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Quantitative Content Analysis Methods in Instructional Technology Research: Defining, Coding, Analyzing and Modeling (DCAM)

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Abstract: *Content analysis has been applied in the research of instructional design and technology to analyze (a) text-based contents, such as online discussions, social media communications, or published articles, and (b) other formats of contents such as videos, audios, or pictures. The purpose of this article is to introduce a method of DCAM (Defining, Coding, Analyzing and Modeling) for content analysis with practice examples. DCAM is a quantitative method generated from a series of studies in instructional design conducted by the author, and supported by the literature in the field. The variables defined from the text-content or other formats of contents can be design related variables, learning related variables, micro-activities in learning, or behavior-performance related learning outcome. In this article, first, nominal, ordinal and scaled coding methods on those variables are demonstrated. Second, reliability measures in content-variable coding are reviewed and explored. Third, parametric and nonparametric statistics methods to examine those variables for content analysis are presented. Finally, some cautions and suggestions to conduct content analysis is discussed.*

Keywords: content analysis, variable coding, micro-activity, density score, predictive modeling, reliability measures, parametric and nonparametric methods

1. Introduction

A widely cited classical definition of content analysis is "a research technique for the objective, systematic, and quantitative description of the manifest content of communication" (Berelson, 1952, p. 18). More researchers and scholars have defined content analysis as a systematic, replicable technique for compressing many words of text into fewer content categories based on explicit rules of coding (Krippendorff, 1980, 1989; Lewis et al., 2013; Maier, 2018; Stemler, 2000; Weber, 1990). The work of content analysis in early years has been focused more on text-based content of communication to "provide an empirical basis for monitoring shifts in public opinion, and examine trends and patterns in the documents" (Stemler, 2000, p. 1). In the literature over the past two decades, the scope of ***content*** and ***variables*** analyzed in the content have been more inclusive with different formats such as psychological characteristics in art drawing (Wheelock et al., 2000), actions observed in videotaped studies (Stigler, 1999), counseling skills in counseling session videos (Liu et al., 2016a), approaches of media frames (Matthes & Kohring, 2008), features and micro-activities in online discussions (Chen et a., 2012; Chiu & Lehmann-Willenbrock, 2016; Hanselman & Liu; 2021), factors of instructional design in e-learning (Liu et al., 2019, 2020), design-components in instructional videos (Li et al., 2018), applications in business ethics (Lock & Seele, 2015), and subjects of communication in senior online communities (Nimrod, 2009). While most early studies presented descriptive analysis and results, the recent studies have explored more statistics methods on comparison, correlation or predictive relationship among the variables identified from those multiple formats of content.

Conducting a content analysis study follows the general procedures as in any quantitative study: (a) starting with the problem, purposes and research questions/hypotheses of the study, (b) determining the criteria to select the content sample (e.g., the criteria for the documents, articles, videos, or social media messages), (c) locating the sample, (d) defining the variables (the exact activities or features) to be analyzed and formulating the measuring/coding system respectively, and (e) conducting the analysis and interpreting the results (Chiu & Lehmann-Willenbrock, 2016; Liu et al., 2020; Maier, 2018; Stemler, 2001). In each of those procedures, there is a list of decisions to make and tasks to perform (Creswell & Guetterman, 2019). For content analysis studies, one critical task is to define and code the variables being analyzed to achieve the purpose of the study. This article focuses on quantitative methods of content analysis in the above procedures (d) and (e). A method of DCAM (Defining, Coding, Analysis, and Modeling) derived from the author's experiences is used to frame and explain the two procedures and tasks.

In content analysis studies in instructional technology and e-learning, what is the content for the analysis? What are the content variables to be analyzed? How are the variables defined, measured, and coded? What types of data are used for the analysis? What statistics tests can be used to analyze the content variables? What are the reliability measures on the variable coding? Addressing those questions, the purpose of this article is to introduce the method of DCAM for content analysis in the field of instructional technology and e-learning, with specific procedures and replicable examples from the literature and the author's work. More applicable strategies of coding and analyzing content variables are also explored. This article focuses particularly on the task operations of the DCAM methods, rather than the design and procedures for an entire study. The following sections are presented in the rest portion the article:

a. Content variables in instructional technology research – defining and coding
b. Reliability measures on variable coding and what to include in a report
c. Statistics methods and examples – analyzing and modeling
d. Cautions and suggestions for conducting content analysis

2. Content Variables – Defining and Coding

In instructional technology research, the *content* for content analysis can be online discussion messages or threads, transcripts from video-based studies, instructional videos or other digital information or applications (e.g., games or web applications). *Variables* defined from different formats of contents can be design related variables, learning related variables, micro-activities in learning, or behavior-performance related learning outcomes (Chen et a., 2012; Chiu & Lehmann-Willenbrock, 2016; Hanselman & Liu; 2021; Stigler, 1999; Liu et al., 2016a, 2016b). The following review describes the *content, content variables, coding methods* and *types of data* for the content variables.

2.1 Micro-activity Variables to Analyze Online Discussions

In studies using asynchronous online discussions as *content*, a post message or discussion thread is usually considered the unit of content. Then the number of units (post messages or discussion threads) is the sample size *N* for the study. In each content unit, some micro-activities can be identified. ***Micro-activities*** are those fundamental and meaningful elements presented in a message or discussion thread such as ideas, answers, solutions, tones of the language, characteristics of learning performance, etc. (Liu & Li, 2022). They are often sorted into different c*ontent variables* for content analysis. Such micro-activities can be coded into binomial, nominal, ordinal or continuous (scaled) variables according to the purpose of a particular study. The following are some examples.

Microcreativity in an online discussion message is defined as "content that is both new and correct" (Chiu & Lehmann-Willenbrock, 2016, p. 246), or micro-activity that is new and correct (Liu & Li, 2022). Meeting with this criterion, microcreativities in a discussion post can be ideas, concepts, answers, solutions, suggestions, examples, or any core content related to the discussion context, which can be coded from words, phrases, sentences, or paragraphs. Some examples can be: (a) a correct answer to a question in a previous turn of message, which can be one word, one number, one or more sentences; (b) a new idea that leads to the solution of a problem; or (c) a meaningful suggestion or justification adding into current discussion such as a correction to some wrong answers or concepts (Chiu, 2008; Chiu & Fujita, 2014). After being identified, microcreativities can be sorted into different theme-variables, and then be coded.

Microcreativity can be coded into a continuous variable by counting the number of microcreativities appeared in a discussion post or thread. Such continuous variable is usually used as a dependent variable in comparative analysis, and as a criterion (dependent) variable or predictor variable in predictive modeling depending on the purpose of the study (Chiu and Fujita, 2014).

It can also be coded into a binary variable, by assigning a value of 1 (yes) when a post presents at least one microcreativity, and 0 (no) when a post does not include any microcreativity. This binary coding is usually applied to short posts with one sentence or just a few words. Such binomial variable can be used as an independent variable in comparative analysis, and a dependent variable or predictor variable in a logit model analysis depending on the purpose of the study (Chiu, 2008; Hanselman & Liu, 2021). Microcreativity characterizes creative thinking and learning outcomes from online discussions. Detailed methods of analysis and examples are introduced in later section of Analyzing and Modeling.

Social Presence is a variable that researchers used to analyze the content in asynchronous online discussions (Chen & Liu, 2020; Doo & Bonk, 2020; Swan & Shin, 2005). Garrison (2009) defined social presence as "the ability of participants to identify with the community (e.g., course of study), communicate purposefully in a trusting environment, and develop inter-personal relationships by way of projecting their individual personalities" (p. 352). In online discussions, social presence is expressed in three categories of communication including interpersonal, open, and cohesive communication (Garrison 2011). Indicator micro-activities can be identified to code social presence in these three categories: (a) interpersonal communication (e.g., affective expression, self-disclosure, and use of humor), (b) open communication (e.g., asking question, referring explicitly to others' message, complimenting others, and expressing agreement with others), and (c) cohesive communication (e.g., referring participants by name, addressing the group as *we, us, our,* and greetings) (Garrision 2011; Hanselman & Liu, 2021).

Density scores have been used to quantify social presence into a *continuous variable* (Lowenthal & Dunlap, 2020; Rourke et al., 2001; Swan & Shih, 2005). A density score for the social presence in a post can be calculated, by taking the count of the indicator micro-activities of social presence within the post, dividing that count by the total number of words in the post, and multiplying by 1000, as shown in the following equation (Rourke et al., 2001).

$$\text{Density Score} = \frac{\#\ \text{of Microactivities}}{\text{Post Word Count}}\ x\ 1000$$

If social presence is studied as one variable in general, the count of indicator micro-activities in the numerator of equation will be the total count of all the communication micro-activities. If the three categories of communication are studied individually as three variables, the count of indicator micro-activities will be separately for each, and three density scores can be calculated for interpersonal, open, and cohesive communication respectively (Hanselman & Liu, 2021). Density score can also be used for some social presence related variable such as ***first/second person language use*** in a massage (Hanselman & Liu, 2021; Tausczik & Pennebaker, 2010).

Social Cue is another variable used to study social presence expressed in online discussion posts (Adler et al., 2003; Chiu & Khoo, 2003; Gunawardena & Zittle, 1997). It is defined as "a group member's expressed personal affect or attitude toward others during a discussion" (Chen et al., 2012, p. 1497). An e-author's personal affect or attitude toward others may be expressed with word, symbol (e.g., "Hi"; "Wonderful!"; "Wrong!"; "☺"; "☹"), or sentences.

A well developed coding decision tree has been used to code social cue (Chiu, 2000; Chen et al., 2012). The social interaction micro-activities in a post can be sorted into positive social cure or negative social cue. The measure of positive social cue is the count of micro-activities with "words, symbol, or emotion expressing positive affective state or positive attitude toward others," and the measure of negative social cue is the count of micro-activities with "words, symbol, or emotion expressing negative affective state or negative attitude toward others" (Chen et al., 2012, p. 1501). For example, a sentence can be a strong negative cue (e.g., "This is completely wrong!!"), or a positive cue (e.g., "You can do it! ☺").

Social cue can be a binary variable when used to identify if a social cue is a positive social cue (code = 1) or a negative social cure (code = 0). It can be a continuous variable as well when using the count of the social cue micro-activities as the measurement (Chen et al., 2012; Lehmann-Willenbrock et al., 2017). The author of this article would make a suggestion to use density score (calculated in the same way as in the density score equation) as the measure for either positive or negative social cure, when analyzing multiple turns of posts or when using a discussion thread as the unit of communication to be analyzed.

Cognitive Presence is defined as the extent to which students in a learning community are able to construct knowledge based on communication with peers within that community (Garrison et al., 1999). Cognitive presence levels the student's meaning making or knowledge construction through learning scenarios comprised of four stages: (a) triggering event: the start point when the learners locate the learning "target" as they feel a sense of unease or discomfort about an idea or concept; (b) exploring event: wherein learners search for additional or alternate information about the idea or concept; (c) integration: the process that the learners integrate the new information with their previous schema into a new concept; and (d) resolution: the stage learners resolve the issue and overcome the problematic understanding from the first phase (Garrison et al., 1999). At the resolution stage, the knowledge construction with new understanding is reached.

Two coding methods are suggested. The first method is summarized from the literature. Cognitive presence in a post can be coded by the level of the four stages as 1, 2, 3, and 4 for triggering event, exploring event, integration and resolution respectively, according to the learning performance described above. The cognitive presence is studied as a nominal or ordinal variable (Garrision, et al., 2001; Hanselman & Liu, 2021; Kovanović, et al., 2015). In a study to predict the final level of cognitive presence the learner achieves, the coding level for a post is the highest cognitive presence level exhibited in that post, even though sometimes multiple levels of the learning performance occurred in one post (Hanselman & Liu, 2021).

The second method is suggested by the author. The cognitive presence in a post or a thread can also be coded with continuous measures. The sum of miacrocreativities or density scores for the cognitive presence characteristics at each of the four stages can be calculated to code the four continuous variables: *triggering event, exploration, integration*, and *resolution*. With some control variables such as time and turn of the post (Chiu et al., 2016), the cognitive and knowledge construction procedures can be studied with in-depth details.

Reading Ease is a variable analyzed in relation to online discussion responses and online interactions among students (Hanselman & Liu, 2021). It is measured by the Flesch Reading Ease Readability score (or the *Readability Ease* (RE) score), indicating how difficult a message in English to be understood. The RE score for a given text ranges from 1 to 100, while higher scores suggest that a post is easier to understand, and lower scores indicate more difficult (Battistella, 2019). The *Readability Ease* (RE) score is calculated with the *Average Sentence Length* (ASL) and the *Average number of Syllables per Word* (ASW) as shown in this equation (Readability Formats Website, 2014):

$$RE = 206.835 - (1.105 \text{ x } ASL) - (84.6 \text{ x } ASW)$$

The measurement for reading ease is not a typical micro-activity coding but it is similar in the way that it counts the fundamental units of the text.

In the literature, more variables and 15 coding instruments have been explored and reviewed for the content analysis of asynchronous online discussions (Wever et al., 2006). The ones introduced in this section have demonstrated the specific methods of using micro-activity coding for content analysis of online discussions. The same methods can be applied for different types of variables to analyze different *contents* as described in the following.

2.2. Design and Learning Related Variables to Analyze Instructional Technology Research

In content analysis studies that analyze instructional technology research, published peer reviewed articles on certain themes of interest are considered the *content*, such as articles on technology and science, mathematics and engineering learning (Liu et al., 2020), Flipped learning (Liu et al., 2016b), and social media and learning (Liu et al., 2019). A study described in an article is usually considered the *unit* of the content. The study can be a quantitative, qualitative, or case study, and generally one study is reported in one article. The number of the units (studies or cases) is the sample size *N*. In each content unit, some design related variables (e.g., *information design, technology design* and *integration design*) and learning related variables (e.g., *collaborative learning* and *motivation*) can be identified, and coded into binomial, nominal, ordinal or continuous (scaled) variables, according to the purpose of a particular content analysis study.

Design related variables for content analysis are derived from the framework of two widely used instructional design models (Liu et al., 2020). First, the ITD three dimension model is initiated by Liu and Velasquez-Bryant (2003), where **I** stands for **I**nformation or learning contents, **T** stands for **T**echnology tools for learning, and **D** stands for the instructional **D**esign principles. The sufficient condition for any technology based learning to be successful is the integration of ALL three dimensions, without missing any single dimension. The dimension of design in the ITD model follows the principles of the second model – ADDIE model, a well applied instructional design model with five stages: **A**nalysis, **D**esign, **D**evelopment, **I**mplementation, and **E**valuation (Gagné et al., 2005; Schlegel, 1995). Tasks in the Analysis stage include needs assessment, learner assessment, cost/resource analysis, content analysis, setting learning goals/objectives and learning outcomes. At the stage of Design, all the operations to achieve the goals and objectives are defined, timeline and personnel are set to execute a to-do list that includes all the tasks need to complete. Following the to-do list, the learning-instructional unit is completed in the Development stage, which can be a lesson, an activity, a course, or a program. At the Implementation stage, the learning-instructional unit is delivered to the learners. The outcomes are to be evaluated at the stage of Evaluation based on the goals/objectives set in the Analysis stage at the beginning. Any issues or problems found from the evaluation would be considered in the next round of redesign (Cheung, 2016; Gagné et al., 2005; Schlegel, 1995).

The ITD model formulates the three fundamental design variables (*information design, technology design* and *integration design*). The tasks in each stage of the ADDIE model can be used to measure and code the three variables.

Information Design is defined as the use of instructional design principles to design the information for learning. It includes the tasks or procedures in the Analysis and Design stages of the ADDIE model (Liu & Velasquez-Bryant, 2003). In most of the studies reported in published articles, the information to be designed includes course materials, curriculum structures, or the subject content put in educational software or courseware. Tasks of design are mostly focused on setting the goals, objectives, and outcomes of learning, developing goal-driven materials or learning-style-driven activities, determining evaluation criteria, developing formative and summative assessment (Abad et al., 2020; Liu et al., 2020).

Information design can be coded as a binary variable or a continuous variable. First, as a binary variable, it receives a code of (1) if the article presents the information/content design activities; or a code of (0) if the article does not report the information design tasks or procedures. Second, the design tasks can be viewed as design micro-activity. In this way, information design can also be coded as a continuous variable by counting the number of such micro-activities of design.

Technology Design is defined as the use of instructional design principles to design a technology application or design the methods, procedures or activities of using existing technology tools to support learning (Liu & Velasquez-Bryant, 2003), which includes the tasks in the first two stages of the ADDIE model. In the literature, most of the instructional technology studies are focused on the design of using existing technology tools (such as Web applications, social media, educational software or games, collaborative learning systems, or learning recommending system) to enhance learning (Dini & Liu, 2017; Liu et al., 2018; Liu, et al., 2019). Tasks of technology design includes needs assessment (estimating the cost, learning curve, accessibility, etc.), selecting technology tools or system for learning activities or to deliver learning contents.

In recent literature, more concurrent technology such as immersive VR (virtual reality) applications (Radianti et al., 2020), and AI (artificial intelligence) applications (e.g., AI-based tutoring program with AI-provided instructions) are used in K-12 and higher education (Boulay, 2016; Su et al., 2022). The design tasks to use VR/AI applications are the same as those in the ADDIE model, while some gaps are found (a) between VR/AI design element and learning theories, (b) between VR/AI usability and learning outcomes, and (c) between developing VR/AI applications and applying them in teaching (Radianti et al., 2020). Those gaps are some typical instances of "lack of design" (Liu & Velasquez-Bryant, 2003) where the design related variable will receive a code of (0).

Similarly, technology design can be coded into a binary variable or a continuous variable with the same methods described for the coding of information design.

Integration Design is the integration of all three dimensions of ITD model and decision making on overall strategies, methods, and plans. It integrates the information design and technology design into the overall plan (Liu & Velasquezbryant, 2003). For content analysis, tasks of integration design can be micro-activities that (a) examine if the technology use (as designed) supports the information-learning procedures or activities (as designed) to achieve the learning goals with expected learning outcomes; and (b) evaluate if the selected learning theories in the design (e.g., behaviorist or constructivist learning theories) are applied consistently in both information design and technology design (Liu et al., 2019, 2020).

The variable of integration design can also be analyzed by the level of technology integration as described in the content article. Cantrell et al. (2007) explored the effects of Type I and Type II technology integration on middle school science learning, where Type I technology integration stimulates passive user involvement such as using Word to type an article or reading an online article, and Type II technology integration stimulates active intellectual involvement such as learning from an interactive game or learning system, or creating a web based application for learning (Irving, 2006; Maddux et al., 2001). These are the two typical types of integration, while other researchers expanded the levels to some more specific stages in transition between passive and active involvements.

Terada (2020) advocates a hierarchy of technology uses – the SAMR integration model (**S**ubstitution, **A**ugmentation, **M**odification, and **R**edefinition) initially proposed by Puentedura (2006, 2013). Substitution is to replace traditional activities or materials with digital version with no functional changes (e.g., from prints to a Word file, or from class lecture to the video of the lecture). Augmentation involves more digital interactive activities (e.g., use a gamified quizzes instead of using paper quizzes). Modification moves the use of technology to a hybrid format, using some learning management system to deliver learning, which allows for task redesign. Learning is fundamentally transformed at the Redefinition level, enabling activities that were previously impossible in the classroom (Terada, 2020). Heick (2022) presents a more comprehensive 5-level technology integration model (Entry, Adoption, Adaptation, Infusion, and Transformation). Details can be found on the website cited in the reference.

In content analysis, integration design variable can be coded in three ways according to the purpose of the study. First, it can be coded into a continuous variable by counting the number of the tasks (the same way as counting micro-activities). Second, it can be coded as a nominal or ordinal variable by identifying the integration levels. Different sets of integration levels (Heick, 2022; Maddux et al., 2001; Puentedura, 2006, 2013) can be used as applied in the literature (Cantrell et al., 2007). If more than one level of the integration design is presented in a study, the highest level will be used for the coding to represent the technology integration level of the study. Third, it can be coded into a binary variable to identify if the integration design is performed in the study, or not (yes = 1, no = 0).

When using the three design related variables in content analysis, if they are coded as continuous variables, they can be used as dependent variables for comparison, or predictor variables for modeling. If they are coded as ranked or binary variables, they can be used as independent variables for comparison study, or as membership identity analyzed in nonparametric tests (as described in the section 4.2.).

In instructional technology research, the effects of some *learning related variables* are often examined. As content analysis variables, the method to identify, measure, and code them are similar. Starting from identifying the attributes of the theory and then identifying tasks to use the theory to support technology based learning. In this article, the author describes three of such variables as examples: *collaborative learning* (Cheng et al., 2014; Domalewske, 2014), *engagement* (Lewis et al., 2011), and *motivation* (Rosli, 2016).

Collaborative Learning emphasizes a social constructivism approach of learning that knowledge is co-constructed through social interaction of group work (Stahl, 2006; Dillenbourg, 1999). Collaborative-learning played a critical role in technology based learning (Chen et al., 2018). While learning occurs through the same stages of engagement, exploration, transformation, presentation, and reflection, collaborative learning highlights the collaboration of group activities that produce learning outcomes (Stahal, 2006). The tasks or micro-activities of collaborative learning can be team building, task analysis, group assignment and performance, project management tasks, time control, peer evaluation, communication performance, synchronous or asynchronous activities (Liu et al., 2018; Mivehchi & Rajabion, 2020; Peppler & Solomou, 2011).

Collaborative learning can also be analyzed by the collaborative activities under each stage of learning (e.g., engagement, exploration, transformation, presentation, and reflection). In that way, each stage may need to be treated as an individual learning-related variable for the content analysis (Lee et al., 2019). For example, to identify or measure the collaborative activities under ***Engagement***, researchers may use engagement as a learning variable. Any collaborative activities that stimulate learners' thoughts, feelings, and activities to learn actively (Lewis et al., 2011) can be considered. Lee and co-authors examined 24 items (activities) of student engagement, and five collaborative activities are loaded into the factor of *peer collaboration,* including (a) study lesson content with others, (b) solving difficult problem with others, (c) work with others on projects, (d) ask others when having questions, and (e) answer others' questions (2019, p.8).

Collaborative learning and engagement can both be coded as continuous variables by counting the collaborative or engagement tasks (the collaborative micro-activities). Again, this coding is based on what is described in the original article(s). Sometime this may be ambiguous if the article to be analyzed does not provide detailed task information in the procedures of their study. They can also be coded into a binary variable to examine if the collaborative learning is considered and engagement efforts is made as described in the study, or not (yes = 1, no = 0).

Motivation is another variable examined in instructional technology studies. It is defined as the general desire or willingness of someone to do something. The two types of often studied motivation are intrinsic and extrinsic motivation (Deci et al., 1999; Rosli, 2016). Individuals who are intrinsically motivated participate in an activity because they gain satisfaction from the task by seeking challenge or developing knowledge. Those who are extrinsically motivated perform a task because of some external reward earned by completing the task, such as money, grades, or other tangible reinforcements (Dini & Liu, 2017; Lei, 2010). In content analysis, most studies to be analyzed address motivation in two ways. First, the study itself tested motivation as a variable and measured it with a well developed instrument. For example, a study examined the intrinsic motivation factors (e.g., challenge, curiosity, control, cooperation, competition, and recognition), or motivation levels (e.g., inclusion, entertainment, and edification) with a well-developed inventory (Cao, 2004; Dini & Liu, 2017). Second, the study described the activities performed to motivate learners, regarding one or more of the factors, or under certain motivation levels (Dini & Liu, 2017). The second is what a content analysis study aims at.

In content analysis, motivation can be coded into (a) a nominal variable by the type of motivation mentioned in a study (e.g., intrinsic = 1, extrinsic = 2, or both = 3), or (b) a binary variable to examine whether any tasks or activities to motivate student learning are performed or not (yes = 1, no = 0).

The measure of *motivation factors or motivation levels* uses well developed inventory, and produces continuous data for the factors or levels (or nominal data by the levels). Generally such data are NOT appropriate for content analysis unless all the studies (articles) selected for the analysis are using the same instrument, examining the effects of the same factors, which is under the scope of meta-analysis (Lipsey & Wilson, 2001), and beyond the focus of present article.

Success. All hitherto described learning related and design related variables can be used to predict the ***success*** of a technology based learning **case** (e.g., the study described in an article to be analyzed). A case is coded as successful (1) when the expected learning outcomes are presented in the article. That is, according to the purpose of the case, significant results are presented, research hypotheses are approved, or expected learning behaviors or performances are observed and recorded. Otherwise, a code of unsuccessful case (0) will be given. With this coding method, either a quantitative study, qualitative study, or case report can be used for content analysis (Liu et al., 2019, 2020), from which a logit predictive model can be developed.

2.3. Variables to Analyze Video-Based Content

In content analysis for video based studies, the videos selected for analysis are considered the content, including instructional videos to teach certain knowledge and skills (Chen et al., 2021; Li, et al., 2018), game videos for interactive learning (Dini & Liu, 2017), or behavioral-observational videos on certain learning experiences or clinic experiences (D'Andrea, 2011; Liu et al., 2016a). An individual video is considered the *unit* of the content. The number of the units (videos selected for analysis) is the sample size *N*.

In some video based studies, video transcripts are used for the content analysis. The same methods to code variables from text-based contents describe in the above sections (***2.1, 2.2***) can be used. D'Andrea and co-authors (2011, 2015) conducted studies on counseling skill learning, in which transcripts (namely the text-based content) were produced from counseling session videos and analyzed. The transcripts were coded by counseling skills and compared at different levels of professional.

In studies that evaluate the quality of instructional video (Li, et al., 2018), or the counseling session on video (Liu et al., 2016a), content analysis on the videos themselves can be performed while the video is playing. Figure 1 shows the *frame by frame* and *second by second* analysis on a counseling session video while it is playing. The counseling skill variables (e.g., open question, feedback on feelings, see Liu et al., 2016a) are identified by frames and by the time (minutes/seconds) during the application of certain skills. Figure 2 shows the *frame by frame* and *second by second* analysis on an instructional video while it is playing. The design variables are identified by frames and by the time (minutes/seconds) during the demonstration of certain design skills. For example, the three design variables 3, 8, and 12 identified from the video are introduction and prerequisite knowledge or skills, assessment provided, and specific criteria to the subject area respectively (Li et al. 2018, p. 964)

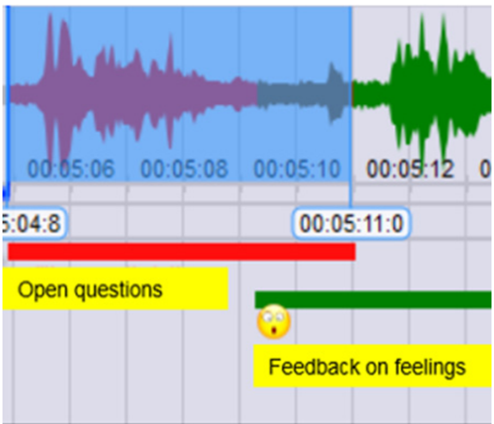

Figure 1
Frame by Frame and Second by Second Counseling Video Using MAXQDA

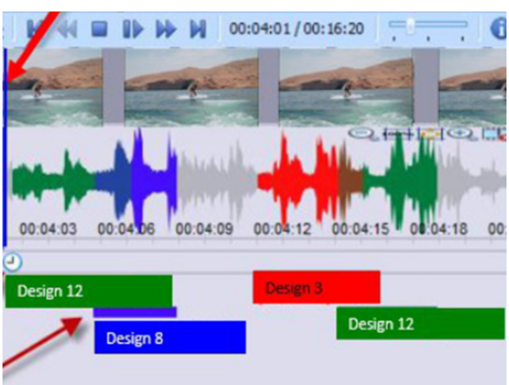

Figure 2
Variable Analysis for an Instructional Video Using MAQDA

In the two examples, 18 counseling skill variables and 12 design skill variables are coded directly while the video was playing (Liu et al., 2016a; Li et al., 2018) using a content analysis software MAXQDA (MAXQDA, 2014). The counseling and design variables can be measured by (a) whether a variable occurs or not, as binary data, (b) the time it occurs (appropriate or not) as binary data, (c) the seconds it lasts as continuous data, (d) the turns and order it occurs as ordinal data, (e) the quality of the skill (levels or scores), and (e) defining certain micro-activities such as a combination of certain skills are performed by looking at the overlap of the timeline in MAXQDA program (D'Andrea, 2015) such as a micro-activity of *theory + application*, or *objective + drill* (Liu et al., 2016a; Li et al., 2018). A further measure on variables identified from video content could be the calculation of an index score for individual variables or the micro-activities, similar to the calculation of density scores for social presence indicators (Rourke et al., 2001).

2.4. Summary

In summary, this section introduces the coding methods for variables often used to analyze three types of *content* (online discussions, published research articles, and videos). For online discussions, all the text/words in a messages are analyzed as the content. For published research articles, the study described in an article is analyzed as the content, rather than *word by word* text of the article. For video content, all behaviors, performances, activities, speeches, or instructions on each frame of the movie/video are analyzed as the content. This section demonstrated the methods that a variable can be identified, measured and coded in the context of instructional technology studies. Furthermore, content analysis necessitates paying special attention to reliability of variable coding.

3. Reliability Measures

3.1. Overview

In content analysis, reliability measures include the measure of *interrater reliability* defined as the extent to which two or more coders reach agreement on the coding decisions, and the measure of *intrarator reliability* defined as the extent to which one coder agreeing him/herself over time (Rourke et al., 2001). A number of indexes have been used to report the reliability: percent agreement P_o (observed percentage), Bennett, Alpert and Godstein's *S* (an index of consistency), Holsti's method, Scott's pi, Cohen's kappa, Krippendorff's alpha, Spearman rho, Kupper-Hafner index, etc. (Holsti, 1969; Krippendorff, 1980; Kupper & Hafner, 1989; Rourke et al., 2001; Scott, 1995; Wever et al., 2006).

The calculation of the reliability measures is based on a common logic: "comparing the level of (dis)agreement achieved (observed percentage of agreement or disagreement) to the level of (dis)agreement that could obtained by chance (the expected percentage)" (Oleinik et al., 2014, p.2705). In other words, "the value $1-A_e$ (where *A* stands for agreement) will measure how much agreement over and above chance is attainable; the value $(A_o - A_e)$ will tell us how much agreement beyond chance was actually found. The ratio between $(A_o - A_e)$ and $(1- A_e)$ will then tell us which proportion of the possible agreement beyond chance was actually observed. This idea is expressed by the following formula: $S, \pi, K = (A_o - A_e) / (1- A_e)$" (Artstein & Poesio, 2008, p. 559).

The common procedures to compute a reliability coefficient are: (a) first find the percentage of agreement among coders, and (b) then correct for chance agreement. The three popularly used methods to conduct such correction for content analysis are Scott's pi, Cohen's kappa, and Krippendorff's alpha (Potter & Levine-Donnerstein, 2009). In addition, Bennett, Alpert and Goldstein's S is another measure that has repeatedly been proposed in the literature as an alternative to Cohen's kappa (Warrens, 2011). In literature, there is no general agreement on which measure should be used (Wever, 2006). The four reliability measures will be briefly reviewed next, mainly focusing on conceptual understanding of the computation formulas and their applications in content analysis rather than the in-depth statistics theories.

3.2. Scott's Pi (π)

Scott (1955) developed a PRE (proportional reduction of error) formula to correct for chance agreement among coders, which is known as the Scott's π formula:

$$\pi = (P_o - P_e) / (1- P_e)$$

Where P_o is the observed percentage of agreement, and P_e is the percentage of agreement expected by chance.

Scott's π corrects the percentage of agreement "for the number of categories in the code, and the frequency with which each is used" (Scott, 1955, p. 323), by comparing the observed distribution of the categories with the expected one. The original formula for calculating π was for the case of two coders. It has been generalized to apply for the case of more than two coders by calculating π for each pair of coders and adding them up (Muñoz-Leiva et al. 2006, p. 526).

In content analysis, for example, two coders reviewed 10 instructional technology research articles on a *collaborative learning* variable (yes or no). π =1 is a perfect score for Scott's π, indicating that both raters agreed exactly on the value of the *collaborative learning* variable for all 10 articles. A Scott π value close to 0 means very little agreement.

3.3. Cohen's Kappa (K)

Another method to correct percentage of agreement for the probability of agreeing by chance only is to compute a kappa. Cohen (1960) developed the kappa coefficient formula:

$$K = (F_o - F_c) / (N - F_c)$$

Where F_o is the number of judgements on which the coders agree, F_c is the number of judgements for which agreement is expected by chance, and N is the total number of judgements made by each judge.

The kappa formula is essentially the same formula as Scott's pi, except that it can account for more than two coders at a time. Again, for chance correcting measures, no standard is available to judge the level of interrater reliability. In the literature, values of kappa between .40 and .59 are considered moderate, between .60 and .79 are considered substantial, and above .80 are considered outstanding (Landis & Koch, 1977; Rourke et al., 2001). Hanselman and Liu (2021) also used kappa to examine the intrarater reliability on the coding of ten variables identified from about 1500 online discussion messages in 608 discussion threads, and received significant kappa coefficients for all ten variables ranging from .588 to .981.

3.4. Bennett, Alpert and Godstein's S

Bennett, Alpert and Godstein's S is also known as the *index of consistency,* a measure that has repeatedly been proposed in the literature as an alternative to Cohen's kappa (Warrens, 2011). The S formula was proposed by Bennett and co-authors (1954):

$$S = [k / (k - 1)] (P_o - 1/k)$$

Where k is the number of categories of the variable (e.g., a two-category code yes or no for a variable), P_o is the observed percentage of agreement between two independent coders.

When P_o ,the percentage of agreement, is used to describe the reliability, it is biased in favor of variables with fewer number of categories. By chance alone, one would expect better agreement on a two-category than on a five-category scale. To correct for this bias, Bennett and co-authors (1954) proposed the index of consistency S, using k (the number of categories) for the correction. The formula can tell that the value of S depends on k, and Bennett, Alpert and Godstein's S is only a function of observed agreement rate and the number of categories for ratings or responses. It tends to underestimate interrater reliability, and as its correction for chance has nothing to do with the proportions in the population, "it cannot indicated the reliability in the population of data" (Krippendorff, 2004, p. 5).

3.5. Krippendorff's Alpha (α)

Krippendorff's alpha is another coefficient that accounts for chance agreement. The alpha formula developed by Krippendorff (1980) is a very complex formula with a set of sub-formulas. It allows for multiple simultaneous coders, multiple values on a variable, and any level of data (nominal, ordinal, interval, or ratio). Computing an alpha requires an m by r contingency matrix to be constructed where m is the number of coders (e.g., can be from 1 to j), and r is the values on a variable (e.g., can be from 1 to k) (Krippendorff, 1980). This article does not intend to demonstrate the calculation process but provide a conceptually understanding of alpha.

Alpha has a similar rationale with pi and kappa, but it refers to the levels of disagreement. Conceptually, $\alpha = 1 - (D_o)/(D_e)$, where D_o is the disagreement observed, and D_e

is the disagreement expected by chance, and one interpretation of Krippendorff's alpha is (Krippendorff, 2004):

$$\alpha = 1 - (D_{within\ units=in\ error}) / (D_{within\ and\ between\ units=in\ total})$$

The value of α indicates the level of reliability. α = 1 indicates perfect reliability. α = 0 indicates the complete absence of reliability. When disagreements are systematic and exceed what can be expected by chance, α < 0. In literature, a cut-off value from .75 to .80 can be used (Rourke et al., 2001), that is, a value greater than .70 can be considered as reliable.

3.6. Reporting Reliability: Coefficients and Beyond

Over years in the literature, there seems no standardized criteria bout what information should be included in reliability report for content analysis studies (Kolbe & Burnett, 1991; Stemler, 2000; Wever et al., 2006). In a review of 128 content analysis studies, 46 studies (35.9%) reported an "overall reliability" for the study, 31 studies (24.2%) reported reliability on individual measures, 11 studies (8.6%) reported ranges of reliabilities, and 40 (31.3%) had no reliability coefficients reported (Kolbe & Burnett, 1999). Among the 88 articles that provided the reliability results to certain extent (88−40 = 48 articles), 41(85%) simply used the coefficient of agreement (P_o) (Kolbe & Burnett, 1999). This reveals the weakness in the reports of reliability methods and results. Especially, the "overall reliability" report is most like to yield misleading, as some low ratings on individual measures may be hidden by pooled results. Regardless of the coefficients used, it is of crucial importance that more information about reliability is reported as the following.

Reliability sample size related information includes: (a) reliability sample size, (b) method that the reliability sample is created, (c) how the reliability sample size is determined, (d) the full sample size, and (e) what percentage is the reliability sample size to the full sample size (Lombard et al., 2002; Urdhwareshe, 2020).

Coder related information includes: (a) number of reliability coders, (b) if the researcher is one of the coders, and (c) hours of training required to the coders (Lombard et al., 2002; Wever et al., 2006).

Coding related information includes: (a) amount of coding conducted by each reliability coders and non-reliability coders, and (b) for intrarater coding, the days between the first and second coding (Hanselman & Liu, 2021; Landis & Koch, 1977; Lombard et al., 2002).

Reliability Coefficients related information includes: (a) the coefficients/indices selected to calculate the reliability, (b) justification of the selection, (c) the interrater or intrarater reliability level for each variable, for each coefficient/index selected, and (d) resource information regarding the coding instrument, procedures and instructions (Hanselman & Liu, 2021; Lombard et al., 2002; Wever et al., 2006).

All the detailed information is necessary for the readers to have a better understanding about the coding reliability for the content analysis study. To this point, the methods of content variable measuring, coding, and coding reliability have been discussed and summarized, which are the tasks in the first two stages (Definition and Coding) of the DCAM method. The next two stages (Analysis and Modeling) with the quantitative data analysis methods will be discussed next.

4. Statistics Methods – Analyzing and Modeling

In the content analysis studies in the field of instructional technology and e-learning, both parametric and nonparametric tests have been used, depending on the purpose of the content analysis study and types of data coding for the content variables.

4.1. Parametric Methods

Regression analysis is one of the popular parametric method currently used in content analysis, including multiple linear regression and logistic regression. A general form of model for regression can be expressed as in the following (Mertler & Reinhart, 2017):

$$Y = f\left(\beta_0 + \sum_{i=1}^{n} \beta_i X_i\right)$$

Where β_0 is the constant, β_i is the estimated weights of X_i. The right side of the equation is the value that enters into a distribution function, which is the same for the normal linear (multiple linear regression) distribution or logit (logistic regression) distribution. The left side *Y* is different in its value and interpretation between linear regression and logistic regression. For multiple linear regression, *Y* is the criterion variable measured with continuous data. The model examines the extent to which the value of Y can be predicted by the linear combination of the predictor variables *X*'s. In logistic regression, the "*Y*" indicates the logit of *Y*, and is coded into binary data (e.g., pass=1, fail=0) or nominal data for multilevel logistic regression. Logistic regression examines the extent to which the probability of *Y* to be 1 (e.g., to pass) can be predicted by the predictor variables (*X*'s) as combined in the logit model (Greene, 1993; Mertler & Reinhart, 2017; Press & Wilson, 1978):

$$logit\ (P(Y=1|X_1, \ldots, X_k)) = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n$$

The following are some examples.

Multiple Regression is a classical method for content analysis. For example, Hanselman and Liu (2021) conducted a content analysis study on student online discussions. In this study, online discussion messages were the *content*. Each initial message and its follow-up responses were treated as a *unit* of the analysis. Several runs of multiple regression analysis were performed.

The predictor variables (*X*'s) were the six characteristic variables identified from the initial discussion post: time from due date (by minutes), word count, reading ease score, first-person pronouns (density scores), second-person pronouns (density scores), and cognitive presence level (ranked levels). Results from two linear models are (Hanselman & Liu, 2021):

• The *first-person pronouns* significantly predict Y_1 – *interpersonal communication* measured by density scores (R^2 = .015, $F_{(1,607)}$ = 9.403, p < .01; t = -2.686, p = .007).

• The *word count* significantly predict Y_3 – *cohesive communication*, measured by density scores (R^2 = .012,$F_{(1,607)}$ = 7.213, p = .007; t = -2.686, p <.01).

Logistic Regression is another popularly used parametric method. Liu and co-authors conducted five content analysis studies to explore the success of technology-based learning cases from 2008 to 2020 (as shown in Table 1). A total of 1,146 studies on five themes from published articles were reviewed as the *content*. Each of the studies described in the 1146 articles were the *units* of the content analysis,

In each content analysis, several predictor variable (*X'*s) were identified from the article in which the study was reported, including technology-, design-, and learning-related variables coded into binary data. When micro-activities of each variable were performed and described in the article, the variable was coded as (1), otherwise, it was given a code of (0).

The *Y* was the probability of a technology based learning case to be successful. When the results demonstrated learning outcomes as expected and described in the article (either significant results or positive impact), *Y* is given a code of (1), otherwise, it was coded as (0). The results of the logistic regression is summarized in Table 1. Logit model was developed for each of the five content analysis studies.

Table 1

Content Analyses in Instructional Technology Research (updated from Liu et al.,2020)

Themes	Case Analysis	Model Nagelkerke R^2	Sig. Predictors	Odd Ratios Min. ~ Max.	References
Using Web 2.0 in teacher education	88 articles	.66	• Info design • Tech design (with integration design)	12.09~21.07	Liu & Maddux (2008)
Effectiveness of flipped learning	216 articles	.26	• Content design • Tech design • Overall design • Active learning • Motivation	2.166~2.497	Liu, Ripley, & Lee (2016b)
Technology in counseling education and practice	261 articles	.25	• Counseling design • Tech design • Overall design	2.286~2.741	Liu, Li, & Shcherer (2016a)
Social media in dynamic learning	276 articles	.49	• Info logistics • Tech logistics • Overall design logistics • Collaborative learning • Active stimulation • Motivation • Objective-driven activities	1.965~4.083	Liu, Chen, & Li (2019)
Technology in science, math, & engineering learning	305 articles	.33	• Info design • Tech design • Integration design • Interactive learning • Motivation	1.903~3.045	Liu, Chen, & Li (2020)

For example, the model from Liu, Chen and Li (2019) on social media in dynamic learning with the significant predictors can be presented as in Figure 3, and the model reads “the probability of a SMSL case to be successful is the logit function of information logistics, technology logistics, overall design logistics, collaborative learning, active stimulation, motivation, and objective-driven activities.”

Logit (P (SMSL=1| X_1, . . . , $X_{k=7}$)) = f (IL, TL, ODL, CL, AS, MO, ODA)

Where:

SMSL = Social Media Supported Learning

P (SMSL=1) indicates *Probability of SMSL to be successful*

f (...) indicates “a function of …”

IL = Information Logistics, TL = Technology Logistics, ODL = Overall Design Logistics,

CL = Collaborative Learning, AS = Active Stimulation, MO = Motivation,

ODA = Objective-Driven Activities

Figure 3

Logit predictive model function (Liu et al. 2019, p. 118)

Leveled Modeling. Liu and co-authors (2020) conducted a content analysis and analyzed 305 studies described in published articles on technology and science, mathematics, and engineering learning. They also proposed a method of *Leveled Modeling* as shown in Figure 4. The model reads “the probability of a SMEL case to be successful is the ***logit function of a set of sub-functions,*** including the functions of *Content Design, Technology Design, Integration Design, Interactive Learning, Motivation,* and *Time*” (p.120).

Logit [*P* (*SMEL*=1|*f*(X_1), . . . , *f*($X_{k=6}$))] = F{ *f(CD), f(TD), f(ID), f(InL), f(MO), f(T)*}

Where:

SMEL = Science, Mathematics, Engineering Learning

P (SMEL=1) *indicates Probability of SMEL to be successful*

f(…) indicates “a function of …” F {…} indicates “the function of *functions*”

CD = Content Design, TD = Technology Design, ID = Integration Design,

InL = Interactive Learning, MO = Motivation, T = Time

Figure 4

Leveled modeling function for SME learning (Liu, et al., 2020, p.120)

In this model, a sub-function (or a sub-model) can be either a logit function or a linear function. For example, the sub-function of technology design *f(TD)* can be a logit function of a set of *TD* tasks or micro-activities (*MA*), and it is to predict the probability of the technology design (*TD*) = 1 (appropriately designed):

$$Logit\,[P\,(TD=1|MA_1, \ldots, MA_k)] = \beta_0 + \beta_1 MA_1 + \cdots + \beta_k MA_k$$

It can also be a linear function if technology design (*TD*) is measured by continuous scores (e.g., density scores, or evaluation scores), the *TD* value can be predicted by a linear combination of the TD tasks or micro-activities (*MA*):

$$TD = \beta_0 + \beta_1 MA_1 + \cdots + \beta_k MA_k$$

In this content analysis example, the leveled modeling is directed and framed by the instructional design and learning theories, and the data hierarchy can be at the level of micro-activities, design and learning variables (*CD, T, ID, InL,* and *MO*), and subject areas (science, mathematics, and engineering). Other sub-functions such as *f(CD), f(TD), f(ID), f(InL)*, or *f(MO)* can be formulated to separate equations in the same way.

If the researchers are interested in exploring whether the success of a learning case in certain subject area relates to certain micro-activities that are featured with certain design principles, a three-level analysis and modeling can be employed. For example, the level-1 model can be at the level of micro-activity, using the tasks or micro-activities as variables, while the level-2 model at the level of design, using types or features of design as variables. Then the level-3 model can be at the level of subject area, using variables that may reflect the styles or methods of teaching and learning in different subject areas. This is an approach of multilevel modeling that builds up the models "by laying out the separate model equations and then combining all equations through substitution into a single-model equation" (Heck et al., 2014, p.9).

Multilevel modeling is also known as hierarchical linear models (or linear mixed-effect model, nested data models, random coefficients), and has become popular in psychology for analyzing data with repeated measurements or data organized in nested levels (Hayes, 2006; Mumper, 2017). Multilevel modeling can be used to specify a hierarchical system of regression equations that take advantage of clustered and hierarchical data structure (Heck & Thomas, 2009). It has been used for content analysis on online discussions. For more examples, Chiu (2000, 2008) and co-authors (2003, 2014, 2016) have developed a series of content analysis studies, in which the multilevel analysis and statistical discourse analysis are performed, and some thoroughly designed examples can be learned.

4.2. Nonparametric Methods

In the content variable data coding as described in section 2, one may not always obtain a data set that can be analyzed with the desired parametric statistics tests. When the assumptions for parametric tests are violated, some nonparametric statistics methods can be conducted. Sometimes, for the purpose of certain study, nonparametric stets may be the best option.

Mann-Whitney U is a nonparametric test that were used in content analysis. When equal variance is not assumed, or the data is skewed, instead of an independent *t*-test (which compares the means of the two groups), Mann-Whitney *U* test can be conducted (which compares the medians of the two groups, even with unequal *Ns*) (Corder & Forman, 2014).

D'Andrea and co-authors (2015) conducted a content analysis on the transcripts of counseling session videos. Twelve counseling skills were coded by the level of the therapist. The dependent variable is the amount of time the counselor talked that demonstrated each of the 12 skills. The independent variable is the level of the therapist (novice, expert). A nonparametric Mann-Whitney *U* was conducted and the results showed differences in the median of the time a skill was performed between the two levels (novice, expert) on three skills: *restatement* (Z = -2.16, p = .029, r = .68), *interpretation* (Z = -2.62; p = .007, r = .83), and *process advisement* (Z = -3.57, p = .001, r = 1.13).

Chi-Square is another nonparametric test when the researcher is interested in the number (or percentage, or proportion) of the examined subjects (people, things, responses, etc.) that fall into a number of categories (Corder & Forman, 2014). It has been a very useful method for content analysis (Boettger & Palmer, 2010; D'Andrea et al., 2011)

In the same study, D'Andrea and co-authors (2015) used Chi square to analyze the skill use by demographic category of the therapist. The frequency of skill-use (the count that each skill was used during a counseling session) was the dependent variable, and the demographic category was the independent variable. Two-way contingency table analysis using crosstabs was performed. Chi square test results revealed no significant differences between gender, school (type of therapy), or degree held by the therapist for any of the skills measured. The two most frequently used skills, regardless of experience level, were *asking questions* and *providing facts, data*, *or opinions*. In another study by D'Andrea and co-authors (2011), Chi square was employed to analyze the frequency of counseling skill use by the level of the therapist (novice, expert), and difference was found that therapist at expert level used the skills appropriately and more often.

Another suggested example to use Chi Square in the content analysis in the field of instructional technology can be the evaluation of the quality of instructional videos. The *content* to be analyzed can be instructional videos where each video will be the *unit*. The content variables can be the design related and learning related variables. The frequency of design-skill use by the producer can be the dependent variable, and the type of the producer (e.g., school teachers, preservice teachers, graduates majoring in instructional technology) can be the independent variable. A two-way contingency table analysis can be performed to examine the differences of skill-use cross the three types of producers. The design-skill use can be coded with a content analysis software MAXQDA (2014).

4.3. More Statistics Methods

There are more methods available for content analysis, although they have not often exhibited in the content analysis literature. For example, parametric comparative methods (e.g., ANOVA, MANOVA, repeated measures), and nonparametric methods (e.g., Kruskal-Whallis test, McNemar and Wilcoxon tests, Cochran's test, Friedman test, etc.) can be applied so long as the variables can be clearly identified from the *content*, and coded into the appropriate types of data for the purpose of the content analysis, and for the tests.

5. Summary and Discussions

This article has reviewed the DCAM (*Defining, Coding, Analyzing and Modeling*) method for content analysis and the tasks performed in each phase. The methods in the examples for variable coding and data analysis can also be applied in other context of content analysis. This final session concludes with (a) cautions and suggestion to write a content analysis report, and (b) thoughts for further directions.

5.1. Cautions and Suggestions

Besides all the requirements to be included in a good research article, some suggestions for writing a content analysis report are shared here for the readers' reference.

The first suggestion is to ***stay with the content***. In content analysis, all the content information about variables, designs, learning activities, or performances is from the messages, articles, other documentations or videos. When describing them, it is good to state in an objective way, such as "the design procedures *as described* in the article were…" or "the significant results *as reported* by the researchers indicate that the learning case received expected learning outcome…" When describing the results or findings from THE content analysis, it may be clearer to state as "based on the studies as described in the content articles, and the analysis on content variables A, B, and C identified from those studies, we found…" In this way, the readers will not be confused between the content and the analysis of the content.

The second suggestion is to provide ***a clear definition*** on any concept, term, method, or specific combined word at the first time they are mentioned. An author does not assume that the readers would understand it automatically. It is better to define it at the beginning than to let readers learn about it after reading 5 pages later. Especially the variables identified from the content. Again, distinguish the variables studied in the *content* and the content variables identified from the content.

Thirdly, it is of crucial importance to provide a ***clear logic*** for your analysis or conclusion and let readers understand the logic. It is good to highlight the logic clearly in the introduction of the paper. An effective method of doing so is to provide a diagram or graphic to visually present the logic. If this logic is not clear, it is hard for readers to understand your findings. Of course, this is true for all kinds of studies, not just for content analysis.

Finally, it is more efficient to use ***technology tools*** in the content analysis. For example, a content analysis software *Leximancer* (https://www.leximancer.com/) is helpful to generate the main themes in the literature, or in the content articles/messages selected. MAXQDA (2014) is a powerful program to analyze text contents and videos.

5.2. Thoughts for Further Studies

Learning from Content Analysis. In the field of instructional design and technology, assessment is always one of the most needed area. While content analysis may provide critical assessment in certain area on what is the strength, what is missing, what is in demand, or what is done inappropriately. Some leading journals in this field have published thousands of articles, which can be a rich source for content analysis. For example, Chen and Liu (2019) conducted a content analysis on one of the leading journals in the field and examined over 1200 statistics tests from 178 articles published in five years from 2014 to 2018. They found that "Among the 178 articles, only two articles (1.1%) reported that a priori power analysis was conducted to estimate the required sample size, and seven articles (3.9%) reported observed power. The majority of educational technology researchers who authored the 178 articles did not conduct priori power analysis to estimate sample size during research planning" (Chen & Liu, 2019, p. 59). They then made suggestions and provided methods to conduct power analysis. Researchers would benefit from this kind of assessment and studies.

Analyzing others' articles is always a good opportunity of learning. It is not simply a review or reading, rather, it takes an in-depth thinking to understand the solid work from others, generate new structured ideas from it, and also locate some to-be-improved areas. The next project might be to explore some new methods for content analysis.

Big Data and Content Analytics. Besides the classical statistics methods reviewed in this article, the rapid development of technology and applications in big data analytics and machine learning has brought a new vision of method for content analysis (Lewis et al, 2013; Liu et al., 2017). Currently, the *contents* for the content analysis are *static* materials. That is, they are digital text-format or video format materials collected by the researchers, analyzed as they are at one time.

When the contents become *dynamic* (e.g., the "coming-in" online communication messages in online courses, or from social media apps), they can be constantly updated and accessed from the online systems. The system will also receive dynamic data for dynamic analysis, which actually is the ***content analytics***. With such dynamic data and the techniques of big data analytics and machine learning, the traditional methods to obtain the content sample, code the variables, analyze the data, and generate the models have transformed to a dynamic level of content analytics. For example, with well-designed *knowledge* input (such as the information of defining a variable, coding rules, and a hypothetical model of what to analyze and to predict), the machine learning process (Bauber & Wangenheim; 2023; Alzubi et al., 2018) may constantly *learn* and generate the dynamic successful-learning model with the dynamic data (e.g., coming-in messages, or learning related information). This is an area to be explored in further research, and the area that keeps us learning.

In summary, this article introduces the DCAM method mainly focusing on defining and coding variables, analyzing and modeling the data. In literature, not many content analysis studies are on the topics of instructional design and technology, except some work on the analysis of online discussions. The author introduces some examples in which design related variables and learning related variables are used to analyze technology integration, technology related learning design, or digital applications for learning. Also the statistics methods in those examples are beyond the traditional descriptive methods. It is expected that this approach may initiate different paths for content analysis, and more solid studies are conducted in this field.

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