digital content analysis method?
    a. Discovering correlations and patterns in how particular concepts or ideas are communicated and identifying bias in communication
    b. **Repeatedly observing individual behaviours over time and producing generalisable knowledge about why they behave like that [CORRECT]**
    c. Knowing the intentions of an institution, group, or individual and illuminating differences and similarities in communication in various contexts

Further Reading

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Web Resources

- A breakdown of how to code qualitative data: https://getthematic.com/insights/coding-qualitative-data/
- A website reviewing digital content analysis software package options. https://www.surrey.ac.uk/computer-assisted-qualitative-data-analysis/resources/choosing-appropriate-caqdas-package

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