Content analysis

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Abstract

Because of the central role mass media and, more recently, social media play in contemporary literate societies, and particularly because of intensive interest in and often concern about the effects of media content on awareness, attitudes, and behaviour among media consumers, analysis of media content has become a widely-used research method among media and communication scholars and practitioners as well as sociologists, political scientists, and critical scholars. This chapter examines the history, uses and methods of media content analysis, including qualitative as well as quantitative approaches that draw on the techniques of textual, narrative and semiotic analysis; explains key steps such as sampling and coding; and discusses the benefits of conducting media content analysis.

1. A brief history of media content analysis

Media content analysis is a specialized sub-set of *content analysis*, a well-established research method that has been used since the mid-eighteenth century. Karin Dovring (1954–1955) reported that the Swedish state church used content analysis in 1743 to test whether a body of ninety hymns created by unsanctioned sources, titled *Songs of Zion*, were blasphemous, or whether they met the standards of the Church. In reviewing this early example of content analysis (which incidentally found no significant difference between unsanctioned and sanctioned hymns), Dovring identified several approaches used by the church, but reported that *counting* words and phrases and the context of their usage was the major focus. This approach remains central to content analysis today.

An early form of *media* content analysis appeared in a 1787 political commentary published by *The New Hampshire Spy*, which critiqued an anti-Federalist essay. The authors of the commentary noted that the terms “well-born” and “aristocracy” were used eighteen times and “liberty of the press” was used thirteen times (Krippendorff & Bock 2009: 1).

Sociologists have been interested in mass media content since the early twentieth century, starting with Max Weber, who saw media content as a means of monitoring the “cultural temperature” of society (Hansen, Cottle, Negrine & Newbold 1998: 92). James Drisko and Toni Maschi (2016: 10) trace the origin of formal academic content analysis to a speech Weber made to the first congress of German sociologists in 1910. In it, Weber advocated for the formal analysis of newspaper content, both advertising and editorial, to identify trends in social change.

Psychologists also began to use content analysis in the mid-twentieth century. Gordon Allport (1942, 2009) applied the method to reviewing case studies and analysis of personal documents to understand the feelings and attitudes of their authors. Other psychologists and psychiatrists also used content analysis to identify patterns of language in transcripts of patient interviews for how they reveal emotions, attitudes, and perceptions. The method has also been used in linguistics, history, and the arts (Mayring 2000).

2. The growth of media content analysis

Media content analysis was advanced as a systematic method to study mass media, notably by Harold Lasswell (1927), initially to study propaganda. This stream of research continued between the two World Wars and during World War II, when it was used to study Nazi propaganda as well as how Allied forces might use propaganda to motivate troops, maintain public support for the war effort, and demoralize the enemy.

During the 1920s and 1930s media content analysis was also applied to investigate the content of movies produced by the burgeoning Hollywood film industry. With the arrival of television in the 1950s, media content analysis proliferated as a research methodology in mass communication studies and social sciences. Media content analysis has been a primary research method for studying portrayals of violence, racism, and representations of women in television programming as well as in films, on the basis that this symbolic content potentially influences attitudes and behaviour. For example, Arthur Berger (1991: 25) broadly describes content analysis as "a research technique that is based on measuring the amount of something (violence, negative portrayals of women, or whatever) in a representative sampling of some mass-mediated popular form of art."

Kimberley Neuendorf describes content analysis as "the primary message-centred methodology" and cites studies showing that "in the field of mass communication research, content analysis has been the fastest-growing technique over the past 20 years or so" (2002: 1–2).

3. Defining content analysis: Contested approaches

Despite its growing popularity as a media research method, content analysis has been the subject of two "controversies" debated over many decades (Berg 2007). The first is whether content analysis is a quantitative or qualitative method, or both.

3.1. Quantitative or qualitative?

Throughout most of its history, content analysis has been defined and executed as a quantitative research method, and content analysis often still uses to this methodological approach. However, an increasing number of researchers are advocating content analysis as a qualitative method, giving rise to mixed method approaches. This "paradigm battle" that has raged within the larger theatre of research "paradigm wars" (Bryman 2008) is evident in definitions and descriptions of content analysis.

One of the earliest formal descriptions of content analysis was provided by Harold Lasswell, Daniel Lerner, and Ithiel de Sola Pool (1952: 34), who said:

> Content analysis operates on the view that verbal behaviour is a form of human behaviour, that the flow of symbols is a part of the flow of events, and that the communication process is an aspect of the historical process … content analysis is a technique which aims at describing, with optimum objectivity, precision, and generality, what is said on a given subject in a given place at a given time.

In the same year, Bernard Berelson defined content analysis in terms that even more explicitly position it as a quantitative method, calling it a "research technique for the objective, systematic and quantitative description of the manifest content of communication" (1952: 18). Similar definitions have been provided by Philip Stone, Dexter Dunphy, Marshall Smith, and Daniel Ogilvie (1966: 5) who, acknowledging the work of Ole Holsti (1969), say that "content analysis is any research technique for making inferences by systematically and objectively identifying specified characteristics within text." Use of the terms "objective" and "objectivity" in these definitions reveal a positivist and structuralist approach that postmodern poststructuralist researchers challenge, as discussed later in this chapter.

More recently, Kimberley Neuendorf says "content analysis is a summarizing, quantitative analysis of messages that relies on the scientific method" (2002: 10). Neuendorf goes on to note that content analysis should include "attention to objectivity-intersubjectivity, *a priori* design, reliability, validity, generalizability, replicability, and hypothesis testing" (10). While also emphatically describing content analysis as a quantitative research method with a capacity to produce generalizable findings, Neuendorf does give recognition to the postmodern notion of *intersubjectivity* (shared interpretation), rather than objectivity, which many researchers now believe is unattainable by humans. However, Neuendorf argues that qualitative analysis of texts is more appropriately described and categorized as rhetorical analysis, narrative analysis, discourse analysis, semiotic analysis, interpretative analysis, or critical analysis (2002: 5–7).

While some continue to insist that content analysis is a quantitative method and refer to qualitative approaches to analyzing texts as textual analysis (e.g., McKee 2003), many other researchers, such as David Altheide (1996), Ellen Hijams (1996), Klaus Krippendorff (2004), and Pamela Shoemaker and Stephen Reese (1996) see it as a mixed quantitative and qualitative method. Shoemaker and Reese argue that there are two traditions of content analysis—the *behaviourist* tradition and the *humanist* tradition. The behaviourist approach to content analysis, pursued by social scientists, is primarily concerned with the effects that content produces. Whereas the behaviourist approach looks forwards from media content to try to identify or predict future effects, the humanist approach looks backwards from media content to try to identify what it says about society and the culture producing it. Humanist media scholars draw on psychoanalysis and cultural anthropology to analyze how media content such as film and television dramas reveal "truths" about a society—what Shoemaker and Reese term "the media's symbolic environment" (1996: 31–32).

These two perspectives inform the age-old debate over whether media *create* public opinion, attitudes, and perceptions (effects) or *reflect* existing attitudes, perceptions, and culture. Most researchers today agree that, with limitations, media content do both.

Shoemaker and Reese claim that social scientists taking a behaviourist approach to content analysis rely mostly on quantitative content analysis, while humanist approaches to media content tend towards qualitative analysis. They say: "Behavioural content analysis is not always or necessarily conducted using quantitative or numerical techniques, but the two tend to go together. Similarly, humanistic content study naturally gravitates towards qualitative analysis" (1996: 32).

Importantly, in terms of methodology, Shoemaker and Reese (1996) go on to note that "reducing large amounts of text to quantitative data … does not provide a complete picture of meaning and contextual codes, since texts may contain many other forms of emphasis besides sheer repetition" (32). Similarly, in discussing media content analysis in *The Media Book*, Chris Newbold, Oliver Boyd-Barrett, and Hilde Van Den Bulck say that quantitative content analysis "has not been able to capture the context within which a media text becomes meaningful" and advocate attention to qualitative approaches as well (2002: 84).

In his widely-used text on social research methodology, W. Lawrence Neuman comments on the quantitative-qualitative dichotomy in content analysis: "In quantitative content analysis, a researcher uses objective and systematic counting and recording procedures to produce a quantitative description of the symbolic content in a text" (2006: 323). But he adds that "there are qualitative or interpretative versions of content analysis." Noted media researcher Charles Wright said content analysis "may involve quantitative or qualitative analysis, or both" (1986: 125). Berg (2007) advocates what he calls a "blended" approach, and Hansen et al. (1998: 91) similarly argue for a mixed method approach in content analysis, saying:

> … rather than emphasizing its alleged incompatibility with other more qualitative approaches (such as semiotics, structuralist analysis, discourse analysis) we wish to stress … that content analysis is and should be enriched by the theoretical framework offered by other more qualitative approaches, while bringing to these a methodological rigour, prescriptions for use, and systematicity rarely found in many of the more qualitative approaches.

Several other media researchers, including James Curran (2002) and David Gauntlett (2002), also refer to quantitative and qualitative content analysis and view the approaches as complementary in determining the likely meanings for and impact of media content on audiences.

3.1.1. Units of analysis

In both quantitative and qualitative content analysis, the units of analysis are typically selected words or phrases used in a particular context, referred to as key words in context (KWIC). These can be part of everyday language or specialized signifiers, such as brand names, place names, or the names of people, depending on the purpose of the analysis and the hypotheses or research questions being investigated. Images such as photographs, cartoons, or frames in films and video can also be studied using content analysis.

The units of analysis (i.e., words, phrases, and images) are assigned to *categories* in the process of content analysis. For example, a researcher might categorize words such as "attack," "assault," "hit," "threatened," and so on into a category called "violence." Researchers studying an organization's reputation will need to establish categories such as "quality," "trustworthiness," "environmental performance," and so on and then count words, phrases, or visual images such as photographs that relate to those concepts. Categorization commonly includes identification of both positive and negative representations of the various concepts and factors studied.

Besides using subject-orientated categories to study topics and messages, media content analysis coding systems also frequently establish categories for coding other variables that determine the salience and likely impact of the content. Typical variables identified and recorded in media content analysis include:

- *Positioning*, such as whether items appear on a front page or as a lead item in broadcast media, among lead items, or towards the back of a publication or end of a broadcast program. Special weightings can also be applied for lead items in particular sections, such as finance or sport;
- *Prominence of mention* of the units of analysis in the item—e.g., headline mentions, first paragraph mentions, prominent mentions, or what are termed "passing mentions";
- *Size or length* of media items;
- *Media weighting* to place more emphasis on high circulation, high rating, or highly influential media vis-a-vis those with small audiences or non-target audiences.

3.1.2. Coding

The most common method of assigning units of analysis to categories is *coding*. Three methods of coding have been used in content analysis as technologies have changed. In early, pre-computer age analysis, coding involved physically marking content with a category number or descriptor, such as alongside a television transcript or press clipping. With the ready availability of computers, coding is increasingly done by recording counts of key words in various contexts in a computer application (see Section 7 of this chapter, "Computer programs for content analysis"). This method can be undertaken using generic computer applications, such as databases or spreadsheets, or with the aid of an increasing range of applications designed for content analysis. The third method of coding that is gaining in popularity, but remains controversial, involves the use of automated coding based on natural language processing (NLP) and machine learning. Examples of applications for both human and automated coding and some of the key considerations in relation to each are discussed in this chapter under Section 7.2., "Human vs. computer coding."

Coding is typically guided by *coding guidelines*, referred to as a *Code Book* in pre-computerized approaches, as the instructions were written in a researcher's notebook. Coding guidelines are comprised of notes and instructions to minimize the effects of human subjectivity among coders doing content analysis. While categorizing explicit mentions of key words is straightforward, the presence of synonyms, similes, metaphors, metonyms[1], synecdoche[2], and language usage such as nuance, sarcasm, and double-entendre require interpretation, which can vary among coders. Cultural factors can also influence interpretation, which may need to be noted. For example, in China the Volkswagen New

Beetle was described in media as a "pretty lemon" (CARMA 2000), which was a positive term locally because of the Chinese association of oranges, mandarins, and lemons with health and fertility. In many Western countries, lemon is used as a colloquial term for a very poor quality car.

Coding guidelines are particularly important when more than one coder is involved, which is a recommended step for operationalizing quantitative content analysis (Neuendorf 2002). Coding guidelines are even more important for qualitative content analysis to achieve *credibility*, *dependability*, and some level of *transferability*, which contribute to the overall *trustworthiness* of qualitative research[3], as noted by Lincoln and Guba (1985), Shenton (2004), and others. Coding guidelines also help maintain quality when content analysis considers latent as well as manifest content, as discussed in the following section.

3.2. Manifest and latent content

Berelson's (1952) definition of content analysis draws attention to the second major historical debate, or "controversy," in relation to this method: whether it focuses only on *manifest* content (what is visible in texts), or whether it takes into consideration *latent* messages and potential meanings as well (what is implied in texts). This has a bearing on whether content analysis is conducted quantitatively or qualitatively and informs how coding is conducted.

Manifest content is obvious—it consists of the words, phrases, and images such as photographs that appear in content. As noted previously, analysis of manifest content primarily relies on counting to identify how many times certain words, phrases, and images appear. In semiotic terms, analysis of manifest content is based on *denotation*—what is explicitly signified.

Neuendorf describes the latent meanings of content as "consisting of unobserved concepts that cannot be measured directly" (2002: 23). Berg (2007: 242) refers to analysis of latent content as "an interpretive reading of the symbolism underlying the physical data," which others refer to as *semantic analysis* (Neuman 2006: 326). For example, description of a government social or health policy only in term of its economic effects can be interpreted as revealing neoliberal values and ideology through what is unsaid (e.g., reference to quality of life and human well-being) as opposed to what is said. Latent analysis can also reveal conceptual frameworks that underpin what is written or said, such as deregulation, privatization, colonization, or technological determinism. Thus, coding of latent content seeks to understand *connotation* in semiotic terms.

Drawing on Berelson, Kim Schøder says that "the quantitative analyst, then, can hope to avoid 'interpreting' his data only if he concerns himself entirely with 'manifest' or denotative, meanings and excludes connotative meanings" (2012: 113). While agreeing that content analysis should be replicable and systematic, Krippendorff (2004) sees no reason why content analysis must be quantitative only. Schrøder notes that Krippendorff "dismisses the exclusion of latent meanings from the researcher's legitimate horizon of interest" (2012: 113).

Analysis of latent messages and potential meanings in content requires a qualitative approach, as it involves interpretation rather than simply counting. Thus, researchers who advocate analyzing latent as well as manifest content to understand the meanings of texts integrate qualitative and quantitative analysis. Media researchers Newbold, Boyd-Barrett, and Van Den Bulck (2002) note: "The problem [with quantitative content analysis] is the extent to which the quantitative indicators are interpreted as intensity of meaning, social impact and the like. There is no simple relationship between media texts and their impact, and it would be too simplistic to base decisions in this regard on mere figures obtained from a statistical content analysis" (80). However, interpretation of connotative meaning requires careful procedures because of the human interpretation involved and the potential for misinterpretation.

4. Types of content analysis and its uses

Berelson (1952) suggested that there are five main purposes of content analysis:

1. To describe substance characteristics of message content;
2. To describe form characteristics of message content;
3. To make inferences to producers of content;
4. To make inferences to audiences of content;
5. To predict the effects of content on audiences.

Drawing on the work of Berelson and noting the use of content analysis in disciplines such as psychology and psychoanalysis, Neuendorf (2002: 53) summarized the four main approaches to, and roles of, content analysis as *psychometric*, *descriptive*, *inferential*, and *predictive*.

While psychometric refers to specialized medical and psychoanalytic uses of content analysis for interpreting the text of patient interviews or statements, the three other approaches are highly relevant to a range of applications, including media content analysis. The first and most basic role, descriptive, provides insights into the messages and images in discourse and popular culture represented in mass media. The inferential and predictive roles of content analysis allow researchers to go further and explore likely effects on awareness, attitudes, or behaviour among consumers of the content. However, researchers need to remain cognisant always that texts are *polysemic*—that is, open to multiple interpretations by audiences. This is further discussed in this chapter under Section 9, “Limitations of content analysis.”

5. Quantitative content analysis

While the preceding discussion shows that contemporary scholarship and research practice apply content analysis in both quantitative and qualitative ways, quantitative approaches are the most common. As Neuendorf (2002) notes, quantitative media content analysis should be conducted in accordance with the *scientific method*. This requires careful attention to research design and key steps in the analysis.

5.1. Sampling

Content analysis can be undertaken on a *census*—i.e., on all units in the sampling frame. This affords the greatest possible representation of the “message pool.” However, a census may not be possible in some cases, particularly in media content analysis where very large content volumes may be collected over a quarter or even a whole year. Therefore, for both time and cost reasons, researchers often need to conduct sampling.

Sampling for quantitative content analysis follows the procedures of quantitative research in most respects to achieve reliability and generalizability—hallmarks of the “scientific method.” Systematic *random*, *quota*, or *stratified* sampling are widely used. Several studies recommend that one of the most reliable methods of probability sampling for analysis of weekday media content, such as newspapers articles and TV news, is a stratified composite sample collected by selecting a sub-sample from certain days or weeks over a period of time (Riffe, Lacy & Fico 2005; Riffe, Lacy & Drager 1996; Riffe, Lacy, Nagovan & Burkum 1996). However, sometimes a *purposive* method focussed on the most relevant media is appropriate.

Media content for analysis is typically collected from specialist media monitoring service providers or organizations such as Lexis-Nexis or Factiva.

5.2. *A priori* design

The scientific approach to research requires *a priori* research design. In the case of content analysis, this means that "all decisions on variables, their measurement, and coding rules must be made before the observation begins" (Neuendorf, 2002: 11). This sounds counterintuitive and confuses many would-be content analysts, who ask "how can you know what the categories are until you have started doing the analysis?" Sometimes analysts succumb to the temptation to add one or more categories during quantitative content analysis as they discover new and unforeseen topics or messages in the content. Given that quantitative content analysis relies principally on counts of key words and phrases denoting or connoting topics or messages, this is problematic because items coded before the category was added may have contained the same or similar key words or phrases. Thus, the counts become unreliable if categories are added during analysis.

Research design requires a clear understanding of the two approaches to data analysis and how these are operationalized.

5.2.1. Deduction and induction

A key principle of the scientific method applied in quantitative research is deduction. A deductive approach starts by identifying hypotheses to prove or questions to answer and, in the case of content analysis, categories into which data will be coded. In short, it begins outside the data and then processes data using logical reasoning and statistical calculations to ensure reliability, moving from the general to the specific. In quantitative content analysis, *a priori* identification of categories is informed by theory and previous studies in the field.

Inductive analysis starts inside the data and proceeds from specifics to the general by identifying key concepts, themes, and elements that exist in the data set and then grouping these into categories to identify patterns and explore how extensively they exist.

In colloquial terms, deductive reasoning is described as a "top down" approach systematically distilling data using pre-determined criteria, while inductive reasoning is a "bottom up" approach openly exploring what is in the data.

As Kuhn (1970) noted in his discussion of paradigms, the requirement for deduction to be based on theories and past research and bodies of evidence is limiting and can stifle innovation and new discoveries. So how is this potential omission of topics or messages overcome in quantitative content analysis?

This apparent dichotomy can be overcome in a number of ways. Neuendorf (2002) says: "Much as a survey researcher will use focus groups or in-depth interviewing (qualitative techniques) to inform his or her questionnaire construction, so may the content analyst use in-depth, often contemplative and incisive observations from the literature of critical scholars." Furthermore, and importantly at a practical level, Neuendorf (2002: 102–103) suggests that a media content analyst can "immerse himself or herself in the world of the message pool" by conducting "a qualitative scrutiny of a representative subset of the content to be examined." In other words, a preliminary reading of a sample of the content to be analysed can familiarize the researcher with the content. This, along with the hypotheses to be tested or research questions to be explored, can inform *a priori* design of the coding system.

5.3. Multiple coders

Even when content analysis is conducted using *a priori* design, deductive analysis, and coding based on detailed coding guidelines, scholars recommend the use of multiple coders as a further step to minimize the influence of subjectivity in coding. The use of multiple coders draws on the poststructuralist notion of *intersubjectivity*—that is, the argument that humans cannot be 100 per cent objective, but do arrive at shared subjectivities (i.e., agreement or consensus). The use of multiple coders ensures that, in the words of Howard Tinsley and David Weiss, "obtained ratings are not the idiosyncratic results of one rater's subjective judgement" (1975: 359). The use of multiple coders allows assessment of the *reliability* of the analysis (see Section 5.4 in this chapter). The use of multiple coders also has a practical benefit in media content analysis as it speeds up the analysis of large volumes of content.

5.4. Intercoder reliability assessment

When multiple coders are used, it is important to conduct intercoder reliability assessment of a sample of items that have been double "blind coded."[4] This ensures that the obtained ratings are not the idiosyncratic results of two or more raters' subjective judgements. Neuendorf (2002: 142) says: "There is growing acknowledgement in the research literature that the establishment of intercoder reliability is essential, a necessary criterion for valid and useful research when human coding is employed." According to scholars specializing in the field, "the reliability sub-sample should probably never be smaller than 50 and should rarely need to be larger than about 300" (Neuendorf 2002: 159).

Several statistical formulae have been developed for measuring intercoder reliability. Researchers propose that coding by multiple coders should be compared at two levels: (a) agreement and (b) covariation. Neuendorf observes that "the best situation, of course, would be one in which coded scores are shown to have both high agreement and high covariation" (2002: 144). However, because even the slightest variation in coding constitutes non-agreement, agreement between coders is often difficult to achieve. Covariation assesses whether, when scores do vary, as they no doubt will in human coding, they go up and down together—i.e. whether there is consistency or a high level of variance.

In a comprehensive online content analysis resources site, Matthew Lombard, Jennifer Snyder-Duch, and Cheryl Campanella Bracken (2010) note that there are "literally dozens" of different measures or indices of intercoder reliability. Lombard, Snyder-Duch, and Bracken (2010), Neuendorf (2002), and a number of other researchers agree that the following, which calculate covariation on a 0–10 scale, are the most reliable and important:

- Scott's *pi* (π);
- Cohen's *kappa* (κ);
- Spearman's *rho*;
- Pearson's correlation coefficient (r);
- Krippendorf's *apha*; and
- Lin's concordance correlation coefficient (r_c).

A recent study of three decades of reporting content analysis in three leading academic journals (n = 672) found that use of intercoder reliability assessment has increased, with Scott's *pi* and Krippendorf's *apha* the most frequently used (Lovejoy, Watson, Lacy & Riffe 2016). However, intercoder reliability assessment is not widely undertaken in professional practice despite content analysis being one of the most used research methods for evaluation of media and communication campaigns (USC Annenberg and The Holmes Report 2016).

Several software programs are available to calculate intercoder reliability assessment, including statistics programs such as SPSS, which can assess Cohen's *kappa* (κ), and Simstat from Provalis Research, which can calculate intercoder reliability statistics. Specialist software programs have also been and continue to be developed for this purpose, including Popping's (1984) AGREE; Krippendorf's Alpha 3.12a; ReCal; and PRAM (Program for Reliability Assessment of Multiple Coders), which remains in Beta but is available free of charge from Kimberley Neuendorf at Cleveland State University (Lombard, Snyder-Duch & Bracken 2010).

Neuendorf (2002) notes that most basic textbooks on research methods in the social sciences do not offer a specific criterion or cut-off figure and those that do report a criterion vary somewhat in their recommendations. However, as a widely accepted rule of thumb she cites Lee Ellis, who says that correlation coefficients exceeding 0.75 to 0.80 indicate high reliability (1994: 91). Roel Popping (1988) suggests 0.80 or greater is required for Cohen's *kappa*, which he cites as the optimal measure, while Mousumi Banerjee et al. (1999) propose that a 0.75 score for Cohen's *kappa* indicates excellent agreement beyond chance. A review of intercoder reliability assessment by Neuenforf and several articles and online publications by Matthew Lombard, Jennifer Snyder-Duch, and Cheryl Campanella Bracken (2002, 2003, 2010) conclude that reliability coefficients of 0.80 or greater are acceptable to all and 0.75 is acceptable in most situations.

Strategies to maximize covariance among coders and address high variance if it occurs include comprehensive coding guidelines; pre-coding training to familiarize coders with variables such as issues and messages for analysis; pilot coding (doing a test or series of tests first); and review of the coding guidelines and retraining if necessary.

5.5. Quantitative data analysis

In addition to testing the reliability of coding, data analysis in quantitative content analysis employs statistical methods involving counts and calculation of percentages and means (averages), as well as modes and medians in some cases. Other quantitative data analysis techniques can include assessment of the statistical *significance* of findings using *t-tests* as well as calculation of *standard deviation* (SD).

Analysis is aided by data reduction and data display, as recommended by Miles and Huberman (1994: 11), who say "you know what you display." In quantitative content analysis, this typically includes production of line, bar, and pie charts, as well as histograms, scatter charts, and Venn diagrams. These can be produced in statistics programs such as Statistical Package for the Social Sciences (SPSS), or by exporting data into software applications such as Microsoft Excel for further manipulation. For example, A–Z sorting in an Excel spreadsheet allows data to be quickly ranked and re-ranked by various criteria arranged in multiple columns. In this way, data can be interrogated and reduced to key findings.

5.6 Latent dirichlet allocation

Before examining qualitative content analysis, it is important to note a second, more recent approach to quantitative content analysis that uses natural language processing (NLP) to produce *topic models* based on *latent dirichlet allocation* (LDA). David Blei, Andrew Ng, and Michael Jordan (2003: 993), who developed LDA[5] in the early twenty-first century, describe the process as:

> A generative probabilistic [i.e., statistical] model for collections of discrete data such as text corpora. LDA is a three-level hierarchical Bayesian model, in which each item of a collection is modelled as a finite mixture over an underlying set of topics.

LDA allows the identification of major topics and their content in terms of the number of words related to each and estimation of the prevalence of those topics within documents and across multiple documents. Findings may then be presented as graphical models. Ken Benoit, who is a leading authority on quantitative content and textual analysis, uses LDA in an R-based application he co-produced called Quanteda (quantitative analysis of textual data) (Benoit et al. 2016). Quanteda uses quantitative statistical methods, but Benoit says that unstructured text (qualitative data) can be effectively and usefully turned into quantitative (i.e., statistical) findings, and reported accordingly. However, LDA is not widely used for media analysis.

6. Qualitative content analysis

Qualitative content analysis has adopted many of the techniques of textual analysis and in some forms is indistinguishable from this method of analyzing texts. As noted by Neuendorf (2002: 5–7), it also borrows techniques from rhetorical analysis, narrative analysis, discourse analysis, semiotic analysis, and interpretative analysis. Therefore, the procedures to apply in this type of analysis are informed by methodological literature in these neighbouring fields of interpretive research (e.g., Denzin & Lincoln 2008; Hijams 1996; Patton 2002; Silverman 2000), as well as in specific guides that support qualitative content analysis (e.g., Krippendorff 2004; Mayring 2000, 2014).

6.1. Sample

Because qualitative research seeks in-depth insights and understanding of particular cases, characteristics, categories, or groups of people rather than statistical data such as means, medians, and modes, it does not require the use of probability sampling as applied in quantitative research. As Matthew Miles and Michael Huberman (1994: 29) point out, sampling strategies for qualitative research are informed by a conceptual question, not by concern for "representativeness." For example, a study designed to gain insights into how stay-at-home dads are perceived by working fathers in the UK will justifiably select its sample from employed men with children in the UK. Similarly, a media content analysis undertaken to help evaluate an organization's reputation might focus on media reporting read by its key stakeholders in its key markets, rather than all media or even a representative sample of media. Qualitative research is often undertaken to gain in-depth insights into particular cases, types, or groups, which necessitates a targeted sampling approach. As Bryman (1988) and others note, well-selected defined cases produce findings that have broad generalizability to particular *contexts*, or what is more appropriately referred to as *transferability* in qualitative research (Lincoln & Guba 1985; Shenton 2004).

Therefore, the most widely used method of sampling for qualitative research is *purposive* sampling (Riffe, Lacy & Fico, 2005: 99). Other methods of sampling for qualitative research include *typical case* sampling, *extreme* or *deviant case* sampling (also known as outlier sampling), *maximum variation* sampling, *revelatory case* sampling, and *critical case* sampling (Glaser & Strauss 1967; Patton 2002; Teddlie & Yu 2007). These methods illustrate the specific focus of qualitative research, compared with the broad generalizable approach of quantitative research.

The non-probability sampling methods used in qualitative research, along with the relatively small sample sizes used in this approach, are sometimes seen as introducing subjectivity and bias, which in turn raises questions about the credibility, dependability, transferability, and trustworthiness of the findings. Lincoln and Guba (1985), Shenton (2004) and others list these as requirements for qualitative research. However, non-probability sampling does not mean that there are no rules or guidelines. Purposive sampling and other targeted methods such as extreme, deviant, or revelatory case sampling must be based on a rationale that justifies why and how such cases are selected.

In situations in which qualitative analysis is used to broadly understand a field, Miles and Huberman (1994: 34) recommend a three-tiered sampling approach involving (1) selecting apparently typical/representative examples; (2) selecting negative/disconfirming examples; and (3) selecting exceptional or discrepant examples. By choosing a combination of typical, disconfirming, and exceptional examples for study, qualitative analysis can explore the boundaries of the data field and identify the range of views or statements, including discordant and extreme ones. Qualitative analysis often intentionally seeks to identify and understand the perimeters of a field, including 'outliers', whereas quantitative analysis is *reductionist* (i.e., it reduces data to means [averages], medians, and modes).

6.2. Inductive analysis

Qualitative content analysis primarily uses inductive analysis, although mixed method approaches may use both deductive and inductive approaches. As noted previously, inductive analysis starts by examining the data to identify the topics, issues, and messages that most frequently occur, and then moves back and forth from identifying specifics in texts to making inferences about what those elements might reveal about the speakers, authors, or audience effects. Thus, inductive qualitative content analysis draws on grounded theory approaches (Glaser & Strauss 1967; Strauss & Corbin 1990).

Like quantitative data analysis, inductive qualitative analysis is aided by data reduction and data display techniques, although these are less statistical than quantitative data analysis. For example, qualitative content analysis findings can be illustrated using 'word clouds' that identify and highlight key themes and patterns. In addition to Miles and Huberman's perennial advice that "you know what you display" (1994:11), Keith Punch says "… good qualitative analysis involves repeated and iterative displays of data" (1998: 204).

Within the hermeneutic tradition (i.e., interpretation), textual analysis and qualitative content analysis employ two main approaches. The first is *narratology*, which focuses on the narrative or story-telling within a text to interpret what meanings are likely to be produced by its structure and choice of words. The second draws on *semiotics* and focuses attention on signs and sign systems in texts and how readers might interpret (decode) those signs (Newbold, Boyd-Barrett & Van Den Bulck 2002: 84). Specific textual elements closely examined in qualitative content analysis include:

- Adjectives used in descriptions which give strong indications of a speaker's and writer's attitude (e.g., "poor" performance; "angry" shareholders; "satisfied" customers; etc.);
- Tonal qualities such as aggressiveness, sarcasm, flippancy, and emotional language;
- Figures of speech such as metaphors and similes;
- The presence of nuance, sarcasm, double-entendre, and other particular uses of language;
- Visual imagery in text; and
- Context factors such as the credibility of spokespersons or sources quoted and power differentials (e.g., experts vs. "lay" person).

Most commercial content analysis methods and systems categorize content as *positive*, *negative*, or *neutral* based on the above factors. Some go further and calculate a score for *tone* or *sentiment* on a 0–10 scale or sometimes even on a 0–100 scale based on multivariate analysis such as the CARMA "favourability rating" (RMP Media Analysis 2014).

While such ratings are useful for indicating the overall qualitative characteristics of content, use of the term 'sentiment' in relation to content is problematic. Sentiment refers to human feelings (i.e., emotions) or a view or opinion that is held or expressed. While content analysis can make inferences about such matters, characteristics of content are not measures of sentiment. Tone is related to voice and speaking and is the more appropriate term to describe content such as media reporting and comments.

7. Computer programs for content analysis

Computers are used extensively in both quantitative and qualitative media content analysis and facilitate research procedures in several ways. In the first instance, with the increasing digitalization of content, computer applications are used for searching and retrieving content. Methods for accessing media content range from direct online media subscriptions and simple Google searches to use of specialist service providers such as Factiva and Lexis-Nexis.

Coding is now mostly recorded in computer applications, even when humans make the coding decisions. One of the first software applications for conducting content analysis was General Inquirer, developed by Philip Stone at Harvard University in 1961 (http://www.wjh.harvard.edu/~inquirer). Today there is a wide range of computer applications for conducting quantitative and qualitative content analysis. One of the most widely used such programs for academic content analysis is NVivo, part of the NUD*IST **(**non-numerical unstructured data indexing, searching, and theorizing) range of data analysis tools produced by QSR (http://www.qsrinternational.com). Other well-known applications for computer-assisted analysis of qualitative data (CAQDAS), also referred to as QDAS (qualitative data analysis software), include MaxQDA (http://www.maxqda.com); ATLAS.ti (http://atlasti.com); Worstat from Provalis Research (https://provalisresearch.com); Textpack; Textstat; Leximancer (http://info.leximancer.com); and the more recently launched QCAMap (https://www.qcamap.org).

There is also a range of more general text analysis applications that can be used for media content analysis. These include proprietary applications such as IBM Text Analytics, SAP Text Analytics, and SAS Text Analytics packages, as well as open source Web-based applications such as R, described as a text mining and sentiment analysis package (https://www.r-project.org).

In the commercial sector, service providers that offer quantitative and qualitative media content analysis include CARMA, which takes its name from "computer aided research and media analysis" (https://www.carma.com); Gorkana in the UK (http://www.gorkana.com), which is part of the US-based Cision Group; Kantar Media, which operates in the UK, USA, and throughout Europe (http://www.kantarmedia.com); and Isentia, which operates across Asia Pacific (http://www.isentia.com).

7.1. Automated coding and analysis

Recently, several application developers and service providers have adopted machine learning based on natural language processing (NLP) to automate coding and analysis of media and other forms of content. Some fully automate coding and analysis, while others incorporate *active machine learning* to partially automate processes. An example of this is Method52, developed by the University of Sussex in collaboration with DEMOS. "Active" machine learning involves the use of algorithms that can be run to retrieve and categorize unstructured textual content, but which allows the researcher to correct the algorithm to fine-tune its interpretation of the content. Active learning is usually accomplished through a series of tests on sub-samples of the content to be analyzed, in which the researcher examines the categorizations made automatically by the algorithm and makes adjustments—what the developers refer to as "marking the homework". In active learning systems, the researcher remains in charge of the analysis, unlike fully automated systems.

7.2. Human vs. computer coding

While computers are highly efficient and effective for retrieving content, and recent developments in NLP and active machine learning indicate that they can automate some aspects of coding and analysis, most researchers reject the concept of fully-automated content analysis. Even in the case of quantitative content analysis, Neuendorf says that "the notion of the completely 'automatic' content analysis via computer is a chimera … The human contribution to content analysis is still paramount" (2002: 40). Here she is referring to the ability of humans to understand nuance, figures of speech that should not be read literally, sarcasm, and other characteristics of language that, despite development in neurolinguistic programming and artificial intelligence, remain beyond the capabilities of computer software.

In addition, Neuendorf points to the problem of "black box measurement." Most automated software programs and service providers using such systems do not reveal the details of their measures or how they construct their scales and indexes. The researcher enters text into “a veritable black box from which output emerges” (Neuendorf 2002: 129). This is inconsistent with the scientific method of research that requires replicability as well as transparency and disclosure of how results are obtained.

In the case of qualitative content analysis, fully automated coding and analysis is even more problematic. For example, despite the ability of algorithms to “learn,” Neuman gives the following example of the word “red” and how it can be used with multiple nuances that are not likely to be visible to a computer:

> I read a book with a red cover that is real red herring. Unfortunately, its publisher drowned in red ink because the editor couldn’t deal with the red tape that occurs when a book is red hot. The book has a story about a red fire truck that stops at red lights only after the leaves turn red. There is also a group of Reds who carry red flags to the little red schoolhouse. They are opposed by red-blooded rednecks who eat red meat and honour the red, white and blue. (2006: 325–326)

Furthermore, and perhaps most important of all, computers cannot consider the *context* of content—that is, what is outside the text and relevant to its interpretation. They only view the text, which can result in narrow and incomplete interpretations of its likely meaning and effect.

8. Benefits of content analysis

One of the major benefits of media content analysis is that it is a non-intrusive research method (Neuman 2006). By analysing the content of media reporting and social media comments, researchers can identify topics and issues that are the subject of debate and/or public concern, and explore discourses by tracking the frequency and dominance of certain ideas and messages, without direct human contact. Furthermore, content analysis can inform inferences about the policies, views, and intentions of various sources, as well as potential audience effects, without directly contacting those sources. This can be important when sources are difficult to reach or unwilling to participate in research. Today, many surveys receive low response rates because the targeted groups are “over-researched” and suffering “survey fatigue.” In some cases, such as an organization wanting to understand the views or activities of its competitors, direct research methods are impractical, and non-intrusive methods such as media content analysis may be the only option.

Another benefit of content analysis is that it can be conducted frequently to longitudinally track issues, topics, and spokespersons, whereas audience research, such as large-scale surveys, are usually restricted to annually or even every few years because of their cost.

9. Limitations of content analysis

While noting its benefits, users of content analysis need to heed Neuendorf’s warning that inferences cannot be made as to producers’ intent or audiences’ interpretation from content analysis alone. Neuendorf (2002) argues that an integrated approach is required involving the use of content analysis with other research, such as audience studies. Similarly, Newbold, Boyd-Barrett, and Van Den Bulck (2002: 16) point out that the meanings of texts for audiences cannot be accessed through analysis of the texts.

In discussing media research broadly, Arthur Berger (2014) identifies four main analysis techniques: semiotic analysis, Marxist analysis, psychoanalytic analysis, and sociological analysis. While the first focuses on texts and the second involves a critical approach, both psychoanalytic and sociological analysis involve audience research, which remains important in media and communication scholarship and practice.

10. Conclusions

Media content analysis draws on the rich heritage of content analysis within both the quantitative and qualitative traditions of this research method. Given the important role of media in societies as sources of information and influence as well as reflections of spokespersons' and public opinions, media content analysis provides a non-intrusive method for identifying views, concerns, and discourses. However, the complex range of factors that influence and shape opinion and the contingent, contextual nature of media effects need to be borne in mind in drawing inferences and predictions from media content analysis. Media content analysis is a valuable method for gaining insights, but usually needs to be conducted in conjunction with other research methods such as audience surveys, interviews, or focus groups to gain a full understanding of message reception, perceptions, attitudes, intentions, and the ultimate impact of communication.

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1 Metonyms are names of places or things used to denote something else through a familiar association, such as using the term "White House" to refer to the President of the United States and his or her administration, or simply "Brussels" to denote the headquarters of the European Commission.

2 Synedoche are terms for part of something that are used to denote the whole, such as saying "wheels" meaning a car or "hired hands" to refer to workers.

3 These key principles are noted because qualitative research does not achieve *reliability*, which is a quantitative research term denoting a high level of probability based on statistical analysis. However, research scholars point out that qualitative research can and should be rigorously conducted and meet these criteria.

4 In double blind coding, two (or sometime more) coders code the same items without seeing each other's coding.

5 Jonathan Pritchard, Matthew Stephens, and Peter Donnelly (2000) are reported to have also developed latent Dirichlet allocation (LDA) around the same time.