Qualitative Data Analysis by Research Tradition

CHAPTER PREVIEW

In this chapter we review the approach of each qualitative research tradition to data analysis. We begin the chapter with some general thoughts about data analysis across the research traditions. Then we examine qualitative data analysis across the five research tradition clusters discussed in Chapter 2 (see Figure 11.1). We begin our review with the “universal” tradition in qualitative designs: the case study. The four remaining clusters involve traditions that address experience and theory formulation, those that investigate the meaning of symbol and text, approaches that explore cultural expressions of process and experience, and the tradition that views research as a change agent. With each tradition, we highlight the similarities and differences among data analysis approaches. We also include several case examples to bring to life what data analysis “looks like” for each research tradition. We refer to researcher reflexivity in data analysis across the clusters; you may want to return to our in-depth discussion of researcher reflexivity in Chapter 5. At the end of the chapter, Table 11.10 summarizes data analytic approaches across the research traditions.

GENERAL THINKING ON QUALITATIVE DATA ANALYSIS ACROSS TRADITIONS

So, you have collected your data—hooray! We also know that this is the moment when the panic can really start to set in. We have already discussed the importance of inviting recursivity into the ways you collect and analyze your data. However, before we get started on our review of data analysis in each of the research traditions, let’s revisit this “panic” for a moment. There are so many things embedded within this feeling. You want to “stay true” to your participants. You are quite possibly (and hopefully) immersed in your study’s data. You may even have come to care about your participants and/or feel a sense of injustice or a desire for justice based on your participants’ stories. Or you might
just be feeling the need to make your dissertation a “done” dissertation. Regardless of why the panic is there, just know that it is a pretty natural part of analyzing data. By now, you know we like top 10 lists, so see Table 11.1 for suggestions to remember before we dive into the specifics of qualitative data analysis for various research traditions.

Another general thought on data analysis is that you should have a data analysis plan. You can call it a strategy—it might even feel like a “plan of battle” at times (although we think it is always best to not position yourself as a researcher “opposite” of your data but find ways to work with your data). Establish your data analysis plan ahead of time and closely align your data analysis activities with this plan. Often this plan includes developing a codebook of some kind (introduced in Chapter 10), where you track the large domains and categories of data, in addition to the subcategories and subdomains of your data.

Also, remember to not lose sight of how your theoretical framework is a lens through which to view your data as you engage in analysis. For example, in our phenomenological study of the resilience of child sexual abuse survivors, we had a feminist and critical theory framework (Singh, Hays, et al., 2010). So, we had a solid data analysis plan. However, as we conducted data analysis, we continually invited our research paradigms into this analysis. The question we asked ourselves was “How true are we being to our theoretical framework?” In this study, this question translated into the extent to which our data analysis focused on themes of empowerment and acknowledgment of contextual factors and experiences of privilege and/or oppression—exactly what our theories demanded we do in our data analysis.

Before we delve into the distinct methods of data analysis within each tradition, we emphasize the “generic” steps of qualitative data analysis presented in Chapter 10. Additionally, Miles and Huberman (1994) provide a list of common features of qualitative data analysis among the research traditions:
When you feel the panic start to take over, remember that you dog-eared this page so you can reread this list (and engage in some deep breathing) to get back on track. Many of these tips are reminders from previous chapters.

1. Data do not “emerge.” We are researchers who “identify” findings. Acknowledge your researcher role and how your biases and assumptions influence how you analyze data.

2. The point above is actually a good thing. We are researchers for a reason—we bring expertise to the data analysis. We are experts on our participants’ data. We can (and should) own this if we are to be able to communicate our findings to an audience postanalysis in the most effective way.

3. It’s not always possible to form one, but remember that a research team increases the quality of your data analysis. Try not to go solo on data analysis.

4. Multiple sources of data require multiple ways to analyze them. Many of these methods we discuss in this chapter. However, the qualitative field evolves and grows constantly. Read this book—and consider any new ways of analyzing data based on your field.

5. Think about how you “think” best, and talk about how this style or process is in common, or not, with your research team members. You don’t want differences in style to be a barrier to your data analysis process.

6. Remember that it’s best to try to disprove and “argue” with your data along the way to ensure that you are doing the best possible data analysis.

7. Be creative. Sometimes you will be challenged in how to proceed with data analysis. This can actually be useful as long as you are not just making things up to make the process easy or to take a shortcut, and are straying incredibly far from your theory and research tradition (which both guide you in your data analysis).

8. Take a vacation from your data analysis and you will often come back “fresh” to see your data in a new light.

9. When you get stuck, revisit your data again and again . . . and again. Your participants’ voices will often point to your path out of the quicksand.

10. Be familiar and have some facility with the range of data analysis techniques across research traditions. You may borrow from a few different traditions. Again, this shouldn’t happen just because you don’t know what else to do, but rather because you have a solid rationale for doing so, and the techniques help you understand, interpret, and communicate your findings most effectively.

You will notice that similar processes are described with different terms in the different research traditions. Honestly, this used to frustrate us! Now, we see it actually as a...
comfort. Each research tradition is undergirded with a particular philosophical bent—and this does and *should* emerge in how data analysis is described within each one. We think that the best way to learn the most about the research tradition that is best for your research project is to get to know all of the various differences and similarities across the research traditions. A helpful way to learn them is to take your research topic and situate them in each of the research traditions. We have several activities in which you can apply data analysis in research traditions and get a true “feel” for the ways each distinctly approaches analyzing data. Let’s get started!

**QUALITATIVE DATA ANALYSIS WITH THE UNIVERSAL TRADITION: THE CASE STUDY**

We have discussed previously the unique position the case study has in qualitative research as the “universal” tradition. Case studies are most often used when a researcher seeks to understand a phenomenon for which there is no in-depth understanding at that point in time (Creswell, 2006). Case studies are “bounded systems”—that is, they have boundaries of time, place, and other delineations (Yin, 2008). Therefore, the researcher tends to have multiple sources of data about the processes within the case study, and thus multiple decisions to make about how to approach data analysis (Schwandt, 2001). These multiple decisions, however, should be guided by the *case itself* and not by the many factors surrounding and/or involved in the case. This is one of the largest challenges in qualitative data analysis with the case study research tradition. It can be tempting to veer off in many interesting directions, which, although interesting, may not illuminate the case itself.

A good way to stay on track with data analysis is to remember what led you to study the case in the first place. The case study strategy is “preferred when the inquirer seeks answers to how or why questions, when the inquirer has little control over events being studied, when the object of study is a contemporary phenomenon in a real-life context, when boundaries between the phenomenon and the context are not clear, and when it is desirable to use multiple sources of evidence” (Schwandt, 2001, p. 23).

So, if you are examining a single case of an immigrant Latina woman living with bulimia and her treatment outcomes in a residential treatment center, there will be numerous “pulls” on you as a researcher to examine the variables influencing the case—such as the family or the media—rather than the case itself. This does not mean you should limit your analysis of numerous data sources. For instance, you may conduct interviews with the participant herself, the family, and her treatment team of counselors and physicians, among others. However, when you begin analyzing data in these interviews that take you away from the case itself, be sure to come back to the research question guiding your case study.

Stake (1995) discussed four major forms of data analysis with case study designs. First, there is **categorical aggregation**, where you examine several occurrences for critical incidents, concerns, and issues within the data you have collected. For our sample study above, the researcher may create broad categories of influences on the Latina woman that have meaning for the case itself. For instance, in interviews with treatment team members, the Latina woman, and her family, you may identify broad categories...
of media influence, peer relationships, religious influences, family dynamics, cultural factors, and negative self-concept.

Distinct from the first is the second form of case study data analysis—direct interpretation—the researcher directly interprets the meaning of a singular critical incident, concern, or issue within the data. This process is similar to taking a single puzzle piece and carefully analyzing this data for meaning before interpreting it within the whole case for its meaning. For our sample study, this could mean taking an influence on the case or a chronological event—the family’s decision to participate in family counseling within her treatment plan, for instance—and separating that critical incident from the case itself to examine its meaning, then placing this meaning within the context of the meaning it lends to the case as a whole.

The third form of data analysis Stake (1995) discussed is pattern identification, wherein the researcher examines broad categories within the case for their relationships or interactions. Returning to our sample study, say the researcher has used direct interpretation of the family’s participation in their daughter’s family counseling treatment plan, and the researcher has also identified the participation of the Latina participant’s partner in couple counseling. From the data collected, the researcher might elect to examine the data from the family counseling and the couple counseling (e.g., critical incidents, broad categories) in terms of their impact on the case. In the fourth form of case study data analysis, naturalistic generalization, the researcher actively interprets the data with an eye toward the ways an audience would be able to transfer or apply the broad categories or findings from the case study to another case(s). With our example of a Latina woman living with disordered eating, naturalistic generalization may include identifying influences on healing and recovery from disordered eating that are rooted in cultural factors.

Creswell (2006) supplemented Stake’s (1995) suggestions for case study data analysis with two additions. First, he recommended that if the researcher notes a chronological sequence of events in a case to use this sequence to guide data analysis. A good example of this type of data analysis was used in Murphy-Berman, Berman, and Melton’s (2008) examination of child abuse and neglect in South Carolina. The researchers used a multiple case study design to explore a sequence of three critical incidents or events in a large child abuse and neglect prevention program in three different communities in South Carolina.

Creswell (2006) also encouraged case study researchers to analyze the case description itself—the details and facts of the case. The tendency in case study data analysis can be to identify the major findings that help an audience understand the phenomenon, its boundaries, and its context more fully—but leave out some of the important details. If you take that approach, it is challenging to “paint a full picture” of the case. So, describe the case—how would you “tell the story” of your data based on your analysis. Remember, this shouldn’t be a magazine article about your case, but it should include the most salient facts and details of the case. Returning to our sample case study of a Latina woman in treatment for bulimia, the details and facts would probably include her diagnosis, her presenting issues, the duration of her treatment, the major “players” in her treatment, in addition to demographic details such as her age, socioeconomic status, and so forth.

Yin (2008) outlined four principles to guide researchers in case study data analysis. First, the researcher should ensure that all data relevant to the case(s) have been the
subject of analysis. A good gut check with this principle is to ask yourself “What data have I ignored and/or neglected to analyze that might contribute to the understanding of this case(s)?” Second, Yin asserted that rigorous case study data analysis should maintain not just the findings that are congruent with one another, but also search out what we discussed before as negative case analysis. The gut check question here is “What in my analysis of this case(s) is indicating a finding that appears to go against major identified findings?”

Third, Yin (2008) gave the researcher permission to highlight the most significant, meaningful findings of the case study in the process of analysis. This point aligns with our previous caution to “stay on course” with understanding your case—as opposed to veering down interesting (but perhaps not as important) roads in data analysis that take you further away from understanding the boundaries of your case rather than bringing you closer to this understanding. Another cautionary note here: Try not to lose the rich complexity and trustworthiness of your data analysis in this process (Drisko, 1997). The gut check question for the researcher here is “Does my analysis reflect the most important findings I have identified in the case?” Finally, Yin advised that the researcher must rely on and use his or her previous knowledge (which could be considered expertise) about the case to drive the analysis forward. This might be the most complex of his principles for case study data analysis. It is not enough to “just observe” the various data of a case study. The researcher brings him- or herself to the data analysis—and should embrace, own, and consider how to use this perspective to produce the highest possible quality of analysis. The gut check question here is “Where am I leaving my expertise as a researcher out of the data analysis?”

Data analysis methods in case study research are inductive because the researcher does not know what the important research challenges of theoretical issues will be before the research commences (Paulus, Horvitz, & Shi, 2006). Therefore, it can be challenging to predict the time necessary to complete case study data collection and analysis. Reis and Diaz (1999) used a case study method to examine academically successful urban female students for a time span of 2½ years. Not every case study, of course, will take this long. What is important about this study is that the research tradition, question, and data collection and analysis process required this amount of time to achieve the researchers’ ultimate goal of describing a case. This particular study also used a blend of analytic techniques across grounded theory (e.g., using axial and selective coding and saturation of the data, which we discuss in the next section).

A first step of case study data analysis often involves a “bounding of the data” (Paulus et al., 2006, p. 366). Based on the suggestions by Stake (1995), Creswell (2006), and Yin (2008), we believe that case study data analysis should strive for a balance of presenting the major facts of a case with a complexity of findings and interpretation that will illuminate prior misunderstandings and/or lack of information about a case and delineate the case from the context in which it resides. We also believe that there is a balance between drowning in the multiple sources of data you have collected and conducting a general analysis of all these sources, and coming up for air and relying on your qualitative data analysis skills. It’s okay to trust in yourself and your own expertise to guide qualitative data analysis. Just make sure that you are answering our “gut check” questions along the way! See Activity 11.1 to put some of these questions into action with case study data analysis.
ACTIVITY 11.1. “Gut Check” Questions for Case Study Data Analysis

In your research team, take your research topic (whether it is a case study design or not) and consider it within a case study design. You are looking at the data you have collected and analyzed. Answer the following questions with regard to your data analysis:

1. What data have I ignored and/or neglected to analyze that might contribute to the understanding of this case(s)?
2. What, in my analysis of this case(s), indicates a finding that appears to go against major identified findings?
3. Does my analysis reflect the most important findings I have identified in the case?
4. Where am I leaving my expertise as a researcher out of the data analysis?
5. How might my research tradition guide me to return to my data collection and analysis and shift the lens with which I analyze my data?

In addition to the “gut check” questions in Activity 11.1, we offer the following tips for qualitative data analysis for a case study tradition:

- Your data analysis should be guided by the case(s) itself, not the factors that influence the case. For instance, in a case study of an urban college counseling center partnership with a local school, you may analyze data from staff members. However, the analysis should focus on how these data elucidate the case itself. Aim to stay “on course” with your analysis. Write your research question on an index card and keep it near you during data analysis, or post your research question on your codebook to help you stay on track.

- Construct a strategy for your data analysis. Is it based on the chronological sequence of events or other boundaries of the case? Use this strategy consistently throughout your analysis.

- Consider the benefits and drawbacks of using each of Stake’s (1995) four recommendations for case study data analysis. You may not use each recommendation, but have a good rationale for which approach you do or don’t use.

- Flyvbjerg (2004) advises that good data analysis and interpretation of case studies should be able to ward off the “so what” question—meaning that the reader of a study should not have this question come to mind at all if the data analysis has been well thought out and guided by the case study itself. (We like this guy’s thinking!)

Case Example 11.1 offers an example of qualitative data analysis for the case study tradition.

CASE EXAMPLE 11.1. Teacher Community in an Early Childhood Education Center

In this case study, Blank (2009) investigated the extent to which an early childhood education center included a focus on teacher community. She defined teacher community as entailing connections between teachers and students, an emphasis on professional development, sources of innovation in teaching, reflective practice, and a culture of its own, among other factors. Blank’s data included participant observations of classrooms and participant development opportunities, in addition to interviews with key school personnel (e.g., principal, teachers).

Blank’s initial analysis involved immersing herself in the data through multiple readings of the participant observations and interview transcripts. This first analysis was general, and she began to identify large codes and to begin to set the stage for comparing her data. She used Stake’s (1995) categorical aggregation and pattern identification to guide this process. The following quote illustrates some of the ins and outs of her data analysis:

I utilized memo-ing (Stake, 2006), “contact summary reports, and periodic interim reports as tools for grouping codes, to show that they are instances of a general concept or themes pertaining to teachers’ views on community that were constructed through analysis: (a) shifting priorities, and (b) preference for privacy. Teachers’ values, school knowledge, external interests, and changes in leadership are examples of codes used to construct understandings of the teachers’ shifting priorities. Interaction contexts, teacher feedback, and recognition of good teaching are examples of codes that were categorized as teachers’ preference for privacy.” (2009, p. 376)

Here is a visual portrayal of Blank’s case study data analysis plan:

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**QUALITATIVE DATA ANALYSIS IN EXPERIENCE AND THEORY FORMULATION: GROUNDED THEORY, CONSENSUAL QUALITATIVE RESEARCH, PHENOMENOLOGY, AND HEURISTIC INQUIRY**

In this section, we discuss data analysis for the research traditions of Cluster 2 (see Chapter 2): grounded theory, consensual qualitative research, phenomenology, and heuristic inquiry. We discuss each individually, and you will notice some overlap in concepts because data analysis in all four traditions seeks to understand an experience and/or generate a theory. We distinguish where some of these overlapping data analysis strategies use similar analytic techniques, yet have different names in the four traditions. We also interweave case examples to bring data analysis “to life” for each tradition. After reviewing the four traditions, see Activity 11.2 on page 357.

**Grounded Theory**

Grounded theory, as we have discussed previously, seeks to generate a theory of a phenomenon (Glaser & Strauss, 1967). Grounded theory data analysis “simultaneously em-
ploys techniques of induction, deduction, and verification to develop theory” (Schwandt, 2001, p. 110). It can be overwhelming to consider how your data analysis will identify a theory of a phenomenon without understanding that there are specific steps to take in this process. Out of all the traditions we discuss, grounded theory is one of the traditions used most often across disciplines (e.g., constructivist grounded theory by Charmaz, 2005) in numerous ways, so there are several ways to methodically approach its data analysis. We summarize eight steps for grounded theory data analysis (Figure 11.2 on page 350), whether you are working as a researcher alone or on a research team.

First, the researcher (or research team) reads through the participants’ transcripts. Ideally, grounded theory data collection and analysis are recursive, so the first data analysis may entail one researcher or several research team members initially looking at one participant transcript that has been collected. Identifying large codes to comprise a codebook, the researcher or research team then comes to consensus on the codes “seen” in the data. Then, the researcher or research team collects and analyzes subsequent data based on this initial codebook. The codebook is then refined between each step of data collection and analysis. Within this refining of data collection and analysis is a process called constant comparison. Schwandt (2001) describes constant comparison as follows:

> Empirical indicators from the data (actions and events observed, recorded, or described in documents in the words of interviewees and respondents) are compared, searching for similarities and differences. From this process, the analysis identifies underlying uniformities in the indicators and produces a coded category or concept. Concepts are compared with more empirical indicators and with each other to sharpen the definition of the concept and to define its properties. (p. 110)

In other words, the researcher or research team is constantly comparing previous data collection and analysis to subsequent data collection and analysis.

As the larger domains are identified and constant comparison is used, the researcher or research team uses a coding process entailing open, axial, and selective coding (Corbin & Strauss, 2008). **Open coding** is a type of wide review of the data answering the question “What large general domains am I seeing in the data?” This might involve key words or phrases provided by the participants or the researchers. Then, **axial coding** is a process that begins to refine the open coding and examine relationships among the large open codes to understand more in-depth what the data are revealing with regard to theory building. Axial coding is a second-tier process by which open codes are collapsed into broader categories or codes. Next, **selective coding** is used to further refine axial codes. Selective coding is truly the step that begins to “look like” a grounded theory of your phenomenon. Selective coding is the most complex coding process in grounded theory, whereby patterns, processes, and sequences are identified among axial codes to generate a theory about a phenomenon.

Corbin and Strauss (2008) urged grounded theory analysts to develop their own unique style of, and techniques for, coding in these three categories. Are you a visual person? You might want to color-code everything. Do you like sticky notes? They might be lifesavers to help you stay organized and track your coding. Whatever helps you keep sight of your goal and purpose—theory building—those are the techniques and style you want to maintain throughout the process.
Let’s take a look at what open coding in a transcript looked like in Singh, Urbano, Haston, and McMahon’s (2010) study of school counselor advocates’ strategies for social justice change. Here is a “raw” transcript excerpt from one participant. (The underlined portions became an exemplar of an open code we defined as “relationship building.”)

You really have to, especially in the position that I am speaking from now, the administrators at local schools are really, is really the key, that you really need to be able to work with. Number one, I think that they will be immediately available to listen to the data that you gather as a school counselor, and any social justice issues that you will have to raise. Forming good relationships with them and making sure they know your job is to be an advocate for students—having them understand that you’re there for students, you care, you do a good job—that is key if you want to make change.

As my colleagues and I (Singh) delved into the axial coding process and revisited transcripts in our research meetings, we identified in the data that the broad open code of “relationship building” involved an action about their role as participants. We had identified a selective code that became “educating others about school counselors’ roles as advocates.” Toward the end of the data analysis, selective coding involved identifying relationships among the selective codes, which we decided to portray in a visual model that signified the close relationships among them. Case Example 11.2 presents additional information about grounded theory analysis for this study, and Perspectives 11.1 (on page 348) highlights research team reflections on grounded theory data analysis.

CASE EXAMPLE 11.2. School Counselor Advocates’ Strategies for Social Justice Change


“Researchers built recursivity into each stage of the research process so that simultaneous data collection and analysis continuously informed each other and, in turn, the emerging grounded theory. After the first two interviews were transcribed, four research team members individually reviewed and coded the transcripts using an open coding process. Open coding involved analyzing each line or paragraph of the transcripts for codes reflecting each participant’s experiences. More specifically, each discrete idea, event, or experience was given a name (e.g., ‘courage,’ ‘dialoguing,’ ‘student empowerment’). To create a codebook for the remaining interviews, researchers used constant comparison with their discrete codes to identify categories that related to a common overarching concept and to discern any discrepancies between their discrete codes.

“After each interview was conducted, transcribed, and coded using this codebook, axial coding was utilized to examine the relationship between each of the pre-established categories. During this stage, the research team created higher-level categories based on the data (e.g., ‘methods of consciousness raising’), thereby contributing to the initial development of a grounded theory of the phenomenon under study. Finally, selective coding was used to refine the theoretical model based on the identification of an overarching core category that accounted for most of the variation in the previously identified catego-
ries (e.g., ‘school counselors’ strategies for systemic change’). Researchers reviewed each
participant’s transcript using the codebook until saturation of findings was attained at
participant sixteen, where no new data were identified.

“Verification standards and procedures were built into each stage of the research pro-
cess. Member checking of transcripts, researcher reflexive journals, routine team meet-
ings, the use of multiple data analysts, and peer debriefing were utilized to maximize
trustworthiness of findings. Researchers identified thick descriptions of the phenomena
to demonstrate credibility of findings. The researchers’ immersion in the data for a year,
during which time the team continually reviewed and coded data as data were collected
and analyzed, further strengthened the credibility of findings. Throughout the research
process, a school counselor served as an internal auditor by attending research meetings
regularly and reviewing the data for accuracy of the coding and theory-building process.
An external auditor reviewed the products of the study (i.e., transcripts, research team
notes, emergent model) for accuracy. Finally, the research team searched for evidence to
disconfirm the emerging theory and modified the theory when necessary to ensure accu-
rate representation of the data” (p. 13).

Here is the visual portrayal of this grounded theory study:

As you proceed with these three types of coding, as a researcher or a team, you
begin to look for causal conditions, intervening conditions, and consequences (Cre-
swell, 2006). **Causal conditions** are factors influencing the phenomenon you are study-
ing. In the Singh, Urbano, and colleagues (2010) study above, the causal conditions
included the school context and the need for advocacy on social justice issues (i.e.,
achievement gap, overrepresentation of students of color in special education class-
Intervening conditions are ways in which participants address these influencing factors. For the Singh and colleagues study, the intervening conditions included the political savvy and consciousness raising that the school counselors reported were infused throughout their advocacy strategies in school. Finally, the consequences are the results of intervening conditions for participants. In the Singh and colleagues study, the consequences included the five general strategies the school counselors reported using for social justice change: initiating difficult dialogues, educating others about school counselors’ roles as advocates, using data for marketing, teaching students self-advocacy skills, and building intentional relationships.

**Perspectives 11.1. Grounded Theory Research Team Members Look Back on Data Analysis**

The perspectives below are from three research team members working on the Singh, Urbano, and colleagues (2010) grounded theory study. Read their perspectives to get a sense of how working on a grounded theory research team “feels” in the data analysis stage.

“The grounded theory data analysis process allowed me to get very close to the experiences and voices of our participants through our data. We became heavily immersed in their collective perspectives, and where these perspectives overlapped in concrete, meaningful ways. The challenges were that the process is messy. It often seemed that we had a swirling, nebulous mass of data that somehow we needed to bring order and structure to. This can be overwhelming, and it takes a lot of conceptual work to develop this structure. I think you have to get comfortable with the constant shifting of structures and rearranging of your model as the theory emerges from your data. I enjoyed the collaborative and intellectually engaged nature of the process. The constant conceptualization and reconceptualization of what you are seeing develop from your data is challenging, exciting, and fun. This is a very active process, and hashing out with your team what your data mean and how they fit in the larger context of your emergent theory is a wonderful experience. I learned tremendously from the perspectives of my colleagues as we wrestled with our data. Because grounded theory data analysis is such a collaborative and interactive process, I think it is important to have a great research team. It’s also important to set the tenor of the analysis process as an open, collegial, communicative process, where all voices and perspectives are valued—those of the participants and also those of the researchers in analyzing the data.”

—ELEANOR MCSHANE, MS

“Prior to becoming part of this research team, most of my research experience had involved quantitative data. Hearing our participants speak to their experiences, and then working to develop a model that honored these voices, was thus new territory for me. Connecting with the participants during the interviews made the data analysis process feel all the more significant to me—having heard the participants’ stories in person, having been granted the privilege of documenting their experiences—made it seem all the more crucial that we develop a model that was truly reflective of their collective message. One of the elements of the data analysis process that seemed most challenging was that the sheer amount of data—the ideas, themes, and concepts that emerged—made it difficult to select those themes that were most significant and that were threaded throughout each of the participants’ stories. In addition, it was also striking to me how I, as a researcher, approached the data that I
collected personally, and the data that I didn’t collect personally. More specifically, there are themes that emerge clearly on the page as you read the transcripts, and then there are feelings, ideas, ‘senses’ that you get when you speak to someone in person. I, and we as a team, had to challenge ourselves always to come back to the data, to the words on the page, to be sure that the themes that were emerging were truly grounded in the written word, and not just in our own interpretations or the feelings we got when we spoke to the participants. To anyone interested in working with qualitative data, I would advise that patience is key. The process of working in the grounded theory paradigm is a long one and can feel unclear at times. It is so important for all members of the team to trust the process—to know that if the team is committed to the data, and to the voices of the participants, the themes and the model that emerge will indeed be a grounded theory.”

—MEG HASTON, MS

“The data analysis process for our grounded theory study was a complicated and rewarding one. We collected about 400 pages of rich data, which were initially overwhelming to sort through. We relied on each other—our research team members—to keep us grounded as we initially sorted through the volume of data during the open coding stage. Our team was passionate about the topic of social justice and became progressively more excited about the emerging theory as we moved from the open coding stage to the axial and selective coding stages. We used our analytic, creative, visual, and comedic selves throughout the analysis process and experienced a shared sense of excitement when our theory eventually reached its final form. One of the greatest opportunities of completing a grounded theory study is the chance to work collaboratively with a group of individuals who share a common interest. Another unique opportunity is the inevitable intimacy of the data analysis process, both among the researchers and with the participants (through their transcribed voices). By the end of the data analysis process, I felt empowered by and connected to 16 social justice advocates (our participants) and three inspirational colleagues (the research team)—quite an incredible experience!

“For me, the greatest challenge of the data analysis process involved sorting through the huge volume of data, which was a circuitous process rather than a linear one. The real challenge here was accepting that the process was not going to be tidy, organized, and straight. I think I would give two pieces of advice for anyone embarking on the data analysis process of a qualitative study. First, select a supportive team that shares a passion or interest for the topic at hand. Second, accept before you even begin analyzing the data that it will be a circuitous process rather than a linear one.”

—ALESSANDRA URBANO, PhD

In selective coding, Corbin and Strauss (2008) emphasized two tasks: identifying a central category and integrating variation into data analysis. The authors discuss the central category as having “analytic power” (p. 146) that is like a black hole: It is a central category that brings all the other codes together. When identifying a central category, they cite Strauss’s (1987) criteria, including that it is an idea that (1) appears frequently, (2) is not forced, (3) is named or phrased in a way that could be further researched in other studies, and (4) evolves in its depth and power to explain the phenomenon. The central idea should also be capable of accounting for variation, or varying explanations, of the phenomenon. Speaking of variation, Corbin and Strauss assert that the variation represented in a final grounded theory data analysis is ultimately important because no phenomenon is static. Ideas ebb and flow within our data—“there is variability with dif-
Different people, organizations, and groups falling at different dimensional points along some properties. … We want to bring out the variations both within and between categories” (pp. 160–161). Using the Singh, Urbano, and colleagues (2010) study, for instance, the central idea was the advocate’s identity. Each participant’s advocate identity contained within it variations—contradictions, divergences, and other ways in which the selective codes indicated variability. We identified and discussed this variability.

So, if this all sounds like a good deal of coding—it is! How do you know when you are “finished” with your data collection and analysis? That is where saturation of the data comes into play in grounded theory analysis. Saturation of the data occurs in the axial coding step, where you as a researcher or research team identify no “new” data in subsequent participants’ transcripts. See Figure 11.2 for a summary of eight steps to organize your grounded theory data analysis.

Consensual Qualitative Research

As we discuss data analysis in consensual qualitative research (CQR), you will see the many similarities it has with grounded theory data analysis. Some of the key features that distinguish CQR analysis are its emphases on consensus, shared power, and frequency counting. There are five main data analysis components in CQR (Hill et al., 1997, 2005). First, a primary research team conducts a domain development and coding process. In this step, each research team member immerses him- or herself in all of the data, reading each participant transcript. As team members read these data, their analysis begins by identifying a list of large domains, categories, or themes. Then the research team meets as a collective group, and each member presents his or her identified domains to one another. The team members argue, debate, and come to consensus on one group of large domains. Then the individual members revisit the data through a second analysis using these large domains to code.

Second, the research team abstracts core ideas within domains (domain abstraction). As the team members reimmerse themselves in the data, they keep an eye out for core ideas that illuminate aspects of domains they have previously selected to examine. Third, members of the research team meet and attempt to reach consensus on these
core ideas through a process of cross-analysis, wherein categories are developed by team members through a consensus-building process. In this process team members examine each category for evidence across all, some, and/or none of the participants. Once the list of categories is finalized, the team members then return to the data and code all participant interviews within these categories. This cross-analysis should result in a separate document that includes a list of domains and within-domain categories common to all participants and any participant data that were not common across participants and/or were not included in another domain or subdomain.

The fourth key component of CQR is the use of an external audit. In this process, a secondary research team comes in to assess the accuracy of the cross-analysis and the creation of domains and subdomains common to all participants. The auditors also examine the data and categories listed as not common to all participants and/or placed in an “other” category. The auditors then communicate their audit to the primary research team, suggesting alterations, revisions, and/or data that were not addressed by the original abstraction of core ideas and cross-analysis. You can see how this process of using what might be termed a primary research team and a secondary research team can be complex, and perhaps even burdensome. However, this is the heart of the rigor of CQR, so it is a critical interaction between these two research teams.

Finally, the fifth data analysis step with CQR involves frequency analysis. Now, we have already discussed in Chapter 10 how we feel about frequency—the benefits and the challenges of frequency counts. Regardless of the epistemological challenges we believe are inherent in “counting” responses in qualitative research, this is a critical aspect of the way Hill and colleagues (1997, 2005) constructed CQR’s data analysis. In this final step, research team members categorize domains into one of four categories: general (all or all but one case), typical (more than half of the cases up to the cutoff for general), variant (at least two cases up to the cutoff of typical), and rare (used for sample sizes greater than 15, two or three cases). See Table 11.2 to see what CQR findings “look like” at the end of the five steps of data analysis.

Okubo, Yeh, Lin, Fujita, and Shea (2007) used CQR to examine the career decision-making processes of eight Chinese immigrant youth. The authors developed and coded the data from transcripts into large domains and subdomains for an initial list, or codebook. Then, the research team members reread each transcript, using the codebook to indicate the domains and subdomains in the data. They invited recursivity into their data analysis by revising the codebook at several stages, based on what they were “seeing” in the data. When abstracting core ideas within domains, the research team members “constructed core ideas individually and then came to consensus” (p. 442). Next, the cross-analysis of data included “bringing all the transcripts together” (p. 442) and utilizing an auditor to assess the accuracy of the data analysis thus far. Finally, the research team addressed frequency issues and categorized their domains as general, typical, or variant, and then portrayed them in a table because CQR asserts that “representativeness can be plotted on [a] table to clearly show the results” (p. 443). The researchers did not note any rare domains.

At the end of Okubo and colleagues’ (2007) CQR data analysis, the research team had identified 10 domains in participants’ transcripts and between three and eight subdomains per domain. Interestingly, all the subdomains were either typical or variant in their frequency. See Figure 11.3 on page 353 for a visual portrayal of the CQR data analysis steps Okubo and colleagues used in their study.
Phenomenology

Phenomenological data analysis differs from grounded theory and CQR in that although all three traditions examine participants’ experiences, phenomenology’s sole focus is to understand the depth and meaning of these experiences (Moustakas, 1994) rather than to generate a theory. One of the reasons we chose to discuss the data analysis of these three traditions in the same section is that the unique similarities and differences in the data analysis among the three can be more easily understood when grouped together. When one engages in phenomenological data analysis, it can be tempting to begin down a road of theory building. However, the integrity and quality of phenomenological data analysis are retained more when the researcher refrains from this temptation. Phenomenology—and its focus on understanding the meaning of participants’ lived experiences—is a powerful perspective in its own right!

Moustakas (1994) is probably most influential in revisiting phenomenological data analysis techniques, summarizing, and expanding the steps for analysis. We include two reviews: Moustakas’s modification of van Kaam’s (1959, 1966) phenomenological data analysis, which includes seven steps, in Table 11.3 on page 354; and his modification of the Stevick–Colaizzi–Keen phenomenological data analysis in Table 11.4 on page 355. Creswell (2006) asserts that he sees the Stevick–Colaizzi–Keen approach used more

<table>
<thead>
<tr>
<th>Domain/category</th>
<th>Illustrative core idea</th>
<th>Frequency</th>
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<tbody>
<tr>
<td>1. The homeless experience</td>
<td></td>
<td></td>
</tr>
<tr>
<td>a. Negative feelings about being homeless</td>
<td>Depression, shame, frustration, injustice, helplessness</td>
<td>Typical</td>
</tr>
<tr>
<td>b. Greater empathy for the homeless</td>
<td>Changed attitudes, greater sympathy</td>
<td>Typical</td>
</tr>
<tr>
<td>c. Homeless persons struggle with substance use, mental illness, and physical illness</td>
<td>Alcohol, drugs, mental and physical illness are problems</td>
<td>Typical</td>
</tr>
<tr>
<td>d. Dichotomy of homelessness</td>
<td>There are two different types of homeless individuals—those who choose to be homeless and individuals who are not homeless by choice</td>
<td>Typical</td>
</tr>
<tr>
<td>2. Perceptions of men and masculinity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>a. Man as the “breadwinner”</td>
<td>Breadwinner, provider, worker</td>
<td>General</td>
</tr>
<tr>
<td>b. No changes in masculinity since becoming homeless</td>
<td>A succinct “no” when asked if they viewed their masculinity differently since becoming homeless</td>
<td>Typical</td>
</tr>
<tr>
<td>c. Others perceive homeless men negatively</td>
<td>Viewed as drunk, looked down upon, outcast</td>
<td>Typical</td>
</tr>
<tr>
<td>3. Changing social status</td>
<td></td>
<td></td>
</tr>
<tr>
<td>a. Aspirations for upward mobility</td>
<td>Desires to change to a higher social class, including not being homeless anymore and discussion of home, family, and job</td>
<td>Typical</td>
</tr>
<tr>
<td>b. Barriers to change identified</td>
<td>“Myself,” financial situation, substance abuse, and/or health</td>
<td>Typical</td>
</tr>
</tbody>
</table>

Steps in Okubo and colleagues’ (2007) CQR data analysis.

**Step 1**
Developing of and coding into domains of career decision-making processes of Chinese immigrant youth (independent team members read and reread transcripts).

**Step 2**
Abstracting of core ideas within domains of career decision-making processes (large domains such as identity development and relationships with family are created).

**Step 3**
Cross-analysis of career decision-making domains for Chinese immigrant youth participants (research team looks at data as a whole).

**Step 4**
Auditor reviews, revises, and communicates alternate perspectives on domains and subdomains of Chinese immigrant youth career decision-making processes.

**Step 5**
Identify frequency of general, typical, and variant domains. There were three domains for eight youth. Domains include lack of role model, confusion about self-identity, and ethnic identity confusion.

**FIGURE 11.3.** Steps in Okubo and colleagues’ (2007) CQR data analysis.
often recently. We believe both modifications provide helpful ways to analyze phenomenological data. See Tables 11.3 and 11.4 for helpful guides through the intricacies of phenomenological data analysis. Specifically, in Table 11.3, we have reproduced Moustakas’s guidelines for phenomenological analysis. For now, we discuss the following components of phenomenological data analysis in greater depth: bracketing, horizontalization, textural description, and structural description.

Padgett (2004) used the phrase of “burrowing inward” to describe phenomenological data analysis—appropriate words to remind us of its purpose: to understand the depth and essence of participants’ lived experiences. At the outset of phenomenological data analysis, the researcher immerses him- or herself in the data. A critical pre–data analysis step is the **bracketing** of researcher bias and assumptions about the study’s focus.

Just as grounded theory and CQR begin a coding process (open, axial, and selective coding, and development of codes, abstracting core ideas, and cross-analysis, respectively), phenomenological data analysis begins with large domains or categories of text. The term used to describe this process is horizontalization. As discussed in Table 11.4, the research team begins to identify nonrepetitive, nonoverlapping statements in participants’ transcripts. This is an important first step not only in analyzing the data,

<table>
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<tbody>
<tr>
<td>Using the complete transcription of each research participant:</td>
</tr>
<tr>
<td>1. <strong>Listing and Preliminary Grouping:</strong> List every expression relevant to the experience. (Horizontalization)</td>
</tr>
<tr>
<td>2. <strong>Reduction and Elimination:</strong> To determine the invariant constituents:</td>
</tr>
<tr>
<td>Test each expression for two requirements:</td>
</tr>
<tr>
<td>a. Does it contain a moment of the experience that is a necessary and sufficient constituent for understanding it?</td>
</tr>
<tr>
<td>b. Is it possible to abstract and label it? If so, it is a horizon of the experience. Expressions not meeting the above requirements are eliminated. Overlapping, repetitive, and vague expressions are also eliminated or presented in more exact descriptive terms. The horizons that remain are the invariant constituents of the experience.</td>
</tr>
<tr>
<td>3. <strong>Clustering and Thematizing the Invariant Constituents:</strong> Cluster the invariant constituents of the experience that are related into a thematic label. The clustered and labeled constituents are the core themes of the experience.</td>
</tr>
<tr>
<td>4. <strong>Final Identification of the Invariant Constituents and Themes by Application:</strong> Validation</td>
</tr>
<tr>
<td>Check the invariant constituents and their accompanying theme against the complete record of the research participant. (a) Are they expressed explicitly in the complete transcription? (b) Are they compatible if not explicitly expressed? (c) If they are not explicit or compatible, they are not relevant to the co-researcher’s experience and should be deleted.</td>
</tr>
<tr>
<td>5. Using the relevant, validated invariant constituents and themes, construct for each co-researcher an <strong>Individual Textural Description</strong> of the experience. Include verbatim examples from the transcribed interview.</td>
</tr>
<tr>
<td>6. Construct for each co-researcher an <strong>individual structural description</strong> of the experience based on the Individual Textural Description and Imaginative Variation.</td>
</tr>
<tr>
<td>7. Construct for each research participant a textural–structural description of the meanings and essences of the experience, incorporating the invariant constituents and themes.</td>
</tr>
<tr>
<td>From the individual textural–structural descriptions, develop a composite description of the meanings and essences of the experience, representing the group as a whole.</td>
</tr>
<tr>
<td>Source: Moustakas (1994, pp. 120–121).</td>
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</table>
but also in managing the data in a way that is efficient. The textural description is similar to the process of how grounded theory and CQR begin to refine the data into new categories. However, the real distinction here is that the textural description always strives to understand the meaning and depth of the essence of the experience.

Depending on how the researcher chooses to manage the phenomenological data analysis, he or she may have a list or visual model that represents not a theory, but the experiences of participants. The list is a result of refining the horizontalization of data into a textural description of the phenomenon’s essence. Then a structural description is identified by the researcher and/or team, identifying multiple potential meanings within the textural description, in addition to variations among these meanings (i.e., what is identified as “opposites” or as “tensions” in the data). You can think of structural description as similar to grounded theory’s axial coding, wherein relationships are identified and understanding of their complexity is sought; or as somewhat similar to CQR’s identification of the general, typical, and variant themes if the tensions between these were fully examined for the essence of their meaning.

Because the goal of phenomenological data analysis is to deeply understand a phenomenon’s essence, we advise that you be familiar with Moustakas’s modifications in Tables 11.3 and 11.4. However, we also encourage you to utilize any techniques with your data analysis that you think are necessary to best understand the essence of your study. Often, this entails creating a case display or writing the “essence” of the phenomenon for each participant, and then combining these individual essences into one composite essence. Think of your phenomenological data analysis via horizontalization and textural and structural description as a metaphorical “sieve” through which to filter all the participant descriptions. What is left in your sieve is the essence of participants’ lived experiences—and your data analysis is continually aiming to get closer and closer

### TABLE 11.4. Moustakas’s (1994) Modification of Stevick–Colaizzi–Keen Phenomenological Data Analysis

<p>| | |</p>
<table>
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<tbody>
<tr>
<td>1. Using a phenomenological approach, obtain a full description of your own experience of the phenomenon.</td>
<td></td>
</tr>
<tr>
<td>2. From the verbatim transcript of your experience complete the following steps:</td>
<td></td>
</tr>
<tr>
<td>a. Consider each statement with respect to significance for description of the experience.</td>
<td></td>
</tr>
<tr>
<td>b. Record all relevant statements.</td>
<td></td>
</tr>
<tr>
<td>c. List each nonrepetitive, nonoverlapping statement. These are the invariant horizons or meaning units of the experience.</td>
<td></td>
</tr>
<tr>
<td>d. Relate and cluster the invariant meaning units into themes.</td>
<td></td>
</tr>
<tr>
<td>e. Synthesize the invariant meaning units and themes into a description of the textures of the experience. Include verbatim examples.</td>
<td></td>
</tr>
<tr>
<td>f. Reflect on your own textural description. Through imaginative variation, construct a description of the structures of your experience.</td>
<td></td>
</tr>
<tr>
<td>g. Construct a textural—structural description of the meanings and essences of your experience.</td>
<td></td>
</tr>
<tr>
<td>3. From the verbatim transcript of the experience of each of the other co-researchers, complete the above steps, a through g.</td>
<td></td>
</tr>
<tr>
<td>4. From the individual textural—structural descriptions of all co-researchers’ experiences, construct a composite textural—structural description of the meanings and essences of the experience integrating all individual textural—structural description into a universal description of the experience representing the group as a whole. (p. 122)</td>
<td></td>
</tr>
</tbody>
</table>

Perspectives 11.2. The “Essence” of Phenomenological Data Analysis

“In our phenomenological study (Singh, Hays, et al., 2010) of the resilience strategies of South Asian American child sexual abuse survivors, I remember that Danica Hays and I often found ourselves musing about when we would arrive at the “essence” of the phenomenon we sought. We had case displays. We had long debates, discussions, and meetings about each participant’s experience of resilience and child sexual abuse. We bracketed our own assumptions and biases consistently. We talked about horizontalization and structural and textural description, and we kept sifting through an immense amount of data. And then one research meeting, it hit us. The essence of participants’ experience was speaking to us through the data. It felt like a moment out of that movie The Matrix, when the ‘grid’ comes to light! It felt like a magical moment. But the truth was that we spent many long weeks laboring over the data, digging deep into participants’ descriptions of the phenomenon. I probably could have recited Moustakas’s modifications of phenomenological data analysis in my sleep! In the end, we had a rich, complex visual model of participants’ experiences that captured their essence indeed.”

—AAS

“One of the many challenges of phenomenological studies for me has been to honor and illuminate their great contribution—providing the essence of a lived experience of a phenomenon, stripped of my experiences of that phenomenon. Being able to bracket and refrain from theory generation is a valuable skill to hone. Bracketing is difficult at times because it takes practice to ‘set aside’ our own experiences and judgments of those experiences. Saying to myself, ‘This, what I know and have experienced, has to be placed outside the study so that I can provide space for what my participants contribute. There is no need to try to take their experience and apply it to others. This only limits others’ descriptions of their essence of the same phenomenon.’ No matter the degree to which I have experienced a phenomenon, it is not as ‘valuable’ to the study as the experiences of those participants with whom I am interacting. Furthermore, their essence does not necessarily apply to others outside the study. (There is a reason you wanted to tell their story in the first place!) Saturation, common in other traditions, is irrelevant. The greatest joy of phenomenology and phenomenological analysis is to be present for your participants and give justice descriptively to their story.”

—DGH

to that essence. See Perspectives 11.2 for our descriptions of the frustrations and joys of phenomenological data analysis.

Heuristic Inquiry

There are many overlaps between heuristic inquiry and phenomenological data analysis because they both “seek to understand the wholeness and the unique patterns of human experiences in a scientifically organized and disciplined way … requiring the researcher to dwell intensely with subjective descriptions and to search for underlying themes or essences that illuminate the meaning of the phenomenon” (Casterline, 2009, p. 2). Moustakas (1990) noted that heuristic inquiry is different from phenomenology in terms of the role of the researcher. In heuristic inquiry the role of the researcher is to not separate his- or herself from the phenomenon being studied. Often, the researcher
has an experience of the phenomenon and thus brings not only his or her expertise to the data analysis, but also experience that must be analyzed.

Moustakas (1990) outlined important steps of data analysis for heuristic inquiry. He used the term illumination to describe the quest of the researcher to identify categories, themes, and patterns of the phenomenon within the data. In this quest, the researcher begins to recognize the depth and meaning of the phenomenon. He also discusses a stage of data analysis called explication, wherein the researcher uses self-reflection to further analyze the structural and textural descriptions that were described in the previous section on phenomenological data analysis. Moustakas then describes the final task of data analysis in heuristic inquiry as creative synthesis. Similar to the final stage of phenomenological data analysis, the researcher seeks the best way to portray the findings as a composite whole. The key difference between this final stage is, again, the experience the researcher has of the phenomenon. Case Example 11.3 illustrates the data analysis steps of a heuristic inquiry.

**CASE EXAMPLE 11.3. A Teacher’s Heuristic Inquiry of Gifted Education**


In this study, Eger (2008) used heuristic inquiry to examine feelings of disempowerment as a teacher advocating for change within a gifted program in an urban school district. During the illumination phase, she identified large domains of common themes across interview data she had collected from key informants within the school and from the research literature in gifted education. In the explication stage, Eger self-reflects on her personal experiences as a researcher and on her shared experiences with the phenomenon. The final data analysis in her study involved creative synthesis, wherein she visually portrayed her findings to depict the essence of the feelings she experienced and the context in which she experienced them.

**ACTIVITY 11.2. Experience and Theory Formulation**

Within your research groups, answer the following questions:

1. What are the unique differences and similarities between grounded theory and CQR data analysis?
2. With your research topic, what would be your data analysis steps if you used a grounded theory approach versus a phenomenological one?
3. What are the unique differences and similarities between data analysis with phenomenology and heuristic inquiry?
4. Take the four data analysis approaches with experience and theory formulation we have discussed in this section. Toward which approach do you naturally gravitate? Which approach do you find challenging?
5. If you have already collected and analyzed your data from an experience and theory formulation research tradition, how might you return to your analysis and refine it based on your discussion within your group?
In this section we review the analytic strategies that employ narratology, biography, and hermeneutics. Especially regarding the analysis of symbol and text in these traditions, we encourage you to immerse yourself in the literature of the field because there are many creative and innovative analytic strategies continually being developed. We focus our review of symbol and text analysis on various aspects of narrative analysis. As a researcher, you should consider tailoring these aspects of analysis to the various other research paradigms within the cluster of symbol and text we have discussed previously (i.e., symbolic interaction, semiotics, life history) and/or applying the more generic data analysis techniques we discussed in Chapter 10.

**Narratology**

Narrative data analysis is used in the narratology tradition. We highlight Avdi and Georgaca’s (2007) review of narrative data analysis techniques used in examining psychotherapy because of the specificity of their types. The authors note five types of analytic approaches that have been used in examining details of client narratives. These five types are distinct in terms of the focus of their data analysis (see Table 11.5).

First is an approach involving general analysis of themes in the client narrative, or thematic analysis. This is a method wherein the researcher identifies central themes and subthemes and their development across counseling sessions. The authors discuss studies that use this analytic technique to note a larger storyline in which these themes and subthemes are subsumed. Other approaches might include analyzing critical incidents within therapy sessions or examining the data for intrapersonal and interpersonal processes within various modalities of psychotherapy.

Second are investigations into the typology of clients’ narratives, or typological analysis. Typology refers to a type of presenting issue clients bring into psychotherapy. They cited Dimaggio and Semerari’s (2001) distinction between “effective” and “ineffective” narratives that are categorized based on the level of organization, integration, and assessment of meaning, coherence, and continuity of clients’ stories. In this type of analysis, Avdi and Georgaca (2007) noted that the focus is on the individual client narrative more than the interaction within psychotherapy or the content.

<table>
<thead>
<tr>
<th>Table 11.5. Types of Narrative Data Analysis</th>
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</thead>
<tbody>
<tr>
<td>1. Thematic analysis</td>
</tr>
<tr>
<td>2. Typological analysis</td>
</tr>
<tr>
<td>3. Dialogical analysis</td>
</tr>
<tr>
<td>4. Narrative process coding system</td>
</tr>
<tr>
<td>5. Whole client narrative analysis</td>
</tr>
</tbody>
</table>

**Source:** Avdi and Georgaca (2007).
The third type the authors discussed is less common: data analysis that takes a
dialogical approach to a client narrative, or **dialogical analysis**. They cite Lysaker, Lan-
caster, and Lysaker’s (2003) study of the narratives of clients living with schizophrenia.
These researchers focused on where the dialogue failed in psychotherapy and suggest-
eted that the failure was evidence of a lack of organization in the narrative or a lack of
interaction. Avid and Georgaca (2007) see this type of narrative data analysis as prom-
ising for noticing positive change in psychotherapy, and they suggest a focus on the
psychotherapist’s role in the discourse as well.

Fourth, Avid and Georgaca (2007) reviewed studies that emphasize the processes
within the client narratives, termed **narrative process coding system** (NPCS; Angus,
Levitt, & Hardtke, 1999). There are three analytic techniques within NPCS. The first, ex-
ternal narrative sequences, describes events. The second, internal narrative sequences,
builds on a description of clients’ subjective experiences (e.g., thoughts and emotions)
and expands these descriptions. The third, reflexive narrative sequences, analyzes the
meaning of client narratives. These three analytic techniques enable “the researcher to
track shifts both in the topics discussed and in the types of narrative processes involved
in a client narrative, within and across sessions” (p. 413).

Fifth, Avid and Georgaca (2007) reviewed a diverse group of studies that focuses
on the whole client narrative, or **whole client narrative analysis**. The authors explain
that this type of narrative analysis is similar to case study data analysis, which empha-
sizes analysis that illuminates the entire “case” of the narrative rather than its diverse
parts. They cite McLeod and Lynch’s (2000) study of a female client’s narrative of the
satisfaction she experiences with her life as she copes with depression. The analysis
focuses not only on the client’s narratives and perspective, but also on those of the
psychotherapist—and how both intersect with one another to build a “whole” client
narrative.

Kelly and Howie (2007) also outline steps for narrative data analysis in a study
they conducted with psychiatric nurses in Gestalt therapy training. Their data analysis
entailed eight steps:

1. Connecting with the participant’s story.
2. Attention to Dollard’s (1946) life history method.
3. Chronological ordering of events and experiences.
4. Core story creation.
5. Verification of core stories.
6. Examination of plots and subplots to identify a theme that discloses their sig-
nificance.
7. Examination of plot structure.
8. Emplotted whole narratives. (pp. 139–141)

Some of the above steps will sound familiar to you from other analytic techniques
we have reviewed. In Step 1 Kelly and Howie (2007) immersed themselves in the data
by reading and rereading the transcripts and listening to original audiotapes. Step 2
involved examining the data through the lens of Dollard’s (1946) life history analytic
techniques to identify the narrative development of cultural context, character values, key players, actions and decisions of character, plot lines, history, and the start-middle-ending of the narrative. Step 3 used the chronology of the narrative to analyze it. The authors color-coded sections of the transcripts according to events during, before, and after the Gestalt therapy training. Step 4 involved the core story creation, which included identifying thematic fragments and subplots of four stories. In Step 5 the authors shared the four identified core stories with their participants to determine the accuracy of their data analysis. Step 6 investigated the plots and subplots to determine the meaning and significance of the narratives. Step 7 focused on the plot structure, returning to the core stories in a microscopic manner. The authors used diagrams to break down each core story and identify major influences on the plot. Finally, Step 8 involved restructuring the four core stories in order to create an entire whole narrative that subsumed them all. In the final version of their manuscript, the authors provided an example of a core story—the story of Mary—as a whole narrative example.

We have presented two strategies for narrative data analysis. Let’s turn to Activity 11.3 to practice analyzing narrative data.

**ACTIVITY 11.3. Narrative Data Analysis**

Select a favorite children’s book and analyze the narrative using one or both of the narrative data analysis strategies discussed in this chapter. (As a class decide on a possible research question to guide the analysis.) Work in small groups to discuss some of the benefits and challenges of narrative data analysis. Discuss your analysis as a class. How might it be useful for a research topic in counseling or education?

**Biography**

Data analysis with biography focuses on the life events and experiences of participants. Creswell (2006) outlined six steps for analysis of the data within the biography tradition. We use an example of a biography of an expert in trauma in order to bring these steps “alive.” In the first step, Creswell encourages the researcher to organize data files into a framework that will facilitate coding. For our example, we may have a series of interviews with the expert herself, in addition to interviews with her peers, clients, and trainees. A natural strategy might to organize the interview transcripts according to the role of the person interviewed. In the second step of data analysis, the researcher combs through the transcripts to identify broad codes or domains. For the biography of a trauma expert, we might identify broad codes in the interviews with her clients as including empowerment interventions, attention to interpersonal skills, and cultivation of hope.

For the third step of data analysis in biography, Creswell (2006) discussed the importance of description that focuses on the chronology of the participant's experiences in life. With our example, this might entail describing the critical incidents the participant identified as pivotal in the development of her interest in trauma, such as witnessing a traumatic event within her family and/or surviving a traumatic event herself. The fourth step involves pinpointing the stories, epiphanies, and any contextual materials...
of the participant’s life. For our trauma expert, this could mean identifying stories she tells about her own trauma practice with clients. We might also describe epiphanies she has had in the development of her trauma experience—such as a particular mentoring or training experience. Then we could explore the contextual materials of these stories and epiphanies that have shaped her—possibly influential texts she read or cultural artifacts in her life.

In the fifth step Creswell (2006) encouraged the researcher to **work toward a theory**, or a framework, that serves as an organizing structure containing the patterns and meanings identified in the data analysis. In our example, we might identify patterns and meanings of “rebirth” after tragic circumstances or resilience in the face of adversity. Thus, an organizing structure of resilience might be the framework or theory we propose in which we are able to describe the many subthemes within the biography. Finally, in the sixth step, the researcher expands the theory or framework in the fifth step to highlight both the distinct and more ordinary aspects of the participant’s life. Back to our example, the biography of our trauma expert might describe both the everyday and extraordinary experiences of resilience within her life.

**Hermeneutics**

Hermeneutic data analysis involves interpreting “sacred” textual data. Recall from Chapter 2 that hermeneutics can be closely aligned with, or even intentionally paired with, phenomenology due to its emphasis on understanding the meaning of text or narratives (Grant & Boersma, 2005).

Diekelmann and Ironside (2005) described the process of hermeneutical data analysis that we categorize in six steps. First, interview transcripts are read in their entirety by members of the research team (which the authors describe as the foundation of hermeneutical analysis of data), and broad domains are identified. In the second step, the research team members initiate dialogue with one another regarding their interpretations of the interview transcripts; this dialogue entails checking analysis of specific text with one another. A third step involves refinement of the broad domains into more distinct categories or abandoning themes that do not hold up across the team members’ analysis. Also, team members may identify new broad themes—a step that may require looking to future participant interviews to confirm. The fourth step requires research team members to explore any contradictions or data analysis unaccounted for in the previous identification of codes. This step may entail interviewing previous participants again.

In the fifth step team members should “read across all texts and write critiques of the interpretations . . . to extend, support, or overcome the themes and patterns identified by hermeneutics” (Diekelmann & Ironside, 2005, pp. 260–261). In the sixth step, the research team identifies patterns that explain the relationship between the domains. This final step does not entail a conclusion. Rather, the authors assert that hermeneutic data analysis does not have an ending, and they cite Benner’s (1994, p. 116) quote that “cycles of understanding, interpretation, and critique” continue. In this manner, researchers are reminded of the importance of acknowledging their own role in deciding when data analysis ends—in addition to analyzing how, why, and when this end point was selected.
Hummelvoll and Severinsson (2001) used a hermeneutic data analysis in a study of health professionals working in an acute psychiatric ward and the care provided in that setting. First, they read their field notes and other textual data several times to become immersed in the data before proceeding with analysis. Second, the authors identified text in the transcripts that revealed the health professionals’ views about the care they provided in the setting. Third, the authors distinguished central themes that were related to their research question. Fourth, they revisited the data to illuminate the central themes by providing examples from the text. Throughout the hermeneutic analysis, others analyzed their researcher reflections and analysis as the process unfolded. See Table 11.6 for an excerpt of their central themes identified in this study’s data analysis. Also see Activity 11.4 to delve further into data analysis with symbol and text.

<table>
<thead>
<tr>
<th>Themes</th>
<th>Content</th>
<th>Statements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thriving</td>
<td>Professional development</td>
<td>“Clinical supervision means a lot to me. I experience both personal and professional development.”</td>
</tr>
<tr>
<td></td>
<td>Significant work</td>
<td>“It is rewarding to establish good relations, observing the patient improve and being a part of his/her progress.”</td>
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<tr>
<td></td>
<td>Good collegiate relations</td>
<td>“We function as a team and consult each other. We have a tone which allows both joking and being serious.”</td>
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<tr>
<td></td>
<td>Being valued</td>
<td>“My opinions are considered, and I can influence decisions concerning treatment and care.”</td>
</tr>
<tr>
<td>Strain</td>
<td>Unpredictable climate and work-related stress</td>
<td>“Efficiency is measured in terms of admissions, and not what we really achieve with our patients.” “You never know what you have to deal with when starting your shift—especially during late evenings and weekends.”</td>
</tr>
<tr>
<td></td>
<td>Feeling inadequate</td>
<td>“It happens that I have a guilty conscience when I come home after my shift because I have partly left my primary patients unattended due to having too many tasks.”</td>
</tr>
<tr>
<td></td>
<td>Diffuse directions in the work situation</td>
<td>“Long-lasting seclusion without clarified attitudes and guidelines causes strain.”</td>
</tr>
<tr>
<td></td>
<td>The patients’ suffering and inadequate quality of care</td>
<td>“It’s hard to experience patients’ suffering. We do not have time to talk with each patient. It leaves me with a guilty conscience.”</td>
</tr>
<tr>
<td></td>
<td>Sole responsibility</td>
<td>“Sick leaves, constantly shifting of assistants, and new colleagues make me busy trying to get acquainted with them and to know what I can expect from them if urgent problems arise.”</td>
</tr>
<tr>
<td></td>
<td>Detrimental physical milieu</td>
<td>“The furniture is worn out, the cleaning is inadequate, and the seclusion unit is not suitable for its purpose.”</td>
</tr>
</tbody>
</table>
In your research teams, answer the following questions:

1. What are the strengths and challenges of narrative data analysis and hermeneutic analysis for your research topic?
2. What type of research team would you want to build for each of these two traditions? Would your research team differ or be the same in each tradition?
3. What similarities and differences do you see across narrative data analysis and hermeneutic analysis?
4. If you have already collected and analyzed your data from a symbol and text research tradition, how might you return to your analysis and refine it based on your discussion within your group?

**ACTIVITY 11.4. Data Analysis with Symbol and Text**

**QUALITATIVE DATA ANALYSIS OF CULTURAL EXPRESSIONS OF PROCESS AND EXPERIENCE: ETHNOGRAPHY, ETHNOMETHODOLOGY, AND AUTOETHNOGRAPHY**

As we discussed previously, ethnography is distinct because it is “the process and the product of describing and interpreting cultural behavior” (Schwandt, 2001, p. 80). In this section, we explore data analysis with ethnography, ethnomethodology, and autoethnography. There are several similarities in the philosophies of the three traditions because they each seek to understand cultural aspects. Let’s review the distinctions in their process of data analysis.

**Ethnography**

Similar to other research traditions, ethnographic data analysis, at its best, should have recursivity built into the data collection and analysis processes, such that the ethnographer begins data analysis immediately. Immersing him- or herself in the data, the ethnographer then identifies broad patterns, categories that exemplify the culture-sharing group. As these categories and patterns are identified, the ethnographer refines them by seeking exemplar data that “tell the story” of a culture-sharing group. Ethnographic data collection—much like case study data collection—may entail a variety of data sources from interviews, participant observations, and focus groups to reviewing public and personal documents and other artifacts relevant to understanding the culture.

Creswell (2006) cited three of Wolcott’s (1994) data analysis techniques as important for ethnographic design: description, analysis, and interpretation of a culture-sharing group. First, the ethnographer uses description by using a chronological, sequential, or some other type of order to describe a culture-sharing group. This might remind you of some of the techniques used in case study data analysis. It should, because the approaches share a similarity: to describe the main events, occurrences, interactions, perspectives, key players, storylines, and so on, of a culture-sharing group. Say, you are conducting an ethnography of graduate students in a qualitative course (you might have already wondered about conducting a similar study of your own class
experience—we sure did!). The order could be framed by the syllabus, progression of topics introduced, themes in class discussions, group dynamics (e.g., who speaks when, how class participation occurs), and/or by other frameworks that would help you the most, as an ethnographer, to understand the culture of that graduate qualitative class.

Once you have decided on the order most appropriate to describe the data, analysis is a “sorting procedure … [that] involves highlighting specific material introduced in the descriptive phase or displaying findings through tables, charts, diagrams, and figures” (Creswell, 2006, p. 182). This is a stage of data analysis wherein you might find yourself using more general qualitative data analysis tools, such as identifying patterns in the data (Wolcott, 1994, as cited in Creswell, 2006). It can be important to identify these patterns not just within the culture-sharing group, such as within our qualitative research class example, but also in terms of “comparing the cultural group to others, evaluating the group in terms of standards, and drawing connections between the culture-sharing group and larger theoretical frameworks … critiquing the research process and proposing a redesign for the study” (Creswell, 2006, pp. 152–153).

Applying this analysis to the example of an ethnography of a graduate qualitative course, you might build on the description of the phenomenon and examine what patterns the ethnographer notes across data sources. You might use some of the data management techniques discussed in Chapter 9, such as case displays or concept mapping, to track these patterns. Examining the patterns in your reflexive journal, comparing the course to another very similar or opposite course, and identifying connections within the patterns might be important to elucidate the culture-sharing group. As the analysis continues to build the description of the culture-sharing group, there may also be patterns and/or themes that you notice as an ethnographer that demand future study or suggest a restructuring of an ethnography for this group. For instance, maybe you notice that the culture of this qualitative class is influenced by fatigue due to a shortened semester, and you note that a longer semester might allow more of the culture-sharing group to be studied. Really, when you are conducting ethnography, it’s the content and process of the culture-sharing group you are analyzing, in addition to your role as a researcher.

How will you analyze your role and influence in the ethnographic research process? This brings us to the idea of the “insider” versus “outsider” discussion with regard to ethnography. Dwyer and Buckle (2009) contend that the issue of whether or not researchers should share “insider” status with their participants is not a dichotomous question. We agree. So if you are conducting ethnographic analysis, be sure to analyze your perspective and the space you occupy as a researcher along the insider–outsider continuum. It is typically not an “either–or” situation. Dwyer and Buckle note:

> There are complexities inherent in occupying the space between. Perhaps, as researchers we can only ever occupy the space between. We may be closer to the insider position or closer to the outsider position, but because our perspective is shaped by our position or closer to our position as a researcher (which includes having read much literature on the research topic), we cannot fully occupy one or the other of those positions. (p. 67)

Hammersley and Atkinson (2007) assert that ethnographic analysis should also seek to examine the situated meaning of a culture-sharing group. Situated meaning
refers to the ways that a local culture experiences and makes meaning of the events within their group. The authors also note that triangulation of data sources is important, comparing data from different chronological stages of data collection and various settings within the culture-sharing group.

Content analysis and domain analysis are also terms used commonly in ethnographic research to describe the process of identifying codes in the data. Content analysis seeks to identify relationships and patterns among words, phrases, and ideas within the data (Altheide, 1987; Graneheim & Lundman, 2004). Domain analysis is a similar process (Spradley, 1979); here is an excerpt from an ethnographic data analysis using domain analysis to examine the use of a reflecting team in couple therapy:

In this study the general research question was “What are couple and therapist perceptions of reflecting team practice?” … [In] transcripts, each sentence is analyzed through what is called a domain analysis to identify emergent themes and categories across interviews from different people in the same setting or culture (Spradley, 1979). In a domain analysis, long, complex sentences are broken down into shorter semantic relationships of meaning. A domain can be represented whenever someone makes a statement about something. That statement can be broken down into three parts: (a) the main concept being talked about—the cover term, (b) the other terms we use to describe that main concept—included terms, and (c) the relationship between the included terms and a cover term—semantic relationship. (Sells, Smith, Coe, Yoshioka, & Robbins, 1994, p. 250)

Floersch (2004) defined practice ethnography as ethnography that “examines the process of practice and investigates how practitioners use theory in practice” (p. 79). He acknowledges that in the study of mental health care or educational settings, an ethnographer must become familiar with the culture of a setting through its specific language and by becoming a witness to the daily lived experiences within the culture. We believe that this type of ethnography is well suited to designs in counseling and education. Floersch includes five steps in practice ethnography:

1. Identification of the disciplinary knowledge/power, or strengths language.
2. Recording the oral narratives of management events.
3. Reading the written text (i.e., case record) corresponding to the event.
4. Comparing the oral and written strengths of narratives with the invented or situated language.
5. Interviewing managers to confirm whether or not the language I identified as situated was a language acknowledged by the practitioner. (p. 81)

Floersch uses an example of his study of medication management in a mental health care setting to demonstrate data analysis with practice ethnography. He used the above techniques to analyze case records, interview transcripts, and his own role as the researcher in this study.

We also encourage you to consider Agar’s (2006) discussion of the five parameters of an ethnography that we think can help guide your data analysis. First, he discusses control: whether you as a researcher have more of a tendency to “take charge” or to “go
with the flow” (p. 7) in your approach to data analysis. Second, he discusses the focus of your ethnographic study. Staying on course with that focus during your data analysis is critical. Third, he discusses the scale of your ethnography. Are you interested in an in-depth examination of a particular phenomenon (e.g., individual experiences) or are you seeking a more global or broader understanding of your topic? Fourth, the events of your ethnography can guide your data analysis. Are you examining one event in one setting or multiple settings and multiple people interacting in those settings? Finally, Agar discusses event links, the recognition that events are particularly situated in time and can be influenced both backward and forward in time and space. How might this be important for analyzing your data?

**Ethnomethodology**

Remember that it is easy to begin to think that ethnography and ethnomethodology are more similar than they actually are. Ethnomethodology is both a method and a theory of a culture-sharing group (Pollner & Emerson, 2001), and this is a difference whose uniqueness translates in terms of how one approaches data analysis with ethnography versus with ethnomethodology. Discourse analysis (Edwards & Potter, 1992) or conversation analysis (Sacks, 1992) are terms you may see used in relationship to ethnomethodology. See Table 11.7 for a comparison of ethnographic, ethnomethodological, and autoethnographic (discussed in the next section) analytic strategies.

A first step in ethnomethodological data analysis is to select if and how you will address the cultural context of the text. De Kok (2008) outlined three issues that complicate this decision. First, ethnomethodology tends to analyze natural speech patterns rather than using, for instance, interview data for analysis. The conversation itself is valued as important—the text and interactions—rather than the interpretation of the

<table>
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<tr>
<th>TABLE 11.7. Comparison of Data Analysis in Ethnography, Ethnomethodology, and Autoethnography</th>
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<tbody>
<tr>
<td><strong>Ethnography</strong></td>
</tr>
<tr>
<td>• Prioritizes analysis of contextual and cultural factors.</td>
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<tr>
<td>• Focuses on recursivity of data collection and analysis.</td>
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<td>• Identifies situated meanings within culture-sharing group.</td>
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<td><strong>Ethnomethodology</strong></td>
</tr>
<tr>
<td>• Prioritizes conversational text in analysis, rather than interpretation of context surrounding text, and stays close to details of text.</td>
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<tr>
<td>• Identifies critical sequential events and meaningful interactions.</td>
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<tr>
<td>• Asks questions of the text to fine-tune data analysis.</td>
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<tr>
<td><strong>Autoethnography</strong></td>
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<tr>
<td>• Uses analytic strategies from ethnography.</td>
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<tr>
<td>• Produces a descriptive narrative about the relationship of the ethnographer to the phenomenon.</td>
</tr>
<tr>
<td>• Ranges in researcher focus from “objective” stance of details and facts to a more “subjective” description of the relationships between researcher and phenomenon and attention to feelings.</td>
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context surrounding it. Second, the numerous contexts at play surrounding any conversation, text, and interactions are viewed as an important reason to stay closer to the details of the occurrence rather than to the contextual factors. Third, acknowledgment of the context is viewed as removing the agency of participants’ text and interactions by placing them into “boxes” of assumptions about their culture (e.g., race/ethnicity, gender). Next, the ethnomethodologist reads transcripts, identifies critical incidents that are sequential, and interactions that are meaningful. Coding is often used to track this identification process. Questions may be asked of the data during analysis to fine-tune ways in which the data can “answer” these questions to illuminate the phenomenon studied. Here is an excerpt from de Kok’s study in Malawi with women and men on the issue of infertility:

Recordings of interviews were transcribed verbatim, according to a simplified version of the standard [conversation analysis] transcription notation (see e.g., Atkinson & Heritage, 1984). In order to be able to examine the sequential organization of talk and the co-construction of meaning, I obtained translations of the interactions between interpreters and respondents (displayed in the extracts in italics). After reading and re-reading the transcripts, I coded the interviews provisionally, based on content, utterance design (i.e., kinds of words, phrases or examples used), or actions performed (e.g., “discarding responsibility”).

Preliminary analysis of the data drew my attention to recurrent reference to the cultural content. I therefore selected extracts in which explicit reference was made to “culture,” “tradition,” “society” or “community” for more detailed analysis, leaving out extracts in which the interviewer explicitly asked about cultural or traditional issues.

I used several “tools” in the analysis. First, I asked certain questions of the data, such as “what is the participant doing in this turn?” (Pomerantz & Fehr, 1997) and “why this (utterance/phrase/action) now?” (Hutchby & Wooffitt, 1998). Second, I made use of findings regarding discursive devices and their functions as reported in the discourse analysis and conversation analysis literature. Third, I paid attention to deviant cases; if a particular extract did not fit in with an analytic claim, I adjusted the claim in order to account for the anomaly, unless certain features in the extracts made them recognizably different from the “average” extract (Potter & Wetherell, 1987; Schegloff, 1968). Throughout the analysis I adhered to the principle that claims should be based on the participants’ orientations and interpretations as displayed in their utterances. (p. 891)

**Autoethnography**

Autoethnography may typically be thought of as solely the autobiography of the ethnographer. However, it has recently become a tradition that attempts to hold both the culture-sharing group and the ethnographer in the ultimate data collection and analysis (Schwandt, 2001). The data analysis techniques used in ethnography apply to autoethnography. The difference is that the aim of autoethnographic data analysis is to produce a descriptive narrative about the relationship of the ethnographer to the phenomenon. Because autoethnography can range in its focus from a more “objective” (entailing attention to the details and facts) stance of the researcher to a more “subjective” description of the relationships between researcher and phenomenon (entailing attention to feelings), the focus of data analysis will necessarily be distinct depending on the researcher focus (Anderson, 2006). However, Duncan (2004) urges autoethnog-
raphers to not give over to feelings in autoethnography, but rather to have authenticity about their motivations to conduct an autoethnography, and to locate their research experience within a theoretical framework to increase the quality of data analysis. Wall (2008) notes the challenges in data analysis of autoethnography, including the degree of honesty and authenticity, or what she terms as “acceptability,” both within academia and with her own self with regard to her autoethnography.

Pennington’s (2007) investigation of autoethnography as a technique used with white preservice teachers in elementary schools working with students of color is a wonderful example of addressing some of the challenges mentioned above. She used critical race theory as a theoretical framework to analyze her own racism in the classroom and her experiences as both an educator and a researcher. She used her theoretical framework, critical race theory, to situate explorations of counternarratives to racism. Pennington also uses her own researcher reflexivity to describe her relationship to the topic of racism and preservice elementary school teachers. Guided by her theory and research tradition, she stays on course with her topic through self-analysis and description of the interaction between her own culture and the culture-sharing group of students and teachers. She writes: “I used myself to understand my participants. I used the similarities we shared, our skin color, our background as white women, and our placement in a school and community of color to provoke and process the discussions about race” (Pennington, 2007, p. 107). See Table 11.8 for tips on data analysis with culture-sharing groups in ethnography, ethnomethodology, and autoethnography.

**QUALITATIVE DATA ANALYSIS WHEN RESEARCH IS A CHANGE AGENT: PARTICIPATORY ACTION RESEARCH**

Participatory action research (PAR) should, of course, incorporate participatory data analysis methods. Stoecker (2005) asserted that PAR approaches have three common elements: an emphasis on utility, a use of diverse methods, and a focus on collaboration. Similar to case study analysis, the management and analysis of data are often immense tasks because the data come from a variety of sources. Just as a case study must endeavor to stay true to the case and not veer off course to data analysis that might be interesting, PAR data analysis must not lose its focus on its action, community and/or

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<tr>
<th>TABLE 11.8. Tips for Data Analysis with Culture-Sharing Groups</th>
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<tr>
<td>1. Address the context of the culture-sharing group. If you elect not to do so, have a strong rationale.</td>
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<tr>
<td>2. Keep your purpose of the study at the forefront of your mind. What are you seeking to describe and why?</td>
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<tr>
<td>3. Select an order or framework for describing the culture-sharing group and/or your relationship to it. Note how chronology, sequence of events, critical incidents, etc., will structure your description.</td>
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<tr>
<td>4. Triangulate data sources (e.g., transcripts, records, artifacts) in your analysis.</td>
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<tr>
<td>5. Look for variation within your description. Where are the “tensions” or inconsistencies within the culture-sharing group?</td>
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<tr>
<td>6. Use general coding techniques throughout your analysis to stay organized.</td>
</tr>
<tr>
<td>7. Don’t forget to analyze and code your own researcher reflexivity.</td>
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stakeholder involvement, and change (McTaggart, 1997). For instance, in a PAR study seeking to increase advocacy for persons with intellectual disabilities, participants were invited to (1) play important roles in each step of the data analysis, (2) identify sites of change in the systems in which they were involved during data analysis, and (3) take action steps during the process of data analysis. In this manner, developing your data analysis strategy in a PAR study must include some flexibility so that you can build in numerous places for you to analyze data collaboratively with your participants.

Another critical aspect of PAR data analysis is reflection. PAR researchers are often guided by a think–act–look focus in their community partnerships; however, self-reflection is an integral process in each of these stages (Koch, Mann, Kralik, & van Loon, 2005). This reflection is important because it helps identify both within, and as a result of, the data analysis opportunities for the next most effective action steps. Therefore, a guiding force of PAR includes ensuring that periods of reflection are recursively built into the data collection, action, and analysis process. See Figure 11.4 of Riel’s (2007) visual portrayal of progressive problem solving with action research.

Similar to many other qualitative research traditions, the data collection and analysis should be recursive. We believe it is best to have key informants from the community you are working with on your research team. However, this is not always possible. If it is not, an important initial decision in your data analysis will be to identify how you will integrate participant voices into the data analysis process (Kidd & Kral, 2005). Often, the dialogue or reflection session is used to create a space wherein participants speak

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**FIGURE 11.4.** Riel’s (2007) visual portrayal of progressive problem solving with action research. Reprinted with permission from Margaret Riel.
with one another and the researcher about the actions they are planning and/or implementing and the experiences they are having in the process (McTaggart, 1997).

These sessions can also serve as spaces in which data analysis is simultaneously conducted. For instance, if your PAR study is a peer-led intervention in middle schools on decreasing bullying and violence, your reflection and dialogue sessions may entail planning, identifying sites of change, and reporting on activities from participants and researchers. Within this meeting, the researcher can also present data—whether they are broad domains the researcher and/or research team is identifying about the change process within the school or analysis of the participation levels of each individual in the PAR sessions—and invite analysis in that moment.

Because of the level of involvement of the researcher and participants in PAR designs, the researcher must be well organized and track how the collaborative partnership is analyzing data because the participants may be already overtaxed by the systems in which they are working. Whereas in other research traditions, the researcher decides when the data analysis ends—such as reaching saturation in grounded theory approaches or illuminating the boundaries of a case study—best practices in PAR should really follow the will and experiences of the participants and/or community in deciding when data analysis should end. Kidd and Kral (2005) remind those engaging in PAR that “the interaction of PAR with local culture can itself be a source of study along with the more specific course and outcome of groups’ efforts” (p. 188). See Table 11.9 for a list of tips for data analysis steps in PAR designs.

Nastasi and colleagues (2000) noted that the cultural/contextual variables specific to this local culture should drive the data collection and analysis. Therefore, collaboratively identifying these variables can be an important way to frame PAR data analysis. We would like to add that data analysis with PAR may borrow analytic strategies from other traditions when it “makes sense” for PAR’s aim toward social change. See Case Example 11.4 for an excerpt from a PAR manuscript describing this approach to data analysis.

CASE EXAMPLE 11.4. Family–School Participatory Action Research


“As a first step toward organizing the data, three members of the research team analyzed the responses independently. Each survey that had a written response was counted as one response. This step of the process involved each member reading over the comments several times while keeping a separate running list of major ideas. A primitive coding system of classifications in which data were initially sorted was developed based on the notes. As a second step, the three independent coders compared their lists, and the numerous codes generated were systematically examined to discern emerging patterns. They transformed these patterns into categories or themes based on inductive content analysis guidelines (Coffey & Atkinson, 1996). This process involved the coders first sharing and discussing their generated codes and the frequency, extensiveness, intensity, or uniqueness of certain ones, and then obtaining consensus on the most important themes that emerged from this discussion. For the third step, these themes were used for the final sorting of the comments; each coder independently sorted the comments based on the four mutually exclusive identified themes. (p. 113)
The four themes identified in this PAR data analysis were:

1. Requests for more communication.
2. Requests for information on ways to help their children.
3. Expressed satisfaction with school.
4. Requests for special parental consideration. (p. 111)

These themes were organized with other data by the school psychologist in the study and shared with the community. The research team met with stakeholders to identify action steps for family–school partnerships, which included:

1. Develop mechanisms for decreasing language, cultural, and overall communication barriers to improve parents’ involvement with the school.
2. Increase efforts to help parents become involved in reading and learning activities at home.
3. Increase opportunities for communication with parents about their individual child’s educational progress and needs, and to provide families with resources.” (pp. 114–115)
ACTIVITY 11.5. Building Action Components into Your Research Design

In your research groups, answer the following questions:

1. How would your research topic change (or not) with a PAR design?
2. Are there action components you could add to your study based on what you have learned about the purpose, focus, and outcome of PAR?
3. What do you think are the challenges to PAR in terms of managing your influence and power as a researcher using PAR techniques?
4. *Empowerment* is a word that is often misunderstood. We don’t believe that we empower people, but rather that we create spaces wherein participants empower themselves. How might your research, whether a PAR design or not, create spaces with the potential for empowerment and change?
5. If you have already collected and analyzed your data from a research and action tradition, how might you return to your analysis and refine it based on your discussion within your group?

WILD CARD 11.1. CAUTIONS FOR THE DATA ANALYSIS “ROAD”

Here are a few general tips for you across the research traditions for data analysis:

1. Stay on course with your research tradition. How is it guiding your data analysis?
2. Balance your expertise and your power of interpretation with listening to the voices of your participants and the data.
3. Ask different questions of your data. It’s not a bad thing if your data offer different, and even diverging, types of evidence. Variation is a good thing in data analysis; it helps you more fully represent your data.
4. Don’t be haphazard in selecting data analysis approaches. Know why an approach is the best fit for your topic. This may mean a blend across traditions—but have a strong rationale for doing this!
5. Don’t rely on one qualitative text (even ours!) to teach you about data analysis. Use this book to get your repertoire of data analysis techniques down. Then, read, read, and read some more about how data analysis is conducted within your field and across disciplines—not just with your topic, but also with your research tradition.
6. Don’t throw in the towel during data analysis! This is a time to persevere, endeavor to do your best quality work, and challenge yourself. If your study were a marathon, the data analysis might feel like the point when you “hit the wall” and your roll might begin to slow. Get reenergized and pour that energy into your analysis.
7. Be creative. Even all the data analysis techniques we have discussed might not provide a specific answer or guide about how to analyze a particular piece of data. Consider the general analytic techniques such as coding, identifying themes, triangulation, and so on, and then acknowledge that you may have to supplement these with a creative approach that makes sense for your data.
8. Be open to pausing your active data analysis to return to data collection if your data are requiring this. Repeat after us: Recursivity, recursivity, recursivity!

9. Don’t get overwhelmed by all the different terms used for data analysis techniques across the research traditions. Turn that anxiety into energy and get to know the similarities and differences in each form of data analysis. You not only will learn the tradition you are using better, you also will become a better qualitative researcher!

10. Don’t forget to analyze your own researcher reflexivity. Yes, we know you have already acknowledged your biases and assumptions at the beginning of your study. But good analysis demands that we analyze how and why we are examining certain aspects of data and not others—it matters in terms of where our analysis ends up!

POSTSCRIPT:
A FINAL NOTE ON QUALITATIVE DATA ANALYSIS

We have spent a good deal of time reviewing the tools each research tradition uses for analysis. Corbin and Strauss (2008) discussed the importance of embracing the researcher’s role in the interpretation of one’s data analysis. They note that beginning qualitative researchers tend to shy away from the power of interpretation, feeling nervous about being “off” in their analysis of the data. Corbin and Strauss agree that data analysis will vary in quality of standards. However, they encourage researchers to “push forward with analysis. With [analysis], we have more to gain than we have to lose” (p. 49). We wholeheartedly agree. Make sure that you are an ethical researcher staying close and true to the data you have collected as you interpret.

There will also come a time when you must “abandon” your interpretation by deciding that your analysis is at a stopping point. Notice that we did not say “done” with your analysis. The process of data analysis and interpretation is one that actually has no end point, so it will feel as if you are abandoning your data. And you are. However, you as the researcher should abandon your data with full disclosure of when, how, and why your decisions are the right ones for your study and are guided by your research tradition, theoretical framework, knowledge of your data, and analytical skills. That is when your interpretation ends … for now.
<table>
<thead>
<tr>
<th>Research tradition</th>
<th>Central principle</th>
<th>Step 1: Reduce data</th>
<th>Step 2: Collect data</th>
<th>Step 3: Memo and summarize</th>
<th>Step 4: Organize text</th>
<th>Step 5: Code</th>
<th>Step 6: Identify themes and patterns</th>
<th>Step 7: Create a codebook</th>
<th>Step 8: Develop a main narrative or theory</th>
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<tbody>
<tr>
<td>Grounded theory</td>
<td>Theory development</td>
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<td>Open coding (Corbin &amp; Strauss, 2008)</td>
<td>Axial coding and selective coding; noting causal conditions, intervening conditions, and consequences (Corbin &amp; Strauss, 2008)</td>
<td>Constant comparison and saturation (Corbin &amp; Strauss, 2008; Creswell, 2006)</td>
<td>Central idea, variations, and visual portrayal of theory (Corbin &amp; Strauss, 2008)</td>
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<td>Consensual qualitative research</td>
<td>Consensus on experience</td>
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<td>Development and coding of domains, researcher consensus (Hill et al., 2005; Okubo et al., 2007)</td>
<td>Abstracts core ideas of domains, cross-analysis, external audit (Hill et al., 2005; Okubo et al., 2007)</td>
<td>Noting frequencies of categories (general, typical, variant, rare; Hill et al., 2005; Okubo et al., 2007)</td>
<td>Presentation of phenomenon</td>
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<tr>
<td>Phenomenology</td>
<td>Essence of phenomenon</td>
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<td>Horizontalization, reduction, and elimination (Moustakas, 1994)</td>
<td>Structural and textual descriptions (Moustakas, 1994)</td>
<td>Individualized structural–textural descriptions (Moustakas, 1994)</td>
<td>Provide composite description of the essence of experience (Moustakas, 1994)</td>
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<td>Heuristic inquiry</td>
<td>Integration of researcher in participant experience</td>
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<td>Illumination and explication (Moustakas, 1990)</td>
<td>Core story creation, verification of core stories, examination of plots and subplots,</td>
<td>Creative synthesis (Moustakas, 1990)</td>
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<td>Narratology</td>
<td>Narrative plots</td>
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<td>Thematic analysis, typological analysis, dialogical analysis, narrative process</td>
<td>Chronologically ordering events and experiences (Kelly &amp; Howie, 2007)</td>
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<td>Emplopped whole narratives (Kelly &amp; Howie, 2007)</td>
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<tr>
<td>Methodology</td>
<td>Description</td>
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<td>Hermeneutics</td>
<td>Sacred texts</td>
<td>Dialogues in research teams and reach consensus (Diekelmann &amp; Ironside, 2005)</td>
<td>Identify broad themes, explore contradictions, and identify patterns (Diekelmann &amp; Ironside, 2005)</td>
<td>Describe symbols embedded in sacred text</td>
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<td>Ethnography</td>
<td>Culture-sharing group</td>
<td>Content analysis (Altheide, 1987; Graneheim &amp; Lundman, 2004) and domain analysis (Spradley, 1979)</td>
<td>Description and analysis through fieldwork (Wolcott, 1994)</td>
<td>Situated meanings of a culture-sharing group (Hammersley &amp; Atkinson, 2007)</td>
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<td>Ethnomethodology</td>
<td>Natural speech patterns</td>
<td>Discourse analysis (Edwards &amp; Potter, 1992) and conversation analysis (Sacks, 1992)</td>
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<td>Identify discourse within social interactions</td>
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<td>Autoethnography</td>
<td>Autobiography of ethnographer</td>
<td>Same as ethnography</td>
<td>Same as ethnography</td>
<td>Describe researcher’s role in culture-sharing group</td>
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<td>Participatory action</td>
<td>Change agent</td>
<td>Study field and reflect on previous action (Riel, 2007)</td>
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<td>Take action, present data to create change for participants</td>
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Note: This table includes selected research traditions in which qualitative data analysis steps have been discussed in the literature.
We began this chapter discussing data analysis strategies for the universal tradition, the case study. Here we emphasized the importance of having the case itself lead the data analysis and the caution about veering into analytic directions that might be interesting influences on the case but that do not elucidate the case itself. Then we reviewed analytic strategies used in experience and theory formulation. Data analytic strategies for grounded theory, phenomenology, and heuristic inquiry use a variety of coding methods designed to identify a theory or the essence and meaning of a phenomenon for participants. Next, we reviewed data analysis with symbol and text. These analytic approaches also use coding strategies, but typically they have a focus on narrative analysis, building a structure for analysis (whether by chronology of events, time, etc.), and/or using the generic coding methods discussed in Chapter 10. We explored cultural expressions of process and experience with ethnography, ethnomethodology, and autoethnography and identified the unique analytic approaches among the three involving the role and perspective of the researcher and the analysis of contextual or cultural influences. Finally, we discussed data analysis used as a change agent in PAR designs, where the process of analysis is guided by social action and, ideally, analytic collaboration with key stakeholders.

**RECOMMENDED READINGS**


