Conducting Mixed-Methods Research

From Classical Social Sciences to the Age of Big Data and Analytics

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Yulia Sullivan

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PREFACE

This book is designed to provide principles, strategies, and guidance on how to conduct mixed-methods research. It is intended to guide social science researchers through the mixed-methods research process by describing the steps to be taken, along with examples and suggestions. In recent years, we have observed a significant increase in interest in mixed-methods research. The popularity of this method can be seen from a growing number of publications using this method in various social science disciplines of fields (hereinafter fields), such as psychology, management, marketing, and information systems. In the early development of mixed-methods research, people who were unfamiliar with this approach would argue about philosophical issues associated with the paradigms debate and whether it is appropriate to mix methods housed in different research paradigms. Today, this approach to scientific inquiry and methods is more widely accepted, with funding agencies and journals encouraging researchers to enhance the rigor of their work and the consequent contributions by using a mixed-methods research approach. However, we observed that, although the interest in mixed-methods research continues to grow, conducting the research and then writing and publishing a mixed-methods paper are fraught with significant challenges. To aid in combating these challenges, this book seeks to assist researchers in various fields to use mixed-methods research effectively.

The target audience for this book includes scholars in various social science fields who are interested in using mixed-methods research. This especially includes graduate/PhD students seeking to develop and use mixed-methods research in theses/dissertations. Instructors teaching a mixed-methods research course can use this book, exercises, and associated slides to teach mixed-methods courses to various audiences. We hope that researchers will find this book useful in guiding them through the research process, from defining research questions to writing articles using a mixed-methods research approach. For researchers who are well trained in either the qualitative and/or quantitative methods, we hope this book will bridge the gap between the two types of research methods by guiding researchers on how to think about the purposes of mixed-methods research, design mixed-methods studies, and develop meta-inferences by integrating findings from both types of methods. We illustrate different approaches of conducting mixed-methods research by providing many examples of published mixed-methods empirical articles from various fields.

This book uses a step-by-step approach for conducting mixed-methods research and we offer several paper templates that will help structure different types of a mixed-methods articles based on the purpose of the study. By doing so, we hope that researchers can effectively communicate the objectives and contributions of their research to their intended audiences.

This book is divided into three sections:

Section 1. Introduction to Mixed-Methods Research
Section 2. Designing and Conducting Mixed-Methods Research
Section 3. Making Contributions and Publishing Papers Using Mixed-Methods Research

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SECTION 1.

INTRODUCTION TO MIXED-METHODS RESEARCH

In the first part of the book, we highlight the distinctions between mixed-methods research and other research methods. It consists of three chapters. In *Chapter 1. Mixed-Methods Research as the Third Research Approach*, we discuss the characteristics of mixed-methods research. We also discuss the strengths and weaknesses of qualitative and quantitative research, and highlight the value of mixed-methods research. In *Chapter 2. Philosophical Foundations of Mixed-Methods Research*, we discuss the philosophical foundations of mixed-methods research, including pragmatism, critical realism, transformative emancipatory, and dialectic stance. For each paradigm discussed, we provide an approach to knowledge creation using mixed-methods research. In *Chapter 3. Nature of Theory in Mixed-Methods Research*, we focus on the role of theory in mixed-methods research. This chapter will help researchers in using mixed-methods research to develop and test theory in the same research inquiry.

CHAPTER 1

MIXED-METHODS RESEARCH AS THE THIRD RESEARCH APPROACH

Mixed-methods research, an approach to research in which researchers mix or combine quantitative and qualitative research techniques, methods, concepts, and languages into a single study or a series of studies (Johnson & Onwuegbuzie, 2004), has been recognized as the third research approach beyond traditional qualitative and quantitative approaches. It has developed a platform of ideas and practices that is credible and distinctive, making the approach a viable alternative to a single method approach (i.e., quantitative or qualitative research approach) (Denscombe, 2008). Its popularity can be observed from an increased number of mixed-methods research articles in journals, conference proceedings, and books across a number of fields (e.g., Halcomb, 2019, published mixed-methods research guidelines in the nursing field; Greene, 2007, Creswell, 2015, Plano Clark and Ivankova, 2015, each published a textbook on mixed-methods research). Various funding agencies around the world, including the National Institutes of Health (NIH) and the National Science Foundation (NSF) in the US, also encourage scholars to use mixed-methods research in their work (Coyle et al., 2018; Guetterman et al., 2019). An NSF task force noted that "evaluators should attempt to obtain the most useful information to answer the critical questions about the project and, in so doing, rely on a mixed-methods approach whenever possible" (National Science Foundation, 2010, p. 57). In 2010, NIH also provided guidelines for investigators on how to properly develop and evaluate mixed-methods research proposals (Creswell et al., 2011). Given an increased interest in this approach, it is imperative not only to know qualitative or quantitative research procedures, but also how to properly use both methods in a single inquiry, study or research program.

Although mixed-methods research has gained popularity in the social sciences, issues regarding its differences from quantitative research (dominated by the positivist paradigm and its variants) and qualitative research (dominated by the constructivist and interpretivist paradigm and its variants) remain. Researchers who have aligned themselves with a particular approach, rooted in a particular paradigm, struggle to accept the *compatibility thesis,* i.e., mixing of qualitative and quantitative research methods. The two dominant research approaches have resulted in two research cultures, leading to a belief that if one decides to use both qualitative and quantitative methods in the same research project, each method should be executed independently because each is based on different paradigmatic assumptions (e.g., Brewer & Hunter, 1989; Morse, 2003).

The lack of knowledge and skills necessary to conduct both quantitative and qualitative research has also been an obstacle to mixed-methods research. Because scholars are commonly trained only in one school of thought, conducting mixed-methods research can be difficult without collaborating with scholars from other/different schools of thought. Even so, using a mixed-methods research approach requires an understanding of not only two dominant research paradigms, but also strategies to accommodate the differences between them and, perhaps more importantly, strategies to leverage the complementarities between them. Due to the lack of training in mixed-methods research, it is common to see little or no integration of findings from qualitative and quantitative studies within a single inquiry. According to Venkatesh et al. (2013), such practice not only leads to *contribution shrinkage* (i.e., missing the opportunity to discover, develop, or extend a theory using findings from different research approaches), but also *communal disutility* (i.e., the entire community of researchers who are interested in the phenomenon under study fails to learn intricacies of the phenomenon because an integrative view is not provided).

To provide clarity and consistency regarding what mixed-methods research is, in this first chapter, we specifically discuss different definitions, characteristics, and value of mixed-methods research. Teddlie and Tashakkori (2003) raised this issue and noted that the disagreement among scholars on the definition of mixed-methods research is "a sign of strength in a field that is still in its adolescence because it indicates that different authors disagree about exactly what a term means but nevertheless think the term is important" (p. 8). In this chapter, we revisit this issue and discuss the status of mixed-methods research as the third research approach. Further, to facilitate the ongoing debate on the incompatibility of methods, we discuss the strengths and weaknesses of each methodology and underscore the role of mixed-methods research in addressing the limitations weaknesses associated with each method. Because this chapter is the foundation on which the remainder of the book is built, we also present a detailed review of the evolution of mixed-methods research over the years that will serve as background for those seeking to understand some of the key debates and issues related to mixed-methods research. By identifying and reviewing the unique aspects of mixed-methods research, this chapter will provide insights about the conduct of good mixed-methods research.

1.1. Defining Mixed-Methods Research

Scholars have been conducting mixed-methods research for decades but referring to it by different terms. Although mixed-methods research has been widely accepted as a legitimate research approach, there have been inconsistencies in the definitions of terms (Teddlie & Tashakkori, 2003). Early articles on the application of mixed-methods research have used different terms, such as multi-method, between or across method triangulation, integrated, hybrid, combined, and mixed methodology, to refer to this type of research (Driscoll et al., 2007). Among these terms, the terms *multi-method* research and *mixed-methods* research have often been confused with one another. Across the literature, multi-method research designs have been used to describe the following (Teddlie & Tashakkori, 2003):

- The use of two or more quantitative methods;
- The use of two or more qualitative methods;
- The use of relatively separate quantitative and qualitative methods; and
- The use of both qualitative and quantitative methods.

To address this inconsistency, Teddlie and Tashakkori (2003) proposed a typology of multiple methods designs that incorporates both multi-method and mixed-methods designs in a consistent manner. They defined multiple methods research as when "more than one method or more than one worldview is used" (p. 11). From this definition, multiple methods research incorporates all the various combinations of methods that include, in a substantive manner, more than one data collection procedure. Both multi-method and mixed-methods research fall under this umbrella (see Figure 1-1).

A multi-method approach allows researchers to use either "two or more qualitative methods" or "two or more quantitative methods." These designs do not require a combination of qualitative and quantitative methods (Teddlie & Tashakkori, 2003; Venkatesh et al., 2013). For example, Fetvadjiev et al. (2018) used a multi-method qualitative design to study the differences and similarities in the predictability and consistency of behavior in two distinct cultural groups/races in South Africa. Their study 1 was a diary study that asked participants to record their behaviors and the situations in which they had occurred. Their study 2 was a laboratory experiment where participants were video-recorded in a laboratory and external observers scored their behaviors.

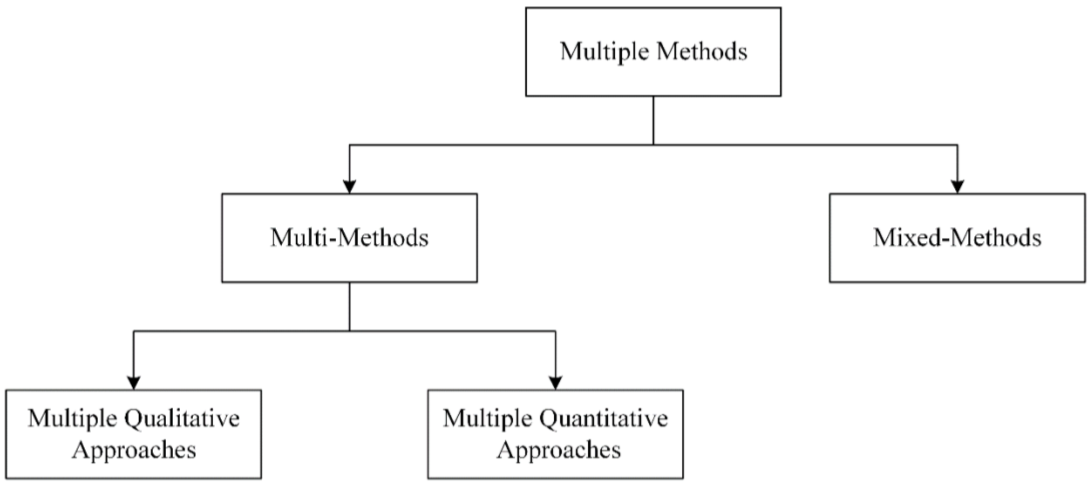

Figure 1-1. Multiple Methods Designs

Mixed-methods designs refer to the use of qualitative and quantitative approaches in the same inquiry or research project. For example, in their second study, Balasubramanian et al. (2018) used data from four surveys and over twenty interviews to examine the effects of deadline-related time pressures on workflows, task sorting, and work quality. The first survey was conducted to understand the role of inventors in the patent application process; the second and third surveys were conducted to understand the incentives and penalties faced by patent attorneys in the patent filing and prosecution process; and the fourth survey included a cost-estimation exercise to estimate the additional monetary costs of errors due to rushing. In-depth interviews with practitioners were conducted to obtain detailed information on the patenting process inside firms, as well as to gain insights on the observed clustering of patent applications.

Consistent with this discussion, we view mixed-methods designs as one category of multiple methods designs. Teddlie and Tashakkori (2003) differentiated mixed-methods research from mixed model research by suggesting that in mixed-methods research, researchers use qualitative and quantitative data collection and analysis techniques, wherein mixing occurs in the method section of the study, whereas in mixed model research, mixing occurs in many or all stages of the study. However, to allow for mixing in various stages in mixed-methods research nomenclatures, we categorize mixed model research as one of the mixing strategies of mixed-methods research, i.e., fully mixed-methods research design, because the difference between these two designs is not restricted to their worldviews, but to where the mixing takes place. We discuss this further in Chapter 5.

1.1.1. Mixed-Methods Research—Method Versus Methodology

An early discussion on mixed-methods research in social sciences can be traced to Campbell and Fiske (1959) who developed the idea of multitrait-multimethod triangulation. They argued that more than one method should be used in the validation process to ensure results from a study are valid and not a methodological artifact. From this early work, some scholars (e.g., Denzin, 1978; Jick, 1979) initiated the use of triangulation as a practice to combine methodologies in the same study. The kind of triangulation involving the use of both qualitative and quantitative methods is called *between (or across) methods* and more recently is known as mixed-methods research. The focus in traditional, early mixed-methods research was on method selection as a tool used to answer research questions. The basic assumption of this early perspective of mixed-methods research is that the weaknesses of one method will be compensated by the strengths of another method (Jick, 1979).

Grounded in the triangulation perspective, Greene et al. (1989) proposed a conceptual framework for mixed-methods research designs by defining mixed-methods research designs as "those that include at least one quantitative method (designed to collect numbers) and one qualitative method (designed to collect words), where neither type of method is inherently linked to any particular inquiry paradigm" (p. 256). Their definition placed greater emphasis on mixing methods for various purposes and less emphasis on paradigms. They noted that "the notion of mixing paradigms is problematic for designs with triangulation or complementarity purposes, acceptable but still problematic for designs with a development or expansion intent, and actively encouraged for designs with an initiation intent" (p. 271). This suggests that, whereas methods can be combined as long as they are appropriate to answer the research questions, paradigms and their assumptions can be ignored and should not be a researcher's focus in an inquiry (Maxwell & Mittapalli, 2010).

After the initial work of Greene et al. (1989), the definition of mixed-methods research has undergone considerable revision. To better understand the evolution of the definitions, we review the definitions and characteristics of mixed-methods research over the years. Different definitions of mixed-methods research from selected sources, sorted by year, are listed in Table 1-1.

Table 1-1. Definition of Mixed-Methods Research

Authors	Definition	Orientation
Jick (1979)	The use of both qualitative and quantitative methods to examine the same dimension of a research problem.	Method
Caracelli and Greene (1993); Greene et al. (1989)	"Those that include at least one quantitative method (designed to collect numbers) and one qualitative method (designed to collect words), where neither type of method is inherently linked to any particular inquiry paradigm" (Greene et al., 1989, p. 256).	Method
Tashakkori and Teddlie (1998)	"Those that combine the qualitative and quantitative approaches into the research methodology of a single study or multiphased study" (pp. 17-18).	Methodology
Teddlie and Tashakkori (2003)	"Mixed method research studies use qualitative and quantitative data collection and analysis techniques in either parallel or sequential phases" (p. 11).	Methodology, data collection,

Authors	Definition	Orientation
		and analysis techniques
Creswell et al. (2006)	"Both a methodology and a method, and it involves collecting, analyzing, and mixing qualitative and quantitative approaches in a single study or a series of studies" (p. 1).	Method, methodology
Tashakkori and Creswell (2007)	"Research in which the investigator collects and analyzes data, integrates the findings, and draws inferences using both qualitative and quantitative approaches or methods in a single study or program of inquiry" (p. 4).	Methodology
Johnson et al. (2007)	"The type of research in which a researcher or a team of researchers combines elements of qualitative and quantitative research approaches (e.g., use of qualitative and quantitative viewpoints, data collection, analysis, inference techniques) for the broad purposes of breadth and depth of understanding and corroboration" (p. 123).	Methodology, research purposes
Driscoll et al. (2007)	"Methods to expand the scope or breadth of research to offset the weaknesses of either approach alone" (p. 19). "Mixed-methods designs can provide pragmatic advantages when exploring complex research questions. The qualitative data provide a deep understanding of survey responses, and statistical analysis can provide detailed assessment of patterns of responses" (p. 26).	Research purposes
Plano Clark et al. (2008)	"A design for collecting, analyzing, and mixing both quantitative and qualitative data in a study to understand a research problem" (p. 364).	Method
Creswell et al. (2011)	"A research approach or methodology: • focusing on research questions that call for real-life contextual understandings, multi-level perspectives, and cultural influences; • employing rigorous quantitative research assessing magnitude and frequency of constructs and rigorous qualitative research exploring the meaning and understanding of constructs; • utilizing multiple methods (e.g., intervention trials and in-depth interviews); • intentionally integrating or combining these methods to draw on the strengths of each; and framing the investigation within philosophical and theoretical positions." (p. 4)	Methodology, research purposes
Leech and Onwuegbuzie (2009)	The use of qualitative research methods for one phase or stage of a research study and quantitative research methods for the other phase or stage of the research study.	Methods, research process

Authors	Definition	Orientation
Teddlie and Tashakkori (2009)	"A type of research design in which QUAL and QUAN approaches are mixed across the stages of a study" (p. 146).	Methodology
Teddlie and Tashakkori (2010)	"The broad inquiry logic that guides the selection of specific methods and that is informed by conceptual positions common to mixed-methods practitioners (e.g., the rejection of 'either-or' choices at all levels of the research process)" (p. 5).	Methodology
Creswell (2015); Creswell and Plano Clark (2018)	Mixed-methods research: • collects and analyzes both qualitative and quantitative data rigorously in response to research questions and hypotheses; • integrates the two forms of data and their results; • organizes these procedures into specific research designs that provide the logic and procedures for conducting the study; and • frames these procedures within theory and philosophy.	Core characteristics, research processes

As can be seen from Table 1-1, a number of scholars (e.g., Tashakkori & Teddlie, 1998; Teddlie & Tashakkori, 2003) broadened the scope of mixed-methods research by shifting the focus from "method" to "methodology" or research approach. Whereas method refers to specific strategies or procedures for implementing mixed-methods research designs, including data collection, data analysis, and sampling strategy, methodology involves a broad inquiry logic or general approach to mixed-methods research that guides the selection of a specific method (Teddlie & Tashakkori, 2010). A well-known article, published by Johnson et al. (2007) in the *Journal of Mixed-Methods Research*, is at the center of this discussion. They asked 21 researchers to define mixed-methods research and obtained 19 definitions. Based on their review, they defined mixed-methods research as "the type of research in which a researcher or a team of researchers combines elements of qualitative and quantitative research approaches (e.g., use of qualitative and quantitative viewpoints, data collection, analysis, inference techniques) for the broad purposes of breadth and depth of understanding and corroboration" (p. 123). In addition to defining mixed-methods research as a methodology, Johnson et al. and a few other researchers (e.g., Creswell et al., 2011; Driscoll et al., 2007) elaborated on the purposes of mixed-methods research in their definition.

In response to the definition of mixed-methods research from a "methodology" perspective, Creswell (2010) noted that "In my own work, I view mixed methods primarily as a method approach . . . because of the difficulty of convincing many individuals that mixing of philosophical foundations is possible . . . In my writings and workshops, I suggest that mixed methods is more than simply the collection of two independent strands of quantitative (QUAN) and qualitative (QUAL) data . . . mixed methods involves the connection, integration, or linking of these two strands" (p. 51). Although Creswell was inclined to support mixed-methods research as a "third methodological movement," Creswell acknowledged that scholars have entered the area of mixed-methods research from different perspectives—i.e., some come from a method orientation and others from a methodology orientation—and thus, differences should be expected. In an effort to integrate these differences into the definition of mixed-methods research, Creswell and Plano

Clark (2018) viewed mixed-methods research as “multiple ways of seeing”—the definition should combine a method, research design, and philosophical orientation viewed mixed-methods as “multiple ways of seeing”—the definition should combine a method, research design, and philosophical orientation.

1.1.2. Characteristics of Mixed-Methods Research

As shown in Table 1-1, Creswell and Plano Clark (2018) proposed four core characteristics of mixed-methods research. In addition to these core characteristics, which focus on the mixed-methods research process, new characteristics have been added over the years. We discuss five characteristics that distinguish mixed-methods research from other research approaches.

1.1.2.1. Use of Both Qualitative and Quantitative Methods

Mixed-methods research needs to employ at least one qualitative method and one quantitative method in the same study or research project (Denscombe, 2008). However, mixed-methods research is more than simply a collection of two types of data; it must clearly specify the sequencing and priority that is given to the qualitative and quantitative elements of the study and explicitly integrate the qualitative and quantitative results (Creswell, 2010; Venkatesh et al., 2013). We argue that such an integration of findings is one of the core elements of mixed-methods research. This integration, or identification of *meta-inferences*, is a key differentiator between mixed-methods research and a single method approach. If researchers do not provide and explain meta-inferences, the core objective of conducting mixed-methods research is not achieved (Venkatesh et al., 2013).

1.1.2.2. Methodological Eclecticism

The second characteristic of mixed-methods research is *methodological eclecticism*, defined as “selecting and then synergistically integrating the most appropriate techniques from a myriad of [qualitative], [quantitative], and mixed-methods to more thoroughly investigate a phenomenon of interest” (Teddlie & Tashakkori, 2010, p. 8). This characteristic is drawn from a rejection of the *incompatibility of methods thesis*, which states that qualitative and quantitative methods cannot be mixed due to fundamental differences between the paradigms underlying those methods (Teddlie & Tashakkori, 2010). Methodological eclecticism means that we are free to combine methods when those methods are the best tools to answer research questions. Thus, the best method for any given study in the social sciences may be purely qualitative or purely quantitative, rather than any mixing. This leads to a characteristic of mixed-methods research, which we discuss in section 1.1.2.4: *focus on both confirmatory and exploratory research questions*.

1.1.2.3. Paradigm Pluralism

The third characteristic of mixed-methods research is *paradigm pluralism*—“the belief that a variety of paradigms may serve as the underlying philosophy for the use of mixed-methods” (Teddlie & Tashakkori, 2010, p. 9). Unlike qualitative and quantitative research, mixed-methods research allows the use of multiple paradigms in a single study or research program. Alternative paradigms that can serve as an underlying philosophy for the use of mixed-methods research include pragmatism, critical realism, and transformative emancipatory. We will discuss different paradigms in Chapter 2. However, because each paradigm has its own assumptions that could be problematic when combined (e.g., inconsistent), this practice should be approached carefully. As noted by Denzin (2012), “it is one thing to endorse pluralism, or multiple frameworks, but it is quite another to build a social science on what-works pragmatism” (p. 83). Although the incompatibility thesis will continue to resurface as long as there are philosophical debates in social inquiry, scholars using a mixed-methods approach should be diligent and persistent in their defense of the compatibility thesis (Teddlie & Tashakkori, 2012). We believe that if scholars embrace pluralism within mixed-methods research, it will lead to stronger inferences and offer richer insights into phenomena being studied compared to using a single philosophical perspective.

1.1.2.4. Focus on Both Exploratory and Confirmatory Research Questions

Research questions are crucial in all research—and this is no different in mixed-methods research. Mixed-methods research enables researchers to address exploratory and confirmatory research questions simultaneously and, therefore, generate and evaluate theory at the same time (Venkatesh et al., 2016). Exploratory questions are characteristically broad questions and have one or more of the following purposes: to find out what is happening, to seek insights, and/or to assess phenomena in a new light (Sim & Wright, 2000). In contrast, confirmatory research questions tend to be more specific and serve to test a theory or hypothesis. In general, researchers can only address one type of research question in a single method approach. A mixed-methods research approach is suitable when researchers need to answer two types of questions—e.g., using a qualitative approach to identify the main constructs and their relationships and using a quantitative approach to test the significance of the relationships.

1.1.2.5. Emphasis on Diversity at All Levels of the Research Enterprise

Diversity as a characteristic goes beyond methodological eclecticism and paradigm pluralism discussed above (Teddlie & Tashakkori, 2010). A diversity emphasis highlights that mixed-methods research can simultaneously address a diverse range of exploratory and confirmatory questions, and it provides an opportunity for assortment of divergent findings due to multiple data sources and analyses involved in research (Teddlie & Tashakkori, 2010).

1.1.3. Value of Mixed-Methods Research

Having discussed the definitions and characteristics of mixed-methods research, we now discuss the differences between such an approach and qualitative and quantitative approaches. By comparing relevant characteristics of qualitative and quantitative research, identifying strengths and weaknesses of each approach, and discussing how mixed-methods research can address the weaknesses associated with one method will help researchers justify the use of mixed-methods research and choose a suitable design.

A good overview of the value of different research approaches is to compare them using a variables and cases approach (Creswell & Plano Clark, 2018). Consider a researcher trying to predict creative performance using the following set of predictors: task autonomy, managerial support, feedback, and task complexity. In a quantitative study, the researcher could collect data using a survey or experiment. The selected method or technique will generate numeric data through standard data collection procedures and instruments with predetermined response categories. In analyzing the data, the key dependent variable, namely creative performance, will be regressed on the predictor variables. The results might show us that creative performance is influenced by one or more of the independent variables. Although we can see how these variables predict creative performance at the aggregate level, quantitative methods and associated analyses do not allow us to observe the participants individually.

In a qualitative study, the researcher could look more closely into a particular case. For example, the researcher could observe behaviors of a specific individual in an organization. The researcher could observe employee A, who is male, has a graduate degree, has passion for his job, and so on. The researcher could look into this employee's work environment—whether he receives sufficient feedback and managerial support; how he responds to such feedback and support, and so on. Document analysis could also be leveraged. The researcher could determine the level of task complexity by analyzing the employee's tasks or job description. These data and other types of data, which are usually text-based, could be analyzed to identify nuances related to how the four predictors play roles in determining creative performance. Such a case-oriented approach looks at each entity, digs deeper into each case, and subjects all cases to a comparative analysis (Creswell & Plano Clark, 2018).

From this illustration, we can see that a variable-oriented analysis in quantitative research is ideal for hypotheses testing, but it can be difficult when dealing with causal complexities, nuances or subsamples, whereas a case-oriented analysis in qualitative research is ideal for finding specific, concrete, directly observed patterns common to small sets of cases, but its findings remain particularistic (Creswell & Plano Clark, 2018).Whereas quantitative research relies on numerical measures, qualitative research typically views subjective descriptions of experiences as data. The role of quantitative researchers in this study is quite different from that of qualitative researchers. Qualitative researchers could be deeply engaged in the setting and among the participants (Ormond et al., 2014), whereas quantitative researchers seek to remain as objective as possible (Mertler, 2016).

One caveat that is rooted in the differences in the ways quantitative researchers conduct studies is that, although quantitative research is generally associated with confirmatory and deductive reasoning, there are many quantitative studies that can be classified as exploratory and use inductive reasoning. For that reason, we do not use these two characteristics to differentiate quantitative research from qualitative research.

The summary of the characteristics, strengths, and weaknesses of each research approach from a collection of sources (Carr, 1994; Creswell & Plano Clark, 2018; Johnson & Onwuegbuzie, 2004; Levitt et al., 2018) is presented in Table 1-2.

Table 1-2. Comparison of Quantitative Research and Qualitative Research

Quantitative Research	Qualitative Research
Characteristics: • Conceptualizes reality in terms of variables and studies relationships between them. • Relies on numerical measures and associated predetermined response categories. • Relies on the collection and analysis of control variables and other numerical data about constructs/variables to describe, explain, predict phenomena of interest.	*Characteristics:* • Advocates prolonged engagement, persistent observations, and triangulation. • Relies on subjective measures and the research design can emerge during the process. • Relies on data in the form of natural language (i.e., words) and expressions of experiences (e.g., social interactions and artistic representations). • Samples are typically smaller than in

Quantitative Research	Qualitative Research
• Samples are typically larger than in qualitative studies. • Hypotheses are often constructed before the data are collected. • Results are relatively independent from the researchers and generalization through sampling is important. • Relies on statistical approaches for data analysis. • Provides precise numerical results.	quantitative studies, but include rich, detailed, and heavily contextualized descriptions from each source. • Tends to engage datasets in intensive analyses and open-ended discovery, rather than verification of hypotheses. • Typically views subjective descriptions of experiences as legitimate data for analyses rather than expecting findings to be generalized across all contexts. • Uses varied forms of techniques, such as narrative, grounded theory, phenomenology, ethnography, case study, and thematic analysis, in detailing the processes and findings. • Data or findings may or may not be transformed into numerical data.
Strengths: • Researchers maintain a detached, objective view in order to understand the facts. • For quantitative, experimental research, researchers can obtain sufficient information to establish the relationship between variables under investigation to enable prediction and control over future outcomes. • Data analysis processes are typically structured and systematic. • Provides greater confidence in the generalizability of results when the data are based on random samples of sufficient sizes. • Useful to study a large number of people.	*Strengths:* • Especially suitable when the research objective is to learn from participants in a setting or a process the way they experience it. • Useful for studying a limited number of cases in depth. • Researchers may have first-hand experience with the phenomenon, thus providing richness. • Data are usually collected from a few cases or individuals so findings cannot be generalized to a larger population. However, findings can be transferrable to another setting. • Researchers can identify contextual and setting factors as they relate to the phenomenon of interest. • Researchers can be responsive to changes that occur during the conduct of a study.
Weaknesses: • Theory used in the study may not reflect participants' understanding. • Many kinds of data are difficult to collect through standardized data collection instruments. • Self-reported information obtained using	*Weaknesses:* • The findings cannot be extended to wider populations with the same degree of certainty as with quantitative research. • Data collection and analyses are often time consuming. • Researchers' perceptions or beliefs may

Quantitative Research	Qualitative Research
questionnaires is subject to many biases. • It is almost impossible to generalize the findings or find support for hypotheses if the sample is too small. • The instruments cannot be modified once the study begins. • In controlled experimental studies, the results depend on the ability of the researcher to manipulate an independent variable in order to study its effect on the dependent variable. Such controlled environments may not represent the natural context in which participants demonstrate their true behaviors.	influence the way they interpret data. • Because researchers interact closely with the participants, they could have difficulty in separating their own experiences from those of the participants. Thus, the results are more easily influenced by researchers' biases. • Participants may not reveal their true behaviors or respond honestly to questions being asked when researchers are present and responses are not anonymous (e.g., social desirability bias).

Gaining an understanding of the strengths and weaknesses of each method puts a researcher in a position to properly mix qualitative and quantitative methods (Johnson & Onwuegbuzie, 2004). A major principle of using a mixed-methods research approach is that *when researchers collect data using different strategies, approaches, and methods, the mixture or combination will result in complementary strengths and nonoverlapping weaknesses* (Johnson & Turner, 2003). For example, in studying knowledge management system use and job performance, Zhang (2017) used a mixed-methods approach that included *a survey* among knowledge workers in an organization and *a follow-up interview* in one business unit to cross-validate the findings and explain unsupported findings. Although a survey enabled the researcher to test hypotheses, it did not allow him to explain why some of the hypotheses were not supported. Because qualitative research is useful for studying a limited number of cases in depth, it provided an opportunity for the researcher to explain the relationships that were not supported in the quantitative study. If the findings are consistent across different approaches, then the researcher can gain greater confidence in his inferences; if the findings are inconsistent, then the researcher has greater knowledge and can modify interpretations and conclusions accordingly (Johnson & Onwuegbuzie, 2004).

Against this backdrop, to aid in the decision to use or not to use mixed-methods research for a given study, we discuss the specific advantages of mixed-methods research next. As we mentioned earlier, the decision to use a mixed-methods research approach should be driven primarily by research questions. If researchers decide to use a single method to address their research questions, they can use Table 1-2 to determine whether any of the weaknesses associated with the selected method are considered major concerns in their study. If so, they should consider using a mixed-methods approach. Mixed-methods research is especially superior to a single method approach in a few areas that we describe next.

1.1.3.1. Researchers Can Use the Strengths of One Method to Overcome the Weaknesses of Another Method by Using Both Methods in the Same Study

As discussed previously, the effectiveness of mixed-methods research rests on the premise that the weaknesses of one method can be compensated by the strengths of another method. Presumably, each method does not share the same weaknesses or potential for bias (Jick, 1979).

One combination, for example, is when quantitative data collected through a survey is combined with qualitative data from interviews. A survey is relatively easy to administer and can reach a larger number of respondents. However, survey questions using standardized scales and measures could lead to unclear data because certain answer options can be interpreted differently by respondents. These weaknesses can be minimized by conducting follow-up interviews with respondents. Although information from an interview is subject to bias introduced by the interaction between interviewers and participants, it allows respondents to elaborate on their responses. Thus, an interview helps a researcher develop a rich(er) understanding. In this case, the qualitative data from interviews help a researcher assess the credibility of the inferences obtained from a quantitative study: e.g., survey (Venkatesh et al., 2013). Venkatesh et al. (2010) is one such project where the initial quantitative study results were explained by interviews (qualitative study) that were done concurrently, with the qualitative study being especially important because the hypothesized model was not supported in the quantitative study.

1.1.3.2. Both Quantitative and Qualitative Data Yield a More Complete Picture When They are Used in Combination

The underlying logic of this advantage is that neither quantitative nor qualitative methods are sufficient in themselves to understand the phenomenon under investigation (Creswell et al., 2004). Given mixed-methods research has the flexibility of employing a wider variety of data collection strategies, the data collected are generally a combination of at least numerical and qualitative (narrative) data. To analyze such types of data, researchers rely on multiple techniques (e.g., using statistical and content analysis techniques). As a result, they yield a more complete picture, as the data from the different methods complement each other.

In the field of health science, for example, Guetterman et al. (2017) argued that mixed-methods data can augment a randomized clinical trial or intervention design by gathering exploratory data before, during, and after trial. Collecting multiple types of data allows researchers to compare the results and, if necessary, perform data transformation that lead to a complete set of findings. Once again, we refer to Venkatesh et al. (2010), whose combination of quantitative and qualitative studies and associated data, led to a more complete understanding of the phenomenon.

1.1.3.3. Improves Data Accuracy and Provides Greater Confidence in Findings

The basic assumption of mixed-methods research is that the combined qualitative and quantitative findings lead to additional insights that cannot emerge from qualitative and/or quantitative studies and concomitant findings alone (Teddlie & Tashakkori, 2010). The integration of findings from two different methods leads to greater insights from the data and produces a fuller understanding of the phenomenon being studied (Levitt et al., 2018).

Vergne (2012), for example, conducted a mixed-methods study of the global arms industry from 1996 to 2007 to predict the amount of negative social evaluations received by organizations. In the first stage of the study, the author conducted interviews with prominent industry players, such as defense experts and industry professionals. The open-ended questions in the interviews sought to identify the categorical structure of the arms industry. The key objective of this data collection was to understand how industry stakeholders classify arms producers. However, the global arms industry, which was the focus of the first study, had only a small number of integrated systems providers. Thus, the author collected quantitative data at the firm level from several sources, including extensive data about products, customers, contracts, performance, and corporate activity from 1996 to 2007 from the 210 largest global weapon systems providers. With a mixed-methods approach, the author could be more confident in the findings and specifically noted that "with a mixed-methods approach, the justification to examine genre or country categories relies on an in-depth knowledge of the industry rather than on the researcher's prior belief that category A matters and category B does not matter (or matter less). Field research eases identification of sources of cross-firm, within-category heterogeneity before quantitative data collection" (p. 1049). Complex phenomena, such as the one in Vergne's study, require researchers to collect different types of data from different sources and perform different appropriate analyses to fully understand multifaceted realities. A mixed-methods research approach can facilitate such a pursuit.

1.1.3.4. Can Be Used to Answer Research Questions that Other Methodologies Cannot

Teddlie and Tashakkori (2003, p. 15) noted that "a major advantage of mixed-methods research is that it enables the researcher to simultaneously answer exploratory and confirmatory questions, and therefore verify and generate theory in the same study." Many of the research projects in the social sciences are usually intended to address two goals: (1) answer an exploratory question about how a phenomenon under investigation occurs; and (2) demonstrate a relationship between two or more variables. A single method approach can only address one of these goals in a single study. However, a mixed-methods research approach enables researchers to achieve both goals in the same study or a program of study.

One such example is Stewart et al. (2017). In this study, they used a mixed-methods approach to explore barriers to the successful implementation of a team-based empowerment initiative within the Veterans Health Administration. Using a longitudinal quasi-experiment design, they examined whether higher-status physician leaders were less successful than lower-status non-physician leaders in implementing team-based empowerment (i.e., confirmatory question). After they tested and confirmed the hypothesis that teams with high-status leaders were less effective in implementing team-based empowerment, they then analyzed qualitative data obtained through interviews conducted during early months of the team-based empowerment initiative to identify common themes for why and how leaders facilitated or obstructed implementation (exploratory questions). In particular, they inductively developed theory about status and team leadership by looking at team member perceptions of providers' reactions to team-based empowerment and specific leaders implementing it. Such an inquiry could not have been conducted exclusively using either a qualitative or quantitative method alone because only a mixed-methods approach leverages the complementary strengths from each type of data. The quantitative data allowed the researchers to test their hypotheses, whereas the qualitative data allowed them to examine the issues in depth from the leaders' perspective. Studying leadership within an organization requires an appreciation for the unique aspects of individual social settings that is best accomplished using a qualitative method, whereas to compare behaviors of two different groups in those social settings a quantitative method is especially suitable. The findings from both approaches provide an understanding that cannot be obtained by either approach in isolation.

1.1.3.5. Can Provide the Opportunity for Generating Divergent Findings

Another strength of mixed-methods research is that it allows researchers to generate divergent findings. Convergence of empirical results from both qualitative and quantitative methods is regarded as an indicator of their validity and strengthens the initial assumptions and theoretical frameworks underlying the study (Erzberger & Kelle, 2003). However, divergent findings are an opportunity to re-examine the initial conceptual frameworks and theoretical assumptions underlying the study (see Chapter 10 for details, including examples).

Summary

- Mixed-methods research is where a researcher or a team of researchers combines elements of qualitative and quantitative research approaches in a single inquiry or program of study for the broad purposes of breadth and depth of understanding and corroboration.
- A major principle underlying the use of mixed-methods research is that when researchers collect multiple types of data using different strategies, approaches, and methods, the mixture or combination will result in complementary strengths and non-overlapping weaknesses.
- The characteristics of mixed-methods research are:
    - the use of both qualitative and quantitative methods;
    - methodological eclecticism;
    - paradigm pluralism;
    - focus on both exploratory and confirmatory research questions; and
    - emphasis on diversity at all levels of research enterprise.
- The value of mixed-methods research is:
    - researchers can use the strengths of one method to overcome the weaknesses of another method by using both methods in the same study;
    - both quantitative and qualitative data yield a more complete picture when they are used in combination;
    - it improves data accuracy and provides greater confidence in findings;
    - it can be used to answer research questions that is not possible with a single method; and
    - it can provide the opportunity for generating divergent findings.

Exercises

1. Discuss the difference between multi-methods and mixed-methods research.
2. Identify an article in your topic your topic or field (or related field) that was a mixed-methods study and answer the following questions:
    a. What is (are) the research question(s) addressed in that study?
    b. What are the characteristics of the mixed-methods approach used in that study?
    c. What is the value of using a mixed-methods approach in that study?
3. Select a particular topic in your field. Identify a qualitative study in this topic and identify a quantitative study in this topic. What could they not accomplish? Discuss how and why a mixed-methods approach would help advance research on this topic (e.g., how can a mixed-methods approach extend the qualitative study or quantitative study).

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CHAPTER 2

PHILOSOPHICAL FOUNDATIONS OF MIXED-METHODS RESEARCH

The purpose of this chapter is to review some of the most common philosophical foundations underlying mixed-methods research. Any research, regardless of which method is used, has a philosophical foundation, and researchers need to be familiar with the paradigmatic assumptions they make throughout the research process (Creswell & Plano Clark, 2018). Mixed-methods research is no different. Prior to using a mixed-methods approach, researchers need to understand the assumptions that provide a foundation for their work. These assumptions shape the research process and influence the research outcomes. The interested reader is referred to Kuhn (1970) for a detailed discussion of paradigms and associated philosophies of science.

In this chapter, we discuss two different stances on mixing paradigms: an alternative paradigm stance (i.e., pragmatism, critical realism, and transformative emancipatory) and a dialectic stance for mixed-methods research. We then bring these elements together to evaluate the applicability of these stances and paradigms in providing philosophical support for mixed-methods research. This goal is achieved by providing an example of how to apply each stance and/or paradigm to research in social sciences. Although the paradigmatic issues in mixed-methods research seem to have generated the most discussion in the history of mixed-methods research—ranging from paradigm wars to conceptual stances in mixed-methods research (see Johnson & Onwuegbuzie, 2004; Teddlie & Tashakkori, 2003), a discussion of the practical orientation focused on applying the paradigmatic assumptions to research and using those assumptions to guide the research process is limited. Thus, rather than discussing and reviewing the development and evolution of role of paradigms, we discuss an approach to knowledge creation within the boundaries set by each paradigm, translating the theoretical terms used to define that paradigm to real-world applications that are compatible with one's research objective, and drawing conclusions on whether the paradigm offers an alternative, flexible approach to mixed-methods research designs.

2.1. Stances on Mixing Paradigms in Mixed-Methods Research

Unlike qualitative and quantitative research, one of the major characteristics of mixed-methods research is *paradigm pluralism*—"the belief that a variety of paradigms may serve as the underlying philosophy for the use of mixed methods" (Teddlie & Tashakkori, 2010, p. 9). With this belief, researchers using a mixed-methods approach embrace the diversity of philosophical and theoretical stances when conducting their research. Although prior studies have proposed a variety of conceptual orientations associated with mixed-methods research, we focus on the two most common conceptual orientations: *an alternative paradigm stance* (i.e., use a single paradigm to provide a philosophical underpinning for mixed-methods research) and *a dialectic stance* (i.e., researchers think dialectically and use multiple paradigms in a single inquiry) (Greene & Hall, 2010; Teddlie & Tashakkori, 2010).

An alternative paradigm stance differs from a dialectic stance in several important respects (Greene & Hall, 2010). First, whereas the alternative paradigm stance presents a coherent system of thought with its own philosophical assumptions, the dialectic stance believes that assumptions from different traditions can be respectfully and dialectically engaged in a dialog to enhance our thinking and produce new understanding of a phenomenon. Second, context and practicality (not philosophical frameworks) are useful guides for practice in the alternative paradigm stance, whereas more than one philosophical, theoretical, and/or mental model framework intentionally guides the study in the dialectic stance. Third, according to the alternative paradigm stance, meta-inferences represent actionable knowledge—"knowledge that can be acted upon" or "knowledge that is directly actionable for improving the important practical problem being studied" (Greene & Hall, 2010, p. 139). In contrast, according to the dialectic stance, meta-inferences represent a respectful integration of diverse lenses on the phenomenon being studied, and they represent insightful understanding that could not be obtained using one framework/method alone.

2.1.1. An Alternative Paradigmatic Stance

The philosophical issues surrounding mixed-methods research have received and continue to receive considerable attention (Creswell, 2010). A paradigm is not only a worldview, but also "shared belief systems that influence the kinds of knowledge researchers seek and how they interpret the evidence they collect" (Morgan, 2007, p. 50; see also Kuhn, 1970). Although an in-depth review of these issues is beyond the scope here, some key methodological implications are worth noting, particularly how they influence the actual practice of mixed-methods research. We begin our discussion by focusing on four philosophical elements of a paradigm: *ontology*—i.e., how we view the existence of the world and society (reality); *epistemology*—i.e., what we believe about knowledge; *methodology*—i.e., what systematic or theoretical approaches can we use to conduct a research study; and *axiology*—i.e., what role do values and ethics play in research (Creswell, 2010; Lincoln & Guba, 2013; Mertens, 2014).

Generally speaking, quantitative research is commonly associated with the philosophical paradigm of *positivism* and qualitative research is commonly associated with the philosophical paradigm of *constructivism* or *interpretivism* (Johnson & Gray, 2010). According to positivists, reality is separate from the individual who observes it (Lee, 1991; Weber, 2004). They believe that human experience of the world reflects an objective, independent reality and that this reality provides a foundation for human knowledge. To achieve a research objective, positivists often use experiments and surveys because these methods allow them to collect numerical (sometimes even objective) data that can be analyzed statistically. At the other end of the continuum, constructivism focuses on relativism. According to constructivists, entities are matters of definition and conversation; they only exist in the minds of the persons contemplating them (Lincoln & Guba, 2013). Based on this ontological assumption, the understanding or meaning of phenomena is highly subjective, mediated by participants' subjective views and knowledge. As noted by Lincoln and Guba (2013), "knowledge is not 'discovered' but rather created; it exists only in the time/space framework in which it is generated" (p. 40). In this form of inquiry, research is conducted by having participants work together with the researchers as equals and by sharing and pursuing the topic in question together.

From an alternative paradigmatic stance, mixed-methods research is commonly associated with *pragmatism* (Johnson & Onwuegbuzie, 2004), *critical realism* (Zachariadis et al., 2013), and *transformative emancipatory* (Mertens, 2007; Mertens et al., 2010). A comparison of these different paradigms is presented in Table 2-1.

Table 2-1. Research Paradigms (Ontology, Epistemology, Methodology, and Axiology)

	Research Paradigm				
Basic Belief	**Positivism (Lee, 1991; Weber, 2004)**	**Interpretivism/ Constructivism (Lincoln & Guba, 2013)**	**Pragmatism (Biesta, 2010; Greene & Hall, 2010; Teddlie & Tashakkori, 2003)**	**Critical Realism (Bhaskar, 1975, 1978; Mingers, 2014; Zachariadis et al., 2013)**	**Transformative Emancipatory (Mertens, 2007; Mertens et al., 2010)**
***Ontology*—** What is reality?	A single reality—there is only one reality and it is independent of our minds. This reality can be studied independently.	Multiple realities—there are multiple realities that are constructed and reconstructed by the minds and need to be studied as a whole.	Both single and multiple realities.	Much of reality exists and operates independent of our knowledge. This reality consists of three domains: real, actual, and empirical.	Multiple realities—there are multiple realities that are socially constructed, but it is necessary for researchers to be explicit about the social, political, cultural, economic, ethnic, age, and disability values that define realities.
***Epistemology*—** How do we know/what counts as knowledge?	Objective, dispassionate—the world can be objectively studied through the experiences of senses.	Subjective—values and beliefs emerge from the interaction between researchers and participants.	Knowledge is viewed as being both constructed and based on the reality of the world we experience.	Epistemological relativism—the process of scientific knowledge is viewed as historical emergent, political, and imperfect.	Knowledge is socially and historically located within a complex cultural context. Respect for culture and awareness of power relations is critical.

	Research Paradigm				
Basic Belief	**Positivism (Lee, 1991; Weber, 2004)**	**Interpretivism/ Constructivism (Lincoln & Guba, 2013)**	**Pragmatism (Biesta, 2010; Greene & Hall, 2010; Teddlie & Tashakkori, 2003)**	**Critical Realism (Bhaskar, 1975, 1978; Mingers, 2014; Zachariadis et al., 2013)**	**Transformative Emancipatory (Mertens, 2007; Mertens et al., 2010)**
Methodology—What approach do we use to carrying out research?	Hypothetico-deductive methods (e.g., experiment, survey).	Hermeneutic/dialectic methods (e.g., case study, ethnography, participant observation, life history).	Methodological appropriateness—methods that can best address the research questions.	Methodological pluralism—retroductive, in-depth historically situated analysis of pre-existing structures.	Researchers can use qualitative or quantitative or mixed-methods research, but there should be an interactive link between them and the participants in defining the focus of research.
Axiology—How do values come into play in an inquiry?	An inquiry can be carried out without the influence of a value system.	Value-laden—tends to be influenced by the researcher's subjective beliefs.	Both biased and unbiased perspectives.	Value-laden.	Respect, beneficence, and justice.

2.1.1.1. Pragmatism

Pragmatism is the most popular paradigm used in mixed-methods research. Scholars advocating pragmatism for mixed-methods research include Biesta (2010), Howe (1988), Johnson and Onwuegbuzie (2004), Patton (1988), Tashakkori and Teddlie (1998), and Teddlie and Tashakkori (2003). According to pragmatism, the only way we can acquire knowledge is through "the combination of action and reflection" (Biesta, 2010, p. 112). Specifically, knowledge is always about the relationship between action and consequences, and objects of knowledge are not isolated entities; the construction of knowledge takes place during the interaction between individuals and the environment (Biesta, 2010; Biesta & Burbules, 2003). Further, according to the pragmatist perspective, different knowledge is simply the result of different ways in which we engage with the world. As noted by Biesta (2010), "different approaches generate *different* outcomes, *different* connections between doing and undergoing, between actions and consequences, so that we always need to judge our knowledge claims pragmatically, that is in relation to the processes and procedures through which the knowledge has been generated so as not to make any assertions that cannot be warranted on the basis of the particular methods and methodologies used." (p. 113). Thus, pragmatism places central importance on research questions being asked rather than on the methods and methodologies being used.

The knowledge creation process in pragmatism based on the actions-consequences relationship is illustrated in Figure 2-1. In this process, pragmatism is a problem-solving, action-focused inquiry (Greene & Hall, 2010). Both individuals and social responses to the environment represent experiences from which knowledge is acquired and refined (Greene & Hall, 2010; Johnson & Onwuegbuzie, 2004). Pragmatism accepts that there are singular and multiple realities that are open to empirical inquiry and orients itself toward solving practical problems in the real world (Creswell & Plano Clark, 2018; Feilzer, 2010). In other words, pragmatism allows researchers "to be free of mental and practical constraints imposed by the 'forced choice dichotomy between postpositivism and constructivism'" (Feilzer, 2010, p. 8).

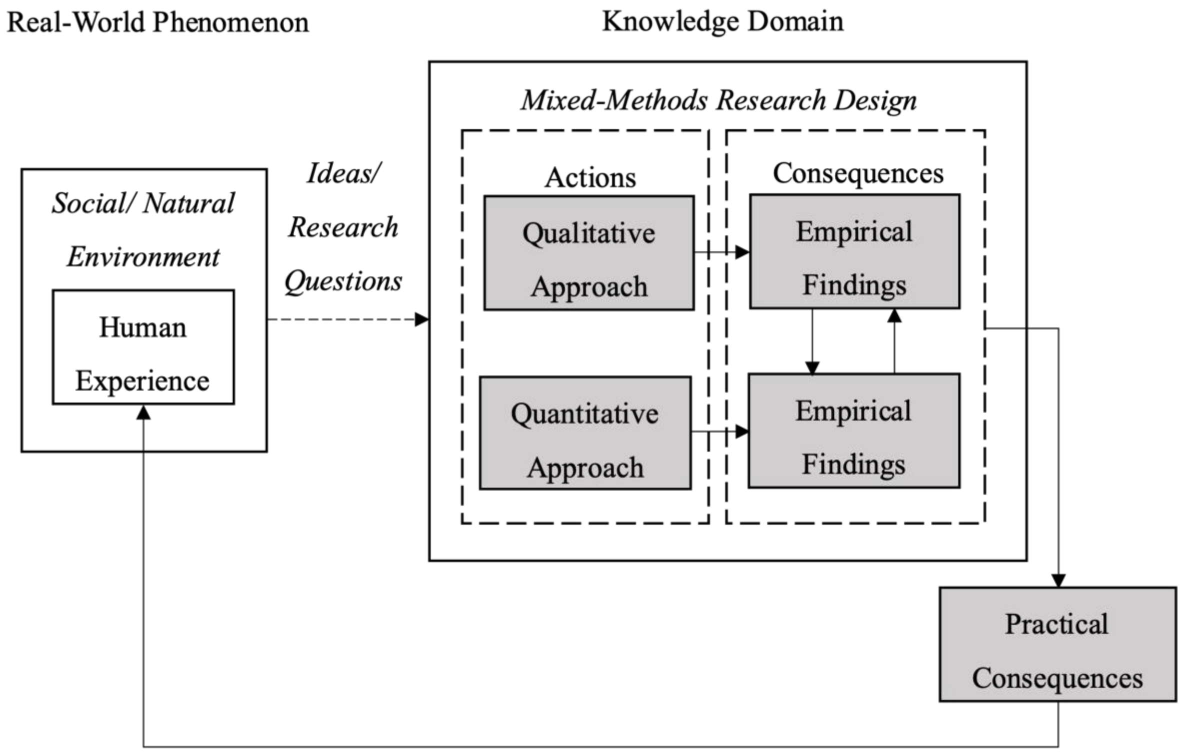

Figure 2-1. Knowledge Creation Process According to Pragmatism

To provide readers with a better understanding of pragmatism, the following are some characteristics of pragmatism (see Feilzer, 2010; Johnson & Onwuegbuzie, 2004; Tashakkori & Teddlie, 1998; Teddlie & Tashakkori, 2003):

- Pragmatism rejects the *incompatibility thesis* and supports the use of both qualitative and quantitative research methods in the same research study or research program (Tashakkori & Teddlie, 1998; Teddlie & Tashakkori, 2003). Pragmatism is *anti-dualist*, questioning the dichotomy of positivism and constructivism and calling for a convergence of qualitative and quantitative research approaches, suggesting that they are not different at epistemological and ontological levels, and they share many similarities in their approaches to inquiry (Feilzer, 2010).
- Pragmatists see research questions as more important than methods or methodologies—i.e., *dictatorship of the research questions* (Teddlie & Tashakkori, 2003). In some situations, a qualitative approach will be more appropriate. In other situations, a quantitative approach will be preferable. In many cases, researchers can put together insights and procedures from both approaches to produce a more complete understanding of the phenomenon under study (Johnson & Onwuegbuzie, 2004). This decision regarding a research approach should depend on the research questions.
- Pragmatism avoids the use of metaphysical concepts, such as truth and reality, that have caused endless discussion and debate (Teddlie & Tashakkori, 2003). Pragmatists thus believe in an "antirepresentational view of knowledge," arguing that research should "no longer aim to most accurately represent reality" but to be useful and to "aim at utility for us" (Feilzer, 2010, p. 8).

- Pragmatism presents a very practical and applied research philosophy (Teddlie & Tashakkori, 2003). Teddlie and Tashakkori (2003, p. 21) recommend researchers "study what interests and is of value to you, study it in the different ways that you deem appropriate and utilize the results in ways that can bring about positive consequences within your value system" (see also Tashakkori and Teddlie, 1998, p. 30). Pragmatism thus allows researchers to select the best methodologies as long as they help in addressing research questions (Morgan, 2007).

2.1.1.1.1. Applying Pragmatism to Mixed-Methods Research

We use a published study on knowledge management system (KMS) use (Zhang & Venkatesh, 2017) to illustrate how pragmatism can be leveraged in mixed-methods research. The objective of that study was to identify key KMS features and build a holistic nomological network around the use of those features. The authors addressed two research questions: (1) "what are the key KMS features that enhance job outcomes?"; and (2) "what are the drivers and consequences of use of the key KMS features?" (pp. 1276-1277). To identify the key drivers of the use of KMS features, they turned to the prior literature on KMS implementations. However, prior research had not fully considered the richness of social interactions in explaining KMS use. They argued that "to help employees overcome knowledge barriers to learning the numerous features of large-scale and complex systems, informal social networks that represent social interactions among employees become a potential solution for employees to overcome barriers to use in general . . . and, more specifically, KMS" (p. 1276). Given informal social networks (i.e., peer support networks) are crucial in facilitating KMS use, they identified such networks as a driver of the use of the key KMS features.

They used a sequential mixed-methods approach—specifically, a qualitative study followed by a quantitative study—to address their research questions. They conducted a qualitative study to identify the key KMS features and then examined the effects of these KMS features using a quantitative study. They noted that "given that there is no strong theoretical foundation for identifying key KMS features that facilitate job outcomes and there is a lack of research on what these features are, a qualitative study for feature validation, followed by a quantitative study for model validation was deemed to be appropriate" (p. 1277). The selection of this study design is consistent with one of the pragmatism assumptions—*research questions should drive method selection*.

In their qualitative study, they conducted interviews with 35 employees. In the first part of the interview, participants were asked questions about the KMS features. In the second part, the interviewees filled out a survey to rate the extent to which they agreed that each of the KMS features on the list helped them fulfill work-related purposes. The questions asked in the interview sessions were based on their literature review to focus on features that helped employees fulfill work-related purposes. Thus, any features that were identified by the interviewees were based on the list provided by the authors. Although these key features were based on the authors' literature review, they argued that the qualitative study was still necessary to help them identify four key KMS system features—i.e., post, search, comment, and rate. When conducting the qualitative study, the researchers embraced and promoted the mixing of methods. They relied on prior literature and used Miles and Huberman's (1994) approach to code and analyze the interview data. This practice is consistent with a pragmatist principle—*reject the forced choice between (post)positivism and constructivism and embrace both points of view* (Teddlie & Tashakkori, 2003). Pragmatically, the researchers used their selected methods to attend to a specific problem and to collect and analyze data that helps answer their research questions.

Using the results of their qualitative study, they developed the nomological network around the use of the four key KMS features that were identified in the qualitative strand of the study. They hypothesized that two forms of peer support: help-seeking ties and help-providing ties will have a positive effect on KMS feature use, and in turn KMS feature use will have a positive effect on job outcomes. They collected longitudinal data from the same organization where they conducted the qualitative study. They used both online and paper surveys, and collected 1,441 usable responses. They also collected network data from each business unit within the organization. Using a partial least squares structural equation modeling technique (PLS-SEM), they found that help-seeking and help-providing ties were positively related to use of the key KMS features, and use of the key KMS features were positively related to two key job outcomes except that post and search were not significantly related to job performance, whereas comment and rate were not significantly related to job performance. They turned to the literature to seek alternative explanations for their unsupported hypotheses. Consistent with pragmatism, the researchers established the credibility of findings by questioning their theoretical assumptions and hypothesizing about consequences (Hall, 2013). They also allowed mixing to occur among participants' perceptions by collecting data from multiple sources.

Overall, this study used a mixed-methods approach by applying some of the principles from the philosophy of pragmatism. They selected their research methods based on their appropriateness to the situation at hand. A mix of methods, a mix of perspectives from multiple data sources, and a mixing/integration of findings lent greater validity to their model and concomitant findings than what they would have obtained from using either a quantitative or a qualitative approach alone. As a result, overall, they were able to enhance and modify prior knowledge on KMS implementations and offer practical solutions to problems associated with KMS implementations.

2.1.1.2. Critical Realism

Critical realism, based on the work of Bhaskar (1975, 1978) and others (e.g., Archer et al., 1998), embraces various methodological approaches from different philosophical positions (Zachariadis et al., 2013). Critical realism is highly pluralist in terms of both ontology and epistemology by recognizing the existence of different types of objects of knowledge: e.g., material objects and forces; social structures and practices; conceptual systems: e.g., reality, knowledge, beliefs, and reasons (Mingers, 2014; Mingers et al., 2013). Critical realism can therefore "accept a wide range of research methods without recognizing the primacy of any particular type or approach" (Mingers, 2014, p. 189). Because a phenomenon being investigated may well have different characteristics, a mixed-methods approach will likely be necessary and critical realism supports this (Mingers et al., 2013).

Unlike pragmatists who argue that "methods can be combined on the basis of their practical utility, and that paradigmatic conflicts can be ignored" (Maxwell & Mittapalli, 2010, p. 146), critical realists recognize assumptions and limitations of both positivism and interpretivism but maintain a strong realist and critical core (Mingers, 2014). Ontologically, critical realism supports the idea of a reality—i.e., *intransitive* object of knowledge—that exists independent of our knowledge or perception of it. However, the generation of new knowledge is the work of humans and depends on the specific details and processes of its production—i.e., *transitive* object of knowledge—that can be established facts, theories, models, methodologies, and methods (Zachariadis et al., 2013). In this sense, critical realists must pay attention to both the object/problem they study and the place/context of the study. Critical realism also accepts a variety of methodological approaches by recognizing three forms of knowledge based on three underlying human interests—the *real*—i.e., represents a reality that may or may not be observable—the *actual*—i.e., a subset of the real—and the *empirical*—i.e., a subclass of observable, experienced events and change (Bhaskar, 1975, 1978; Zachariadis et al., 2013). Empirical events, which can be observed or experienced, should facilitate the relationship between transitive and intransitive objects of knowledge.

Critical realists recognize that our access to this world is limited and always mediated by our perceptual and theoretical lenses (Mingers et al., 2013). Critical realists allow for a degree of *epistemological relativism* (Zachariadis et al., 2013, p. 857) by accepting the possibility of alternative explanations to any phenomenon and argue that "all theories about the world are grounded in a particular perspective and worldview, and all knowledge is partial, incomplete, and fallible" (Maxwell & Mittapalli, 2010, p. 150). Whereas positivism focuses on the use of quantitative methods and statistical data analysis, and constructivism generally embraces qualitative methods and text analysis, critical realists use either type of method but adopt particular positions on issues such as the role of values in research (Mingers, 2014).

The main scientific methodology of critical realists is called *retroduction,* which is essentially the same as abduction (Mingers, 2014). With retroduction, critical realists look for underlying *generative mechanisms*—"the ways of acting of a thing," "the causal powers and liabilities of objects or relations," "capacities of behavior," and "tendencies of structures" (Volkoff & Strong, 2013, p. 821). Mingers et al. (2013) noted that the essential methodological step in critical realism studies is "to move from descriptions of empirical events or regularities to potential causal mechanisms, of a variety of kinds, some of which may be nonphysical and nonobservable, the interaction of which could potentially have generated events" (p. 3). Causality in the form of a generative mechanism is a core and defining feature of critical realism (Bhaskar, 2002). In contrast with a general understanding of causality in social science ("A causes B"), causality as a generative mechanism can be reformulated as "A generates B in context C." Thus, for a critical realist, causality is "a process of how causal powers are actualized in some particular context, a process in which the generative mechanisms of that context (C) shape (modulate, dampen, etc.) the particular outcomes" (Walsh, 2014, p. 154). This retroductive approach allows researchers to use a wide variety of methods where qualitative and quantitative approaches can be integrated in order to hypothesize and identify the generative mechanisms that cause the events we experience (Zachariadis et al., 2013). This process of knowledge creation in critical realism is illustrated in Figure 2-2 (reproduced from Zachariadis et al., 2013).

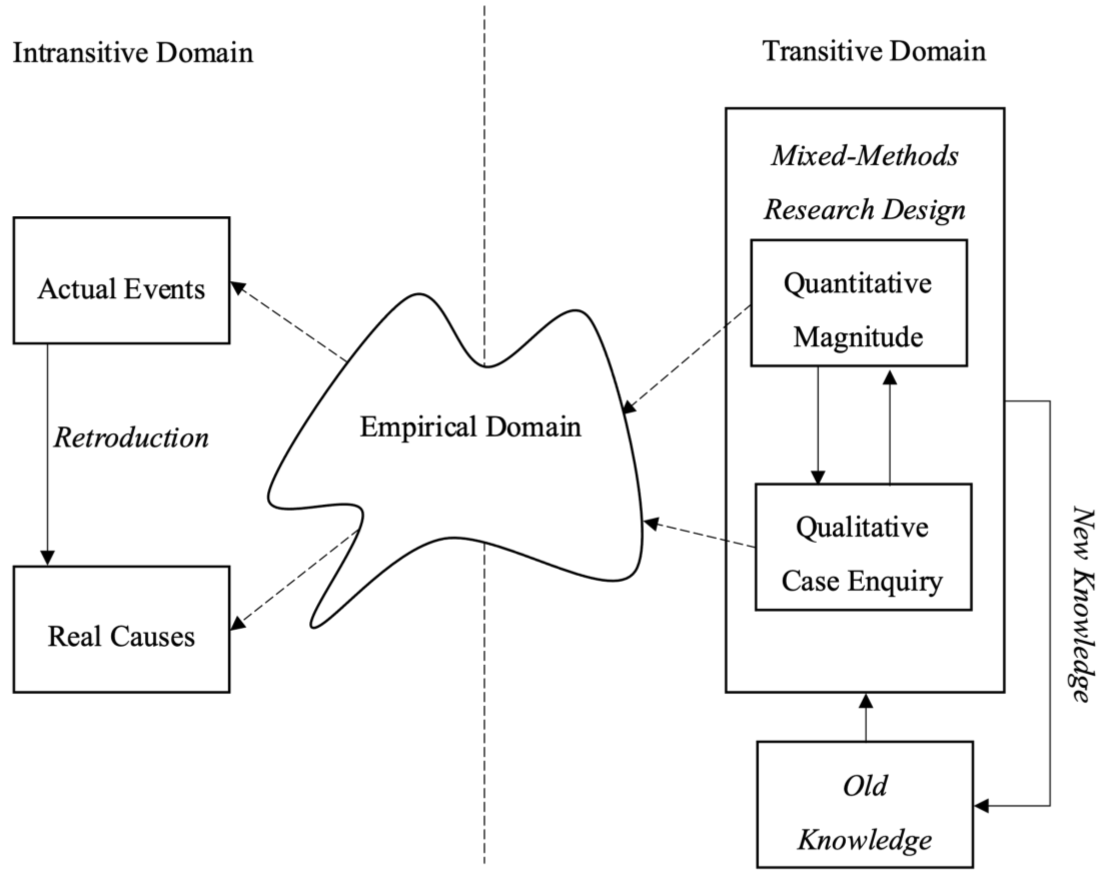

Figure 2-2. The Retroductive Approach of Critical Realism for Knowledge Creation

In addition to the retroductive approach to knowledge creation, Maxwell and Mittapalli (2010) identified several aspects of critical realism that are relevant to mixed-methods research:

- *A process approach to causality.* Critical realism views causality as "fundamentally referring to the actual causal mechanisms and processes that are involved in particular events and situations" (p. 155). To explain the actual causal mechanisms, critical realists rely on a retroductive approach, as discussed previously, which allows them to move between the knowledge of empirical phenomena, as expressed through events to the creation of explanations (or hypothesizing) in ways that hold ontological depth (Zachariadis et al., 2013).
- *Seeing mind as part of reality*. Critical realism recognizes different aspects of entities, including mental concepts, events, and processes. Critical realists argue that mental events and processes are real phenomena that can be causes of behavior, rather than simply abstractions from behavior or constructions of the observer (Maxwell & Mittapalli, 2010). It also supports the idea that individuals' social and physical contexts have a causal influence on their beliefs and perspectives. Thus, critical realism can provide a framework for better understanding the relationship between individuals' perspectives and their actual situations.
- *Validity and inference quality.* According to critical realism, validity is not a matter of procedures, but of "the relationship between the claim and the phenomena that the claim is about" and thus, it must be assessed in the specific context of a particular study (p. 158). This suggests that rather than focusing on whether correlated empirical phenomena are causally linked, critical realists focus on establishing whether the generative mechanism hypothesized

or uncovered is involved in the observed events in the field (Johnston & Smith, 2010; Zachariadis et al., 2013). This principle also allows researchers to identify plausible threats to the conclusions drawn in a given study, which depend on the context and purposes of the study as well as the methods used.

- *Diversity as a real phenomenon*. Critical realists believe that diversity is, in itself, a real phenomenon. Qualitative and quantitative research have tendencies, theoretical as well as methodological, to ignore or suppress diversity in their goal of seeking general accounts (Maxwell & Mittapalli, 2010). Mixed-methods research with a critical realism perspective, however, provides one way to help overcome this diversity limitation by requiring researchers to examine different levels of abstraction of a multi-layered world using different methods (Zachariadis et al., 2013).

2.1.1.2.1. Applying Critical Realism to Mixed-Methods Research

Our literature review suggests that the application of critical realism to mixed-methods research is still limited. It could be due to a lack of training on this paradigm as well as an insufficient number of practical examples on which researchers can rely. To provide a better idea of how critical realism can be applied to mixed-methods research, we offer two different examples: one from the information systems field (Walsh, 2014) and one from the health science field (Smirthwaite & Swahnberg, 2016).

The first example is a published article by Walsh (2014) on a strategic path to study information technology (IT) use through users' IT culture and IT needs perspectives. The author used a mixed-methods approach to address the following research question: *how do users' IT culture and IT needs influence IT use?* A mixed-methods approach was appropriate to address this research question because "there has been an essential impetus in the IS research community in recent years to unfold the features of different IT designs and to investigate their related specific properties that influence people's perceptions and use" (p. 147). Using theories from the fields of information systems (IS), psychology, and sociology, the author specifically adopted a critical realist stance with an exploratory (grounded theory) mixed-methods approach.

The author investigated the use of an open-source e-learning software platform called Moodle in a European business school, where this software was mostly used as an exchange platform for professors and students. The author used both secondary data from the existing literature and primary data consisting of quantitative and qualitative data. The quantitative data were collected through surveys and were analyzed using partial least squares (PLS), a structural equation modeling (SEM) technique. The qualitative data were collected through interviews and the transcripts of these data were hand-coded and presented in parallel with the quantitative results. All the data collected (i.e., data from the literature, primary data collected for the study) were analyzed together with the secondary data. Consistent with a critical realist view, the author opted for the relationships between concepts that appeared to best fit the whole dataset. Because qualitative and quantitative data analyses were done simultaneously, while taking into account all data as one set, and constantly comparing and analyzing all data as they were collected, the author justified the models by drawing from literature and/or quotations from interviews and/or quantitative reports. The author openly remained in an exploratory stance and iterated across all data throughout the research process, thus letting the data speak and guide the emerging theory (p. 153). Consistent with the critical realism perspective, the author assumed that the reality is multi-faceted and may be perceived differently by different individuals and in different contexts.

Given that the author used a critical realist stance, the focus was on establishing *causality*. The author integrated qualitative and quantitative data analyses to generate theoretical propositions that emerged through iterations between the quantitative and qualitative data. The author was able to propose new relationships among users' individual IT culture, their utilization of the e-learning platform, and the relationship of various constructs to their perceived IT needs (global, contextual, and situational). For example, one of the relationships that emerged from both qualitative and quantitative data was "individual IT culture mostly has a positive influence on the individual's global IT needs" (p. 155). To arrive at this proposition, the qualitative data from the interviews were analyzed and then each respondent's level of IT acculturation were quantitatively assessed using the individual's IT culture (IITC) score. Based on the results, the author concluded that a causal relationship exists in the "substantive area and investigated context." The author noted that "using quantitative data and methods does not forcibly confer a hypothesis-testing positivist stance. Being clear and open about the way we conducted our mixed-method research helped us remain true to our own paradigm/worldview—i.e., critical realism" (p. 163).

Another example of a mixed-methods study with a critical realism paradigm focused on the (in)equity in healthcare conducted by Smirthwaite and Swahnberg (2016). They conducted two empirical studies, a quantitative study (Smirthwaite et al., 2014) and a qualitative study (Smirthwaite et al., 2017) in the context of cataract extraction. From a critical realist perspective, they noted that "[it would be] more interesting to identify the mechanism(s) causing medical gender bias than it would be to focus on how the concept of medical gender bias itself is constructed . . . Since critical realism builds on the claim that there exist causal mechanisms that have consequences in the real world it is better able to make sense of the physical mechanisms endangering women's health, the shortening of women's lives when erroneous surgery is performed on their bodies, and the social/cultural mechanisms that prevent surgeons from performing the right operations" (p. 485). They discussed three forms of knowledge, i.e., real, actual, and empirical domain, from the critical realist perspective—*real*: "the generative mechanisms affecting waiting times for cataract extraction emerge from intersecting power structures related to gender, ethnicity, class, and age"; *actual*: "care seeking behavior shaped by intersecting gender norms, class norms, and norms related to ethnicity and age interact with the notions, values and assumptions of health care staff concerning men and women's need for care"; and *empirical*: "analyses of focus group interviews show, for example, how assertive behavior tends to be legitimized for male patients, and how men's need for cataract extraction is constructed as being more important/urgent than women's" (p. 487). They were also interested in feminist and gender research in the field of health and caring science. Thus, some elements of the use of a transformative emancipatory paradigm (discussed next) were also identified in their study.

In their quantitative study, they analyzed waiting times. The data were collected from database/register data of 102,532 patients who had cataract extraction performed in 2010-2011. They found that the existence of longer waiting times correlated with patients having good visual acuity and being female, as well as with being older, retired, born outside of Nordic countries, having a low income, and lacking education at a university level. From a critical realist perspective, they considered this study unsatisfactory because they were not able to conclude anything about what *causes* these differences in waiting times from these data alone. Also from a critical realist perspective, this study alone was unable to inform us about the primary object of science, *causal mechanisms*.

In their qualitative study, they sought to identify factors that contributed to the existence of longer waiting times for women having cataract extraction. Two clinics (one with a larger gender gap and one with a marginal gender gap) participated in the study. They selected two research sites with different gender gaps in order to identify attitudes and gender constructions of relevance for understanding why men have shorter waiting times than women do, and why there was a difference in the gender gap between the clinics. One focus group interview was conducted at each site. The authors noted that "if we assume that the opinions/notions/prejudices/experiences about women and men that the doctors expressed in the focus groups reflected their ordinary opinions, and that they were not something that we created by interviewing them, furthermore, then we—underpinned by critical realism—could claim that we *discovered* rather than *caused* or *constructed* them" (p. 489). They found that at the clinic with a larger gender difference, jokes with misogynist and racist connotations were not considered sensitive issues. At the clinic with smaller gender differences, however, they found that prominent persons at the clinic expressed an interest in and were aware of gender inequality. The majority of the findings were described as causal mechanisms that hinder equity in waiting times.

Overall, this research differentiates three forms of knowledge (real, actual, and empirical domain)—consistent with the critical realist perspective. For example, from the real domain, the authors hypothesized that "the generative mechanisms affecting waiting times for cataract extraction emerge from intersection power structures related to gender, ethnicity, class, and age" (p. 487). From the actual domain, they found that the care seeking behavior was shaped by intersecting gender norms; class norms and norms related to ethnicity and age interacted with the notions, values and assumptions of health care staff concerting men and women's need for care. From the empirical domain, they demonstrated that the statistical analyses and calculations of the mean value showed that women in general spent a longer time on the waiting list than men did; and the analyses of the focus group interviews showed, for example, how assertive behavior tended to be legitimized for male patients. The strength of critical realism was clearly demonstrated, producing truth-like knowledge about reality.

2.1.1.3. Transformative Emancipatory

The transformative emancipatory paradigm reflects "explicit recognition of values and knowledge of self and community that form a basis for methodological decisions" (Mertens et al., 2010, p. 195). This paradigm is driven by the dissatisfaction of researchers and members of marginalized communities with the dominant research paradigms and practices because those paradigms fail to serve the needs of those who have traditionally been excluded from positions of power in the research world (Mertens, 2007; Mertens et al., 2010; Sweetman et al., 2010). The transformative emancipatory paradigm's axiological assumption rests on the recognition of power differences and ethical implications that derive from those differences in terms of discrimination, oppression, and being made to feel marginalized (Mertens et al., 2010). The transformative emancipatory paradigm's ontological assumption rejects cultural relativism and recognizes the influence of privilege in determining what is accepted as "real" and the consequences of accepting one version of reality over another (Mertens et al., 2010). In this sense, reality is socially constructed and shaped by a variety of factors, including social, political, ethnic, and cultural lenses (Mertens et al., 2010).

The transformative emancipatory paradigm's ontological assumption leads to the epistemological assumption that "understanding the culture and building trust are deemed to be paramount" (Mertens, 2009, p. 57). Accordingly, knowledge is not neutral and is influenced by human interests. Knowledge reflects the power and social relationships within society, and the purpose of knowledge construction is to aid people to improve society (Sweetman et al., 2010). A researcher, according to this paradigm, is someone who recognizes "inequalities and injustices in society and strives to challenge the status quo, who is a bit of a provocateur with overtones of humility, and who possesses a shared sense of responsibility" (Mertens, 2007, p. 212). Therefore, the relationship between researchers and participants is a critical determinant in achieving an understanding of valid knowledge from the perspective of the transformative emancipatory paradigm.

In transformative emancipatory mixed-methods research, a researcher might make use of a variety of quantitative and qualitative methods to determine the focus of research, with a specific concern for power issues (Mertens, 2007). A transformative emancipatory mixed-methods research inquiry has "the need for community involvement, as well as the *cyclical* use of data to inform decisions for next steps, whether those steps are related to additional research or program changes" (Mertens et al., 2010, p. 199) and the cyclical model for transformative emancipatory research is presented in Figure 2-3. As illustrated in this Figure, community participation is needed at the beginning, throughout, and at the end of each research study (Mertens, 2007; Mertens et al., 2010). The goal is to have research that "serve[s] the ends of creating a more just and democratic society that permeates the entire research process, from the problem formulation to the drawing of conclusions and the use of results" (Mertens, 2003, p. 159), hence the need to have a cyclical and mixed-methods research approach (Mertens, 2007).

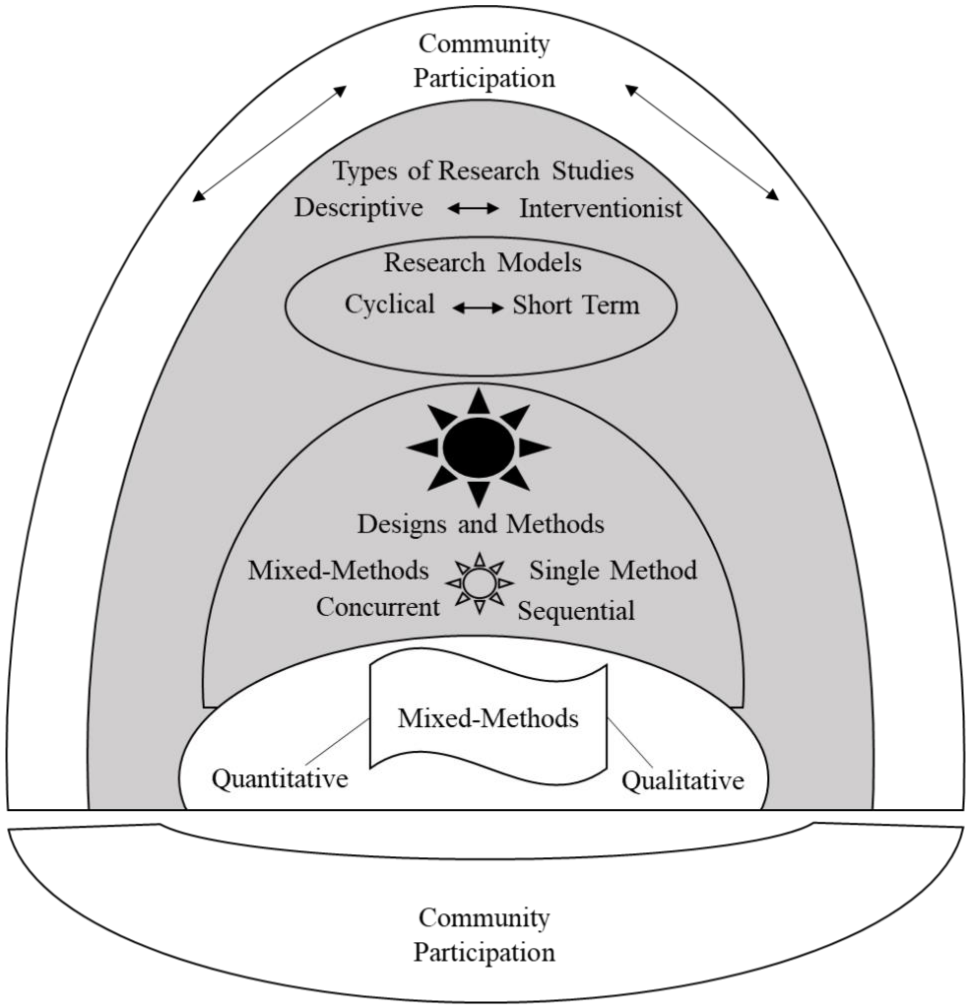

Figure 2-3. Cyclical Model for Research Using a Transformative Emancipatory Paradigm

2.1.1.3.1. Applying Transformative Emancipatory Paradigm to Mixed-Methods Research

We use a study of women's social capital conducted in a regional city in Australia by Hodgkin (2008) to illustrate the application of the transformative emancipatory paradigm in mixed-methods research. This article demonstrates how qualitative and quantitative methods can be integrated in feminist research. The objectives of the study were to draw attention to the lack of gender focus in studies of social capital and to make more visible women's contributions to society. There were two research questions driving the study: (1) do men and women have different social capital profiles?; and (2) why do women participate more in social and community activities than in civic activities? In order to address these research questions, the author first mapped the different patterns of participation based on gender and then explored how the role of "mother" alters the activities in which women become involved and the reasons for this.

The study used an explanatory sequential mixed-methods design. The purpose of mixed-methods research in this study was complementarity—the author sought elaboration, enhancement, and clarification from the results of one method with those of the other. In the first stage of the study, the researcher used a survey method. This method enabled the researcher to describe, explore, and to some extent, explain aspects of the differences between men and women on social, community, and civic participation within the sample. In the second stage of the study, the author conducted in-depth, one-on-one interviews with 12 women who had been involved in the first stage of the study. The goal of this second stage was to explore women's social interaction processes. The author was interested in describing aspects of their lives, which was based on their narration of their experiences.

The findings from the quantitative study showed a difference between men and women in social and community participation and, to a limited extent, civic participation. Women were more involved in social participation in group activities than men were. Although the quantitative data gave a broad snapshot of women's and men's participation in social and community activities, they did not tell the readers what the underlying motivation for such participation was, the experience of this, and the feelings associated with giving up other types of activities. A closed interaction between the author and the participants in the second stage of the study enabled the author to understand why women became involved in such activities. The findings revealed that the experience of motherhood, more than anything else, influenced their decision to get involved in social and community activities.

In this study, members of the community (i.e., local residents) were involved throughout the research process. This involvement allowed for a much richer understanding of gender and social capital. A pattern of differences between men and women was observed at different levels of social, community groups, and civic participation. A cyclical use of data is evident—the results from the quantitative stage of the study pointed the researcher to gather qualitative data in order to understand how women construct meaning around their involvement in social, civic, and community settings.

2.1.2. Dialectic Stance

The dialectic stance in mixed-methods research involves using multiple paradigmatic traditions and mental models, along with more than one methodology and type of method within the same study (e.g., Greene, 2007; Greene & Caracelli, 2003). A dialectic stance aims to generate an important understanding of a phenomenon being studied through the juxtaposition of different lenses, perspectives, and stances (Greene, 2005). Thus, this stance provides "a meaningful engagement with difference, an engagement intended to be fundamentally generative of insight and understanding that are of conceptual and practical consequence" (Greene & Hall, 2010, p. 124). Two major characteristics of the dialectic stance are:

- It recognizes the legitimacy of multiple paradigmatic traditions (Greene & Hall, 2010). A dialectic stance represents "multiple ways of seeing and hearing" (Greene, 2007, p. 20). This stance embraces paradigmatic and methodological differences, and seeks to integrate them in a dialogic manner (Greene & Caracelli, 1997). It also emphasizes the importance of different people with different mental models contributing ideas to research and practice (Greene, 2007; Johnson, 2017). For example, one can address the same research question using two different methods, each rooted in a distinct paradigm. One can then make multiple inferences corresponding to different worldviews and compare the results.
- It involves the use of data from one approach to directly inform the other in an iterative way. In practice, a researcher who adopts this stance would examine the results of a particular method and consider how the paradigm underlying the study impacted the results. Then, the

researcher would analyze how the results from one method corresponded to the results from other methods, each with their own philosophical assumptions (Betzner, 2008).

A mixed-methods way of thinking offers opportunities to engage meaningfully with differences that we encounter in our study context—e.g., differences in ethnicity, gender, religion, country, culture (Greene & Hall, 2010). Because the dialectic stance invites multiple ways of seeing and ways of knowing, a multiplicity of different perspectives is engaged, as are diversity and variation in the substance of what is being studied (Greene & Hall, 2010).

Building on this dialectic stance, Johnson (2009) proposed a *dialectical pragmatism stance* as an alternative philosophical stance for mixed-methods research. This paradigm is a combination of a dialectic approach and pragmatism. By integrating the dialectic perspective and pragmatism, Johnson (2009) noted that dialectical pragmatism is especially tailored to mixed-methods research. Whereas pragmatism embraces the use of multiple methods to meaningfully generate information to address research questions (Morgan, 2007), the dialectic stance suggests researchers using a mixed-methods approach should carefully listen to and consider the opposing viewpoints when developing a workable solution for a mixed-methods research study. This new mixed-methods research perspective can, therefore, provide ways for researchers to understand and properly integrate multiple paradigms, values, and methodologies to produce more complete knowledge about the phenomenon under study.

Summary

- Mixed-methods research is characterized by paradigm pluralism—i.e., the belief that a variety of paradigms may serve as the underlying philosophy for mixed-methods research.
- One of the major assumptions of pragmatism is that different actions or approaches generate different outcomes or consequences. Pragmatism places central importance on the research questions rather than on methodologies or methods.
- Critical realism recognizes assumptions and limitations of different paradigms. It embraces epistemological relativism by accepting the possibility of alternative explanations for any phenomenon. The main scientific methodology of critical realists is retroduction.
- The transformative emancipatory paradigm reflects explicit recognition of values and knowledge of self and community that form a basis for a methodological decision. A transformative emancipatory paradigm for mixed-methods research suggests the need for community involvement, as well as the cyclical use of data to inform decisions on what the next step is in the research process.
- A mixed-methods researcher can also use a dialectic stance. This stance recognizes the legitimacy of multiple paradigmatic traditions and involves the use of data from one approach to directly inform the other in an iterative way.

Exercises

1. Select an article that uses a mixed-methods approach in your field and identify the paradigmatic assumptions made in that article.
2. In your research area, identify a research question of interest. How would you apply the pragmatist paradigm in a study that you may conduct? Explain how the paradigmatic assumptions influence your study design.

3. Building on your answer to question #2 above, how would you apply the critical realist paradigm in a study that you may conduct? Explain how the paradigmatic assumptions influence your study design.
4. Building on your answer to questions #2 and #3 above, how would you apply the transformative emancipatory paradigm in a study that you may conduct? Explain how the paradigmatic assumptions influence your study design.

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CHAPTER 3

NATURE OF THEORY IN MIXED-METHODS RESEARCH

Having considered paradigmatic stances in mixed-methods research in the previous chapter, in this chapter, we focus on the role of theory in mixed-methods research. Theory is defined as "a statement of relations among concepts within a set of boundary assumptions and constraints" (Bacharach, 1989, p. 496). Theory allows researchers to understand and predict outcomes of interest and also allows them to describe and explain a process and sequence of events (Colquitt & Zapata-Phelan, 2007). According to Bacharach (1989), the goal of theory is to "organize (parsimoniously) and to communicate (clearly)" (p. 496). Bacharach also argued "if [theory] is not testable, no matter how profound or aesthetically pleasing it may be, it is not a theory" (p. 512). Theory should help us organize our thoughts, generate coherent explanations, and improve our predictions, which in turn helps us achieve a better understanding of the phenomenon of interest (Hambrick, 2007).

Although quantitative and qualitative researchers have long histories of inquiry into the nature of theory (e.g., Cook & Campbell, 1979; Eisenhardt & Graebner, 2007; Kerlinger & Lee, 2000; Suddaby, 2006), this topic has received limited attention in mixed-methods research. For example, in a handbook on mixed-methods research (Teddlie & Tashakkori, 2010), theory is only discussed briefly in the introductory discussion about the philosophical assumptions and theoretical lenses used in mixed-methods research. Creswell (2010) noted that "neither Tashakkori and Teddlie (2003) nor Greene (2008)[1] addressed directly the theoretical perspectives discussion that has developed in the mixed-methods field in recent years" (p. 55). Although theory is more specific and less general than worldviews or paradigms (Creswell & Plano Clark, 2018), we believe that a detailed discussion about the role of theory in mixed-methods research is crucial because theory can serve as an educational device that can raise awareness about a specific set of concepts in research (Colquitt & Zapata-Phelan, 2007), particularly in mixed-methods research where multiple perspectives are commonly employed to investigate the phenomenon of interest.

It is well known that the relationship between theory and research is reciprocal; theory development relies on research and research relies on theory (Fawcett & Downs, 1986). Brown (1979), as cited by Fawcett and Downs (1986), characterized the relationship between theory and research as a *dialectic*—a transaction whereby theory determines what data are to be collected and research findings provide challenges to accepted theory. Meleis (2007, p. 188) noted that "completing isolated research projects that are not cumulative or that do not lead to the development or corroboration of theories has limited usefulness." Thus, theory and scientific research exist in a close and interactive relationship (Koh, 2013). Given the importance of theory in research, we argue that researchers using a mixed-methods approach should understand the role of theory in research and consciously use theory to explain, predict, and understand the meaning, nature, and challenges associated with the phenomenon under study.

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[1] These two articles are considered primary references for the discussion about the philosophical and theoretical foundations of mixed-methods research.

3.1. Theory in Quantitative Research

Theory is a core component of both quantitative and qualitative research. Theory building or theory development is "the degree to which an empirical article clarifies or supplements existing theory or introduces relationships and constructs that serve as the foundation for new theory," and theory testing is "the degree to which existing theory is applied in an empirical study as a means of grounding a specific set of a priori hypotheses" (Colquitt & Zapata-Phelan, 2007, p 1284). One perspective holds that qualitative research has exploratory research objectives (i.e., focus on theory initiation and theory building) and quantitative research has confirmatory objectives (i.e., focus on theory testing and theory modification). However, others argue that both exploratory (i.e., theory building) and confirmatory objectives (i.e., theory testing) can be achieved using either qualitative or qualitative research methods (e.g., Bendassolli, 2013; Colquitt & Zapata-Phelan, 2007; Dubin, 1978; Lynham, 2002).

Theory in quantitative research explains what researchers expect to find (Creswell, 2015). In this context, theory is used to explain, predict, generalize, and inform research questions and hypotheses tested in the study (Creswell, 2015). From a quantitative research perspective, theory is defined in terms of the relationships between independent and dependent variables (Colquitt & Zapata-Phelan, 2007). As noted by Kerlinger (1979), theory is "a set of interrelated constructs (variables), definitions, and propositions that presents a systematic view of phenomenon by specifying relations among variables, with the purpose of explaining natural phenomenon" (p. 64). Theory is also associated with conclusions that can be drawn based on hypotheses. For example, Honderich (1995) viewed theory as "a general statement (or hypotheses) from which particular inferences may be deducted" and "observations can then be seen as confirming or falsifying hypotheses" (p. 385). Thus, theory in quantitative research is primarily evaluated by its ability to explain variance in a criterion variable of interest (Bacharach, 1989).

The process of theory building and theory testing in quantitative research is illustrated in Figure 3-1. A research objective is exploratory (i.e., theory building) if the goal of the study is to examine patterns from data collected by the researchers. Building a theory using a quantitative approach is typically conducted in a different fashion from how it is done in qualitative research (Colquitt & Zapata-Phelan, 2007). The most common method of theory building in quantitative research is to use a hypothetico-deductive approach (Dubin, 1978). In the early stage of theory development, the goal is to create a conceptual framework of the theory (Dubin, 1978). Researchers can start with either a pre-existing theory that is relevant to the research questions (when prior theory exists) or preliminary review of relevant literature (when prior theory is limited or does not exist). Theory building, by relying heavily on data and less on pre-existing theory, is possible and strongly encouraged in quantitative research. Kaplan (1964) described this approach as "the most widely accepted reconstruction of science" (p. 9) in which "the scientist, by a combination of careful observation, shrewd guesses, and scientific intuition arrives at a set of postulates governing the phenomena in which he is interested" (pp. 9-10; see also Lynham, 2002, pp. 243-244). After establishing or building a conceptual model, researchers aim to establish the validity of the theory's propositions. In subsequent tests, researchers can examine mediators and moderators that explain those core relationships. Eventually, in still further tests, they can expand the theory by adding antecedents or consequences that are not part of the original formulation. Over time, a stream of such studies can provide input for a more comprehensive theory (Colquitt & Zapata-Phelan, 2007). For example, goal setting theory of motivation by Locke and Latham (1990) was based on 22 years of empirical research (Colquitt & Zapata-Phelan, 2007; Locke & Latham, 2004).

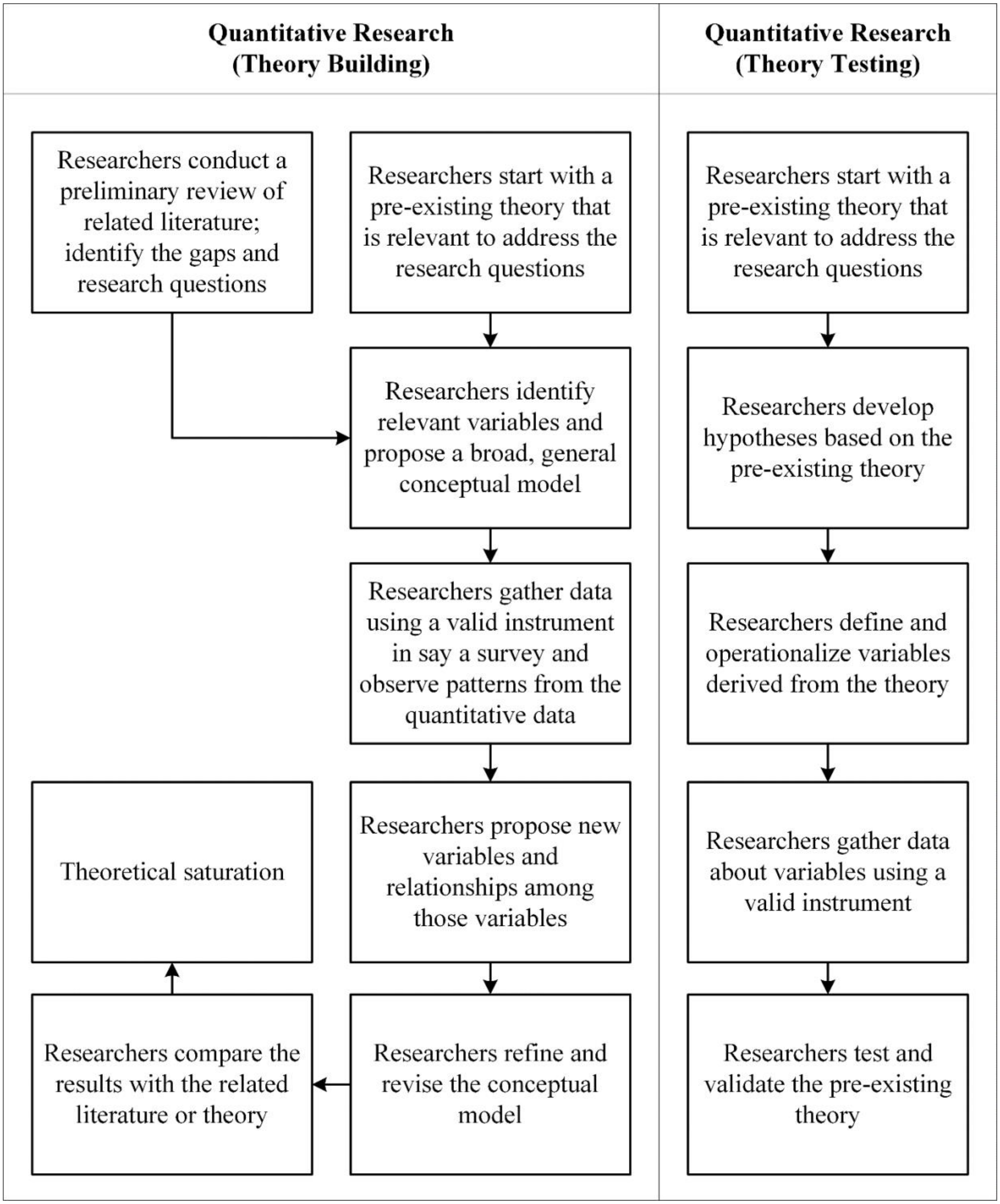

Figure 3-1. Theory Building and Theory Testing in Quantitative Research

Conversely, a quantitative research objective is confirmatory if the goal of the study is to use data to test hypotheses. An example of a quantitative study for theory testing is Müller-Stewens et al. (2017) in marketing. This paper found, with a series of seven quantitative studies (i.e., multi-methods research), support for their key hypotheses. Specifically, they examined the effect of gamified information presentation (i.e., conveying information about a product innovation in the form of a game) on consumer adoption of that innovation. Drawing on several theories, including computer-mediated communication (Hoffman & Novak, 1996) and the theory of flow (Csikszentmihalyi, 1990), they hypothesized that gamified information presentation promotes consumer innovation adoption and that it does so through two parallel psychological processes: (1) by increasing consumer playfulness; and (2) by enhancing the perceived vividness of information presentation. To test these hypotheses, they conducted seven studies, including two field experiments. The results showed that for gamified information presentation to increase innovation adoption, information should be integrated into the game. They noted that the research contributed to the literature on information presentation formats. It also contributed to the domain of experiential marketing by demonstrating how playful experiences govern individual buying behavior.

3.2. Theory in Qualitative Research

Theory in qualitative research is typically used as an explanation as well as a lens that informs different phases of the research (Creswell, 2015). A process for theory building in qualitative research has been proposed by several scholars. For example, Glaser and Strauss (1967) detailed a comparative method for developing grounded theory; Yin (1984) described designs of case study research; and Eisenhardt (1989) described the process of inductive theory development using case studies. These authors have detailed their approach for developing theory using qualitative methods. In general, this approach relies on continuous comparison of data and theory beginning with data collection (Eisenhardt, 1989). Figure 3-2 illustrates the process of theory building and testing in qualitative research.

As illustrated in Figure 3-2, theory building in qualitative research can either start with a priori theory/specification of constructs or with only some reference to extant literature. A priori theory provides researchers with a firm empirical grounding for the emergent theory (Eisenhardt, 1989). Sarker et al. (2013) emphasized the importance of theoretical engagement in qualitative research by suggesting that authors should adopt and integrate up-front theory into the study, despite the possible (mis)conception that qualitative researchers should not be too theoretically pre-determined when conducting inductively oriented qualitative research (e.g., Glaser & Strauss, 1967). Proponents of the use of a priori theory in qualitative research believe that unspecified theoretical expectations or a lack of pre-existing theory may lead researchers to replicate existing findings, adding little to existing theoretical knowledge, or to produce a massive amount of data without any clarity on how these data could lead to novel insights (Andersen & Kragh, 2010). An example of a qualitative study that uses a priori theory is Nielsen et al. (2014). Using a case study technique, Nielsen et al. drew on institutionalization theory to propose a new conceptualization of information technology (IT) institutionalization based on the “traveling of ideas” metaphor that distinguishes between theorization of ideas about IT use across an organizational field and translation of such ideas into practical use of IT within particular organizations. They used a priori theory and identified what was lacking from the existing literature—how “field-level dynamics and organizational processes coevolve” (p. 180).

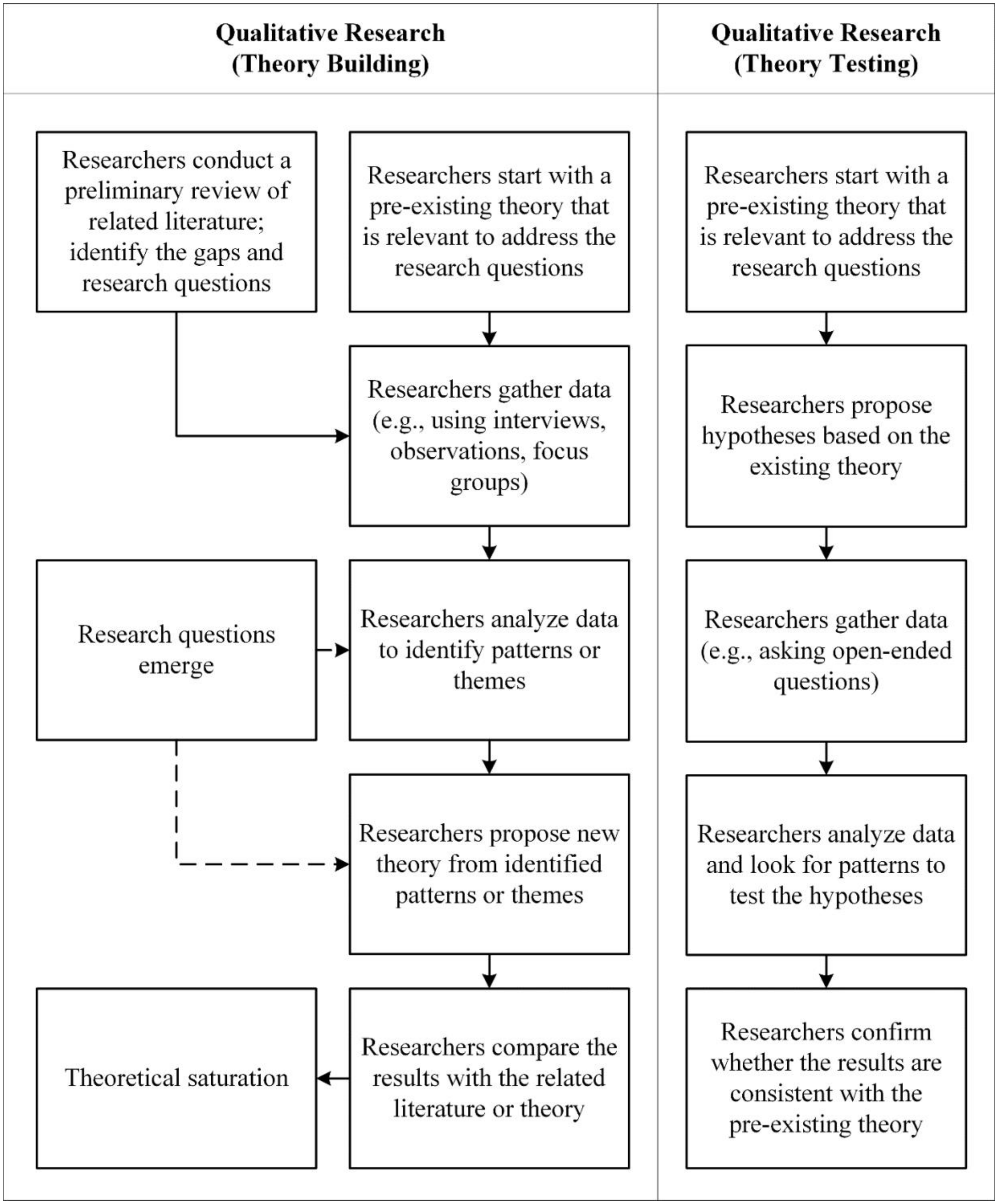

Figure 3-2. Theory Building and Theory Testing in Qualitative Research

Nonetheless, it is also common in qualitative research to start with only some or no theory because a priori theory is believed to bias or limit the findings (Eisenhardt, 1989; Glaser & Strauss, 1967). Eisenhardt (1989) noted that "although early identification of the research question and possible constructs is helpful, it is equally important to recognize that both are tentative in this type of research. No construct is guaranteed a place in the resultant theory, no matter how well it is measured. Also, the research question may shift during the research" (p. 536). This approach allows researchers to switch their research focus as the study advances and in turn enables them to generate new concepts or themes from open-ended, qualitative data (Onwuegbuzie & Leech, 2005).

Although confirmatory questions are not commonly associated with qualitative research, many researchers, particularly mixed-methods scholars (e.g., Onwuegbuzie & Leech, 2005; Patton, 1990; Tashakkori & Teddlie, 1998), suggest that qualitative research can be used for theory testing. For example, Cometto et al. (2016) used questionnaires and follow-up confirmatory interviews to examine the implementation of innovation projects in six different countries over a period of three years. They used qualitative interview results to validate the findings from a quantitative study.

The consensus that both quantitative and qualitative studies can be used for either theory building or theory testing is consistent with one of the characteristics of mixed-methods research—*the compatibility thesis* (see Chapter 1 for more details). As noted by Tashakkori and Teddlie (2003), "in practice, confirmatory qualitative research is not an impossibility . . . neither is exploratory quantitative research. Naturalistic observation can be used to explore causal relationships . . . and focus group might be considered a type of experiment" (p. 71). Next, we discuss the role of theory in mixed-methods research and suggest how one can use mixed-methods research to develop and test theory in the same study or a series of studies.

3.3. Theory in Mixed-Methods Research

Building and testing theory play an important role in integrating quantitative and qualitative approaches. Philosophical perspectives of mixed-methods research, discussed in Chapter 2, should guide the theoretical orientations used in a research study (Newman et al., 2003) because theories and paradigms are commensurate, i.e., theory is nested within and under paradigms (Mertens et al., 2010). Kuhn (1970) indicated that through the theories they embody, paradigms prove to be constitutive of all normal science activities, including underlying assumptions made, problem definitions, areas of investigation, questions posed, data interpretations, and conclusions drawn at the end of the research process. When paradigms change, there are usually significant shifts in the criteria used to determine the legitimacy of problems and proposed solutions because all theories, as well as the methods generated by them, are established based on paradigms (Kuhn, 1970; Ratcliffe, 1983). This relationship between theory and paradigms is known as the *Kuhn Cycle* (see Figure 3-3). From a paradigm perspective, theory resides at the epistemological level, and it helps inform the choice of methodology and methods (Creswell, 2010). This relationship implies that using a mixed-methods approach should take a theoretical position that is consistent with their paradigm.

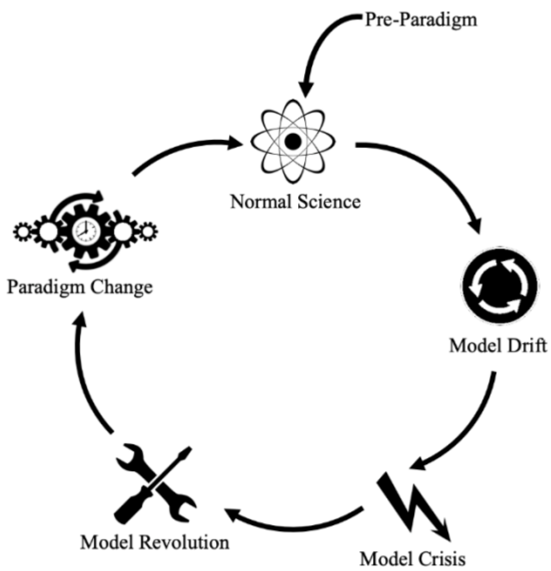

Figure 3-3. The Kuhn Cycle

A pragmatic view of mixed-methods research suggests that both quantitative and qualitative studies can have either exploratory or confirmatory research objectives and both objectives are linked by a theory (Onwuegbuzie & Leech, 2005). Theory in mixed-methods research offers a conceptual framework and implicit/explicit assumptions that guide researchers in achieving a common goal and de-emphasizing differences and incompatibilities between quantitative and qualitative methods (Chen, 2006). Thus, mixed-methods research provides opportunities for the integration of a variety of theoretical perspectives, such as structuration theory and social network theory, and it allows researchers to generate and test theory in the same research inquiry (Teddlie & Tashakkori, 2006). For example, one can develop a theory using a case study approach by creating theoretical constructs and propositions (Eisenhardt, 1989), and test the theory using hypothetico-deductive approaches, such as surveys and experiments. Using qualitative method before a quantitative one allows researchers to develop or extend theory, identify specific dependent and independent variables, develop a measurement instrument, determine the adequate level of analysis, or give more attention to process research (Molina-Azorin, 2012).

The process of conducting mixed-methods research is "an iterative, cyclical approach to research" that includes both deductive and inductive logic in the same research inquiry (Teddlie & Tashakkori, 2012, p. 781). This cyclical approach to research may also be conceptualized in terms of the distinction between building theory and testing theory that involves creative insights that may lead to the creation of new knowledge (Teddlie & Tashakkori, 2010). One way for this cycle of research to move is from specific observations to general inferences, then from those general inferences to tentative hypotheses (Teddlie & Tashakkori, 2010). Using this cyclical approach, researchers may start at any point in the cycle—either from theories or abstract generalization or from observations or other data points (Teddlie & Tashakkori, 2012).

Figure 3-4 illustrates how theories are used, informed, refined, and created using a mixed-methods research approach. One can use mixed-methods research to test a theory—i.e., an arrow from mixed-methods research designs to the existing theory—and develop a theory—i.e., an arrow from mixed-methods research designs to the new theory. To achieve the goal of building and testing theory in the same research inquiry, researchers can start from an existing theory to more specific predictions or from observations collected using mixed-methods research designs to more general inferences. The relationship between the existing theory and the new theory suggests that the new theory with certain properties may be influenced by the existing theory—i.e., what are other possible answers in the current literature—and that the new theory can be used as an alternative answer to the same phenomenon under investigation.

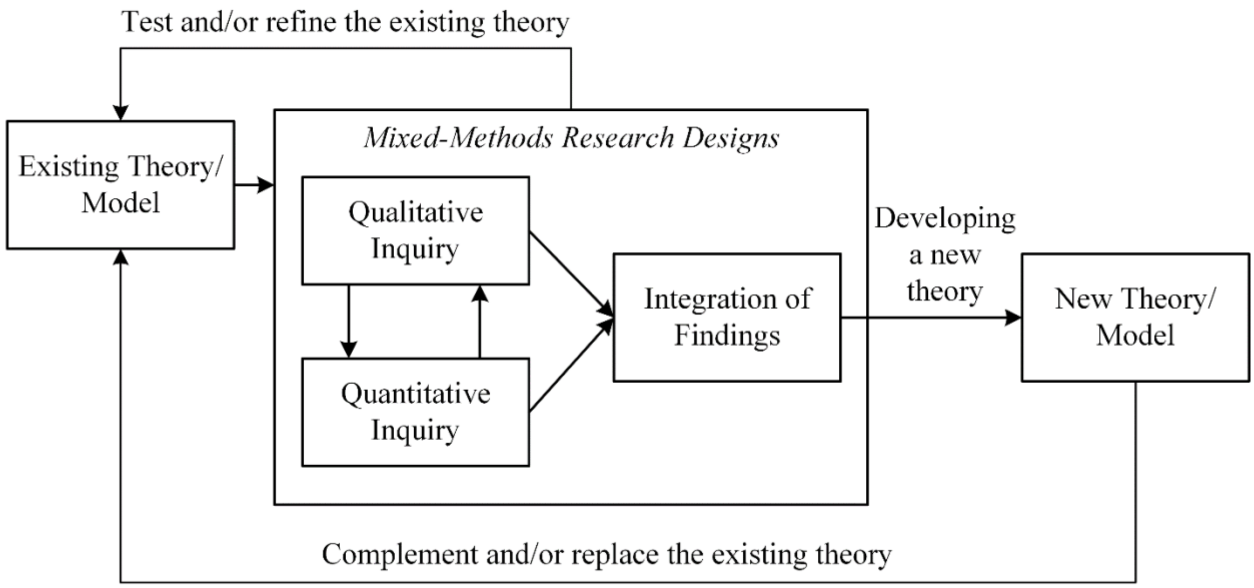

Figure 3-4. A Cyclical Approach to Mixed-Methods Research

Theory building requires an ongoing comparison of data and theory and the continuous refinement between theory and practice. Mixed-methods research has the ability to embrace quantitative and qualitative data and embrace multiple paradigms. New theory does not emerge immediately but will be developed over time, as research is extended using a different method and as more data are collected and analyzed. Only after researchers have observed similar phenomena using different methods will confirmation or disconfirmation of the new theory begin to emerge. Through this iterative process, mixed-methods research can holistically contribute to all phases of theory development. Thus, using a mixed-methods approach, one can make strong contributions by building and testing theory.

3.3.1. Evaluating Theory Using Mixed-Methods Research

Having discussed the process of building and testing theory in mixed-methods research, we now focus on how to evaluate theory that is developed using mixed-methods research. Based on previous work (e.g., Bacharach, 1989; Weick, 1979), we recommend five primary criteria using which theory may be evaluated. These include (1) *simplicity*: i.e., ease of understanding; (2) *accuracy*: i.e., conformity to the truth; (3) *generalizability*: i.e., extension to the other domain; (4) *falsifiability*: i.e., refutation is possible; and (5) *utility*: i.e., usefulness of theoretical systems. Although researchers usually have to make trade-offs among these criteria (Weick, 1979), we argue that mixed-methods research enables researchers to combine these theory elements by using different methods to compensate for the weaknesses associated with another method. For example, qualitative research is often accurate but potentially not generalizable and often lacking in simplicity (Shah & Corley, 2006). On the contrary, large-sample quantitative studies might be categorized as being simple and generalizable (Shah & Corley, 2006) but they fail to provide richness and/or insights into the participants' personal experiences. Hence, the meaning participants ascribe to the phenomenon studied is largely ignored (Yilmaz, 2013). In summary, "any *single method* of data collection results in trade-offs in the resulting theory's simplicity, generalizability, and accuracy" (Suls et al., 2010, p. 24).

A mixed-methods approach is one solution to build theory that is rich and testable. For example, researchers can start with qualitative methods to build an initial theoretical framework and then use quantitative methods to simplify the complexity of the framework and test the framework. Such an approach will enable researchers to build theory that is accurate, simple, generalizable, falsifiable, and useful. Next, we provide two examples of how theory is built, tested, and refined using mixed-methods research.

3.3.2. Theory in Mixed-Methods Research Practice

We provide two exemplars from previous research to illustrate how theory is developed, tested, and refined using mixed-methods research. The first paper, by Sarker et al. (2018), published in *Information Systems Research*, used border theory as a metatheoretical framework to develop and empirically test a model of organization-related and globally distributed software development (GDSD)-related antecedents of work-life conflict (WLC). The second paper by Stewart et al. (2017), published in *Academy of Management Journal,* explored barriers to the successful implementation of a team-based empowerment initiative within the Veterans Health Administration.

3.3.2.1. Sarker et al. (2018)

The research objective was "to identify the key organization-related and distributed software development-related factors that affect the [work-life conflict] WLC of IT workers involved in GDSD" (p. 104). The authors used a combination of the health and wellness perspective and the talent management perspective. To achieve their research objective, they used the metatheoretical lens of border theory (see Clark, 2000). This theory suggests that individuals often switch borders within their "lifespace" daily—they move back and forth from their "work region" to their "family and life region." They also drew on the general and information systems-specific literature on work-life balance (WLB) for identifying WLB-related constructs.

They used a mixed-methods research approach—a qualitative study followed by a quantitative study—to empirically examine the phenomenon of WLC. The purpose of using mixed-methods research in this work was *developmental*—the qualitative study informed the identification of appropriate variables and the development of hypotheses. As a part of the design, in phase 1, they used an exploratory case study to elicit key factors to be included in their research models, noting that "comprehensiveness of the model needed to be balanced with considerations of parsimony" (p. 105). In phase 2, they tested the model using a survey of GDSD professionals from three countries—the United States, the United Kingdom, and India. To justify their mixed-methods research design, they noted that "in the absence of a significant body of knowledge on the antecedents of WLB/WLC in the GDSD setting, it is not only appropriate but also necessary for us to incorporate elements unearthed through the exploratory case study or interviews from the field into the model, prior to empirically testing it through a survey" (p. 105).

In the first stage of their study, they used a layered approach to develop their theoretical model. First, they used border theory as a metatheoretical lens to identify and organize the broad categories of variables that help explain WLC and to articulate the definitions of those categories. Second, they drew on the general WLB/WLC literature to identify certain key constructs specified by border theory. Third, they used interviews as part of an exploratory case study to interpretively generate the key context-related constructs within each category specified by border theory. Finally, they used microlevel theories to justify the proposed relationships and to develop hypotheses related to the factors identified in the previous steps. Their qualitative data analysis revealed a number of relevant categories (e.g., extent of physical border, extent of temporal border, flexibility of border, permeable of border) and factors (e.g., location dispersion, time difference with remote members, flexibility of work schedule) that played a role in determining the level of WLC in the context of GDSD. Using border theory, in conjunction with the findings from the case study, they identified the GDSD-specific factors affecting WLC and the effect of WLC on important outcome variables. They developed a theoretical model and proposed hypotheses to be tested in the second phase of the study.

In the second phase of the study, they conducted a survey of IT professionals involved in GDSD in the United States, the United Kingdom, and India. The survey was administered by an external organization and the sampling technique might be considered "purposive random sampling." To measure the constructs identified in the first phase, they used established scales, whenever possible. They used structural equation modeling to analyze their survey data. The results indicated that most of their hypotheses were supported.

In sum, this article shows how theory is developed and tested using a mixed-methods approach. Using border theory as a metatheoretical framework, they developed and empirically tested a theoretical model related to the WLC of employees working in GDSD environments. They identified key antecedents and consequences of WLC within GDSD settings and thus contributed to the WLC literature. They also validated border theory and demonstrated how it could be adapted and empirically tested in a different context.

3.3.2.2. Stewart et al. (2017)

Stewart et al. (2017) used a parallel mixed-methods approach, i.e., quantitative and qualitative data were collected independently but simultaneously, to explore barriers to the successful implementation of a team-based empowerment initiative within the Veterans Health Administration. They sought to develop and test a theory about status and team leadership. Based on a review of the existing literature, they first developed a hypothesis that teams with high-status leaders, i.e., leaders who are physicians, were less effective in implementing team-based empowerment than were teams with low-status leaders. They then tested this hypothesis using a longitudinal quasi-experimental design by obtaining a performance outcome measure from VHA administrative records for all providers in one of twenty-one geographical divisions for a period spanning seven months before and thirty-seven months following the introduction of team-based empowerment. This resulted in the collection of pre- and post-intervention data for a sample of 224 providers. They analyzed the quantitative data using discontinuous growth modeling analyses. The results provided support for their hypothesis that teams led by higher-status physician leaders would be less effective in implementing team-based empowerment compared to teams led by lower-status non-physician leaders.

To further understand the process that underlies resistance from "high-status leaders", i.e., equivalent to the moderating effect of "team leader status", they adopted a qualitative approach. They collected the qualitative data in parallel with the quantitative data. Semi-structured interviews were conducted prior to the quantitative analysis. During the interviews, they focused broadly on identifying facilitators and barriers associated with the implementation of team-based empowerment. The qualitative data were analyzed using the procedures described by Miles and Huberman (1994). After they identified themes and categories within themes, they looked for patterns between categories. They identified the patterns in which high-status leaders had difficulty embracing the new identity of an empowering leader that in turn corresponded with ineffective delegation. This was a possible explanation for why teams with high-status leaders were less effective in implementing team-based empowerment than were teams with low-status leaders.

Their study is an example on how mixed-methods research can be used to *test* and *refine* a theory. They used a quantitative approach to validate and test the relationships they hypothesized in their conceptual model. To further investigate why their hypothesized relationships were significant, they conducted a qualitative study. Their qualitative analyses not only illustrated why some leaders facilitate while others resist team-based empowerment, but also uncovered specific patterns of leader behaviors. Using the findings from quantitative and qualitative approaches, they were able to refine the theory and provide evidence of "why" and "how" team leader status influenced the relationship between team-based empowerment and team effectiveness. For example, they noted that "combining specific identity responses that we observed with theoretical concepts expressed by other researchers allows for further refinement of our theoretical explanation underlying the status-empowerment link" (p. 2280).

Summary

- Theory in quantitative research is used to explain, predict, generalize, and inform research questions and hypotheses tested in the study, whereas theory in qualitative research is used as an explanation as well as a lens that informs different phases of the research process.
- Although there is a view that qualitative research focuses typically on exploratory research objectives and quantitative research focuses on confirmatory objectives, both research objectives (theory building and theory testing) can be achieved using either quantitative or qualitative research methods.
- Mixed-methods research provides opportunities for the integration of a variety of theoretical perspectives and enables researchers to build and test theory in the same research inquiry.
- Theory building and testing in mixed-methods research is considered "an iterative, cyclical approach to research" (Teddlie & Tashakkori, 2012, p. 781) that includes both deductive and inductive logic in the same research inquiry.
- Theory in mixed-methods research can be evaluated using five primary criteria: simplicity, accuracy, generalizability, falsifiability, and utility.

Exercises

Select an article in your field (or a related field) that uses a mixed-methods approach and evaluate how the authors use theory in that article. Answer the following questions:

1. What was the purpose of the study? Did the article attempt to build a theory or test a theory or both?
2. How did mixed-methods research help achieve the goal of theory building and/or theory testing?
3. If the article built a theory, evaluate the quality of the theory using five primary criteria discussed in this chapter.

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SECTION 2.

DESIGNING MIXED-METHODS RESEARCH

In the second section of the book, we focus on how to conduct mixed-methods research. This section consists of five chapters. In *Chapter 4. Appropriateness of Using a Mixed-Methods Research Approach*, we focus on the importance of research questions and purposes of mixed-methods research. In *Chapter 5. Basic Strategies for Mixed-Methods Research*, we discuss six aspects of mixed-methods design: design investigation strategies, strands of the study, mixing strategies, time orientation, priority of methodological approach, and sampling design strategies. We also discuss the relationships between mixed-methods purposes and mixed-methods design. In *Chapter 6. Mixed-Methods Data Collection Strategies*, we focus on mixed-methods data collection strategies, including mixed-methods sampling strategies. In *Chapter 7. Qualitative and Quantitative Data Analysis Strategies*, we discuss qualitative and quantitative data analysis strategies as well as potential threats to validity in qualitative and quantitative research. In *Chapter 8. Mixed-Methods Data Analysis Strategies*, we discuss various data analysis strategies for mixed-methods research as well as the quality criteria in mixed-methods research.

CHAPTER 4

APPROPRIATENESS OF USING A MIXED-METHODS RESEARCH APPROACH

From the discussion of worldviews and theory in mixed-methods research in the previous chapters, it should be apparent that mixed-methods research encourages diversity in all aspects of the research enterprise. This perspective embraces the *compatibility thesis* that focuses on research questions for conducting mixed-methods research. Researchers are free to combine different methodologies that are most appropriate to address their research questions (Teddlie & Tashakkori, 2009). In other words, the choice of methodology depends on the capability and complementarity of different methods to generate different kinds of knowledge and value (Zachariadis et al., 2013).

When determining whether mixed-methods research suits a particular set of research objectives, the researcher needs to make a set of decisions associated with *research questions* and the *purpose* of mixed-methods research (Venkatesh et al., 2013, 2016). These two elements, together with theoretical perspectives and paradigms, make up the foundation of design decisions that researchers need to make (Venkatesh et al., 2016). Research questions are shaped by the purpose of a study and in turn form the methods and design of the investigation (Tashakkori & Creswell, 2007). Obviously, when researchers examine mixed-methods research questions with interconnected qualitative and quantitative research approaches, the end product of the study will also include outcomes from both approaches (Tashakkori & Creswell, 2007). Given the importance of both research questions and purposes for determining the appropriateness of mixed-methods research, we discuss different types of research questions and purposes of mixed-methods research that can be used as a foundation for the design and conduct of pursue mixed-methods research.

4.1. Research Questions

Research questions are important in mixed-methods research because researchers often make use of the paradigm of pragmatism in which research questions drive the methods used in a study (Onwuegbuzie & Leech, 2006; Tashakkori & Teddlie, 1998). Research questions in mixed-methods research not only determine the type of research design, but also the sampling design and data collection and analysis techniques (Onwuegbuzie & Leech, 2006). Research using a mixed-methods approach should demonstrate the need for such an approach to answer research questions that clearly include the interconnected qualitative and quantitative components in the study (Tashakkori & Creswell, 2007). Agee (2009) suggested that good research questions do not necessarily produce good research, but poorly constructed questions will likely create problems that affect all subsequent stages of a study. Good research questions form the basis for good research because they allow researchers to identify what they want to know by creating a research boundary and focusing on finding answers in a coherent way (Kinmond, 2012).

In mixed-methods research, researchers typically must develop at least one qualitative research question and one quantitative research question. A qualitative research question is generally "open-ended, evolving, and non-directional" (Onwuegbuzie & Leech, 2006, p. 482), and it involves asking the kinds of questions that focus on the why and how of human interactions (Agee, 2009). As an open-ended and evolving question, a qualitative question can change during the process of research to reflect an evolving understanding of the problem (Creswell & Plano Clark, 2018). To develop qualitative research questions, Agee (2009) suggested that researchers adopt an iterative approach to questioning—i.e., researchers start with a broad question and then narrow down this question into several sub-questions that can be used during data collection. In the first iteration, a research question is generally tentative and exploratory to give researchers a tool for articulating the primary focus of the study. This question should be an overarching question to allow researchers to capture the basic goals of the study in one or two major questions (Creswell & Creswell, 2018).

Unlike a qualitative research question, a quantitative research question focuses on the relationships among variables (Creswell & Creswell, 2018). Most quantitative research questions are descriptive (e.g., what is the perception of task complexity among managers?), comparative (e.g., what is the difference in skill acquisition processes between men and women?), or associative (e.g., what is the relationship between autonomy and job satisfaction?) (Onwuegbuzie & Leech, 2006; Venkatesh et al., 2016). Quantitative research questions can be written in the form of questions and/or hypotheses (Creswell & Creswell, 2018). Although the most common way of writing a quantitative research question relies on a theory, i.e., research questions logically follow the relationships among variables in the theory, we argue that quantitative research questions can also emerge from identifying a gap in the literature in which a priori theory may be insufficient to explain the phenomenon of interest. This method of identifying a research question can be found in exploratory quantitative research. Specifically, researchers create their research questions based on a conceptual framework (i.e., researchers' understanding of how a research problem will be best explored, the specific direction the study will have to take, and the relationship among different variables in the study) (Grant & Osanloo, 2014). This is best summarized by Miles et al. (2020) who defined a conceptual framework as consisting of the key factors, constructs or variables, and relationships among them.

A mixed-methods research question is somewhat different from qualitative and quantitative research questions. Onwuegbuzie and Leech (2006) defined mixed-methods research questions as those "that embed both a quantitative research question and a qualitative research question within the same question" (p. 483). Mixed-methods research questions also necessitate that both qualitative and quantitative data be collected and analyzed either concurrently, sequentially, or iteratively before the question is addressed (Onwuegbuzie & Leech, 2006). Creswell and Creswell (2018) indicated that a strong mixed-methods research study should have a mixed-methods research question in addition to qualitative and quantitative research questions.

According to Plano Clark and Badiee (2010), when researchers write research questions in their mixed-methods study, they should consider four dimensions to describe their research questions (see Table 4-1). The first dimension is the *rhetorical style—question format*. One can state a research question using three different formats: (1) question; (2) aim or objective statement; or (3) hypothesis. The second dimension is *rhetorical style—level of integration*. Based on the level of integration, research questions can be presented in three different ways: (1) one can independently write qualitative and quantitative questions; (2) one can write separate qualitative and quantitative research questions and supplement them with a mixed-methods research question that focuses on the nature of integration; or (3) one can write an overarching mixed-methods research question that can be broken down into separate quantitative and qualitative sub-questions (Tashakkori & Creswell, 2007; Venkatesh et al., 2016). The third dimension is *the relationship between one* *research question and another*. According to Plano Clark and Badiee (2010), if researchers have multiple research questions in a study, the research questions may be independent of each other (e.g., the qualitative research question is "how are social networks used for business activity?" and the quantitative research question is "does position in the social network impact job satisfaction?") or dependent on each other (e.g., the qualitative research question is "how do employees come up with creative ideas?" and the quantitative research question asks "is there a positive relationship between factors that determine creativity and job performance?"). The last dimension focuses on *the relationship between the questions and the research process*. This relationship may be either *pre-determined* or *emergent*. Research questions are pre-determined when a theory or prior literature is used to guide the research questions, whereas research questions are emergent when they evolve throughout the phases of the research process. A summary of the elements of research questions including their examples is presented in Table 4-1.

Table 4-1. Research Questions in Mixed-Methods Research

Dimension	Category	Example
Rhetorical style—question format	Question	Kim et al. (2014) used mixed-methods research to address the following research questions: (1) "How do the instructors interpret and apply 'flipping' to their classroom?"; (2) "What are the students' perceptions of the value of the flipped classroom?"; and (3) "What are suggestions for the design of the flipped classroom?" (p. 38).
	Aim/objective	Stewart et al. (2017) used a mixed-methods approach with a research objective to "explore the paradox of why leaders resist the implementation of team-based empowerment even though such a transformation holds promise for improving both personal and organizational outcomes" (p. 2267).
	Hypothesis	Adam et al. (2018) conducted a mixed-methods research study to examine the relationship between living abroad and self-concept clarity. They conceptualized their research question in a hypothesis: "living abroad changes a key structural aspect of the self: self-concept clarity" (p. 16).
Rhetorical style—level of integration	Qualitative + quantitative research questions	Ivankova et al. (2006) conducted a study to understand students' persistence in a distance learning doctoral program. In the first, quantitative, phase of the study, the research question focused on "how selected internal and external variables to the [Educational Leadership in Higher Education] program (program-related, adviser- and faculty-related, institution-related, and student-related factors as well as external factors) served as predictors to students' persistence in the program" (p. 6). In the second, qualitative, phase of the study, the research question addressed "seven internal and

Dimension	Category	Example
		external factors found to be differently contributing to the function discriminating the four programs: program, online learning environment, faculty, student support services, self-motivation, virtual community, and academic adviser" (p. 6).
	Qualitative + quantitative research questions + mixed-methods research question about the nature of integration	Venkatesh et al. (2016) presented an illustrative study of mixed-methods research. The qualitative research question was "what are the factors that determine household PC adoption among adopters and non-adopters" (p. 466); the quantitative research question was "does [Model of Adoption Technology Household] explain household adoption and non-adoption of PCs?" (p. 466); and the mixed-methods research question was "in what way do the results from quantitative data collection (study 2) support or refute the results from qualitative data collection (study 1)?" (p. 457).
	An overarching mixed research question	Using a mixed-methods research approach, Wisler (2018) examined the moral philosophy difference between the ethical decision-making process of CEOs leading U.S. and non-U.S. strategic business units (SBUs) of luxury goods organizations. The overarching research question was "to what extent, if any, does a difference exist in ethical decision-making processes based on ethical and moral paradigms between U.S.-led and European-led CEOs of U.S. luxury goods company SBUs?" (p. 467). Some of the specific research questions asked were "Does a difference exist in economic egoism between U.S.-led and European-led [CEOs] of [SBUs] within luxury goods companies?" and "Does a difference exist in reputational egoism between U.S.-led and European-led [CEOs] of [SBUs] within luxury goods companies?" (p. 448).
Relationships among research questions	Dependent	In the illustrative study reported in Venkatesh et al. (2016), the quantitative research question depended on the results of the qualitative research question. The mixed-methods question depended on the results of both qualitative and quantitative research questions.
	Independent	Brady and O'Regan (2009) used mixed-methods research to answer three research questions: (1) "What is the impact of the [Big Brothers Big Sisters] program on the participating youth?"; (2) "How is the program experienced by stakeholders?"; and (3)

Dimension	Category	Example
		"How is the program implemented?" (p. 273). They used a survey to answer the first research question, whereas the second and third questions were answered using two different qualitative methods (i.e., interview and document reviews, respectively). The relationships among these research questions are independent because each of the questions focuses on a different aspect of the same research inquiry and thus each question can be answered concurrently.
Relationships between research questions and the research process	Pre-determined	In the illustrative study reported in Venkatesh et al. (2016), the relationship between the research questions and the research process is pre-determined—the research questions are based on the authors' understanding of the literature.
	Emergent	Sonenshein et al. (2014) used a mixed-methods design to examine the role of self-evaluations in influencing support for environmental issues. They proposed an emergent research question: "How do issue supporters' everyday experiences influence their self-evaluations?" (p. 9). After unpacking issue support challenges, self-assets, and self-doubts using grounded theory, they conducted a quantitative study using an observational method to answer the second research question: "How do patterns of self-evaluations relate to levels of issue-supportive behaviors?" (p. 9).

4.2. Purposes of Mixed-Methods Research

The major purpose for conducting research is to answer research questions (Newman et al., 2003). However, research questions do not provide the reason for addressing them. Only when a research study has a purpose is there a reason for conducting the study. Newman et al. (2003, p. 173) noted that "the purpose is not the question. Purpose is not design. Purpose is not methodology. Purpose is not data collection or analysis. Purpose is not categories of research questions. . . Purpose is focus on the reasons why the researcher is undertaking the study. And purpose should not be kept disconnected from the research question and the methods." Given such a definition, purposes of mixed-methods research should provide the rationale for conducting mixed-methods research (Greene et al., 1989).

There are seven possible purposes of mixed-methods research: (1) *compensation*; (2) *corroboration*;[1] (3) *diversity*; (4) *developmental*; (5) *complementarity*; (6) *completeness*; and (7) *expansion* (Greene et al., 1989; Tashakkori & Teddlie, 2008; Venkatesh et al., 2013, 2016). Although each purpose is important and valuable in its own right, we have listed them in what we

[1] The literature uses the terms corroboration and confirmation interchangeably. In this book, we only use corroboration, as the term confirmation is used in a different context (expectation-confirmation theory).

view to be an increasing order of value from the perspective of research endeavors. For instance, although compensation is useful, its added value is methodological in nature, whereas, at the other end, expansion can provide richness in the form of an intervention. The summary of these purposes is presented in Table 4-2. The quality of a mixed-methods study is directly associated with the purpose of mixed-methods research—whether the purpose is accomplished by the end of the study (Teddlie & Tashakkori, 2009). Mixed-methods research can serve multiple purposes and thus can provide implications to various audiences (Newman et al., 2003). An explicit recognition of these purposes by mixed-methods researchers may also help readers to understand the goals and outcomes of a mixed-methods research article (Venkatesh et al., 2013). Thus, the explication of the purposes for conducting mixed-methods research is considered mandatory in mixed-methods research practice (Venkatesh et al., 2013). Next, we discuss each purpose, drawn from Venkatesh et al. (2013), in more detail.

Table 4-2. Purposes of Mixed-Methods Research

Purpose	Definition
Compensation	Used to address the weaknesses of one type of method using the other type of method (Tashakkori & Teddlie, 2008; Venkatesh et al., 2013).
Corroboration	Used to assess the credibility of inferences obtained from one approach of the study using another approach of the study (Tashakkori & Teddlie, 2008; Venkatesh et al., 2013).
Diversity	Used to obtain divergent views of a single phenomenon (Venkatesh et al., 2013).
Developmental	"Seeks to use the results from one method to help develop or inform the other method, where development is broadly construed to include sampling and implementation, as well as measurement decisions" (Greene et al., 1989, p. 259).
Complementarity	Different methods are used to assess different facets of a phenomenon, yielding an enriched, elaborated understanding of that phenomenon (Greene et al., 1989).
Completeness	Used to provide a holistic view of the phenomenon that cannot be achieved by one approach only because the full picture is more meaningful than the findings from either a qualitative or quantitative method alone (Teddlie & Tashakkori, 2009).
Expansion	Used to extend the breadth and range of the phenomenon by using different methods for different components of the phenomenon (Greene et al., 1989).

4.2.1. Compensation Purpose

The goal of mixed-methods research with a compensation purpose is to offset the weaknesses of one type of method by using the other type of method (Tashakkori & Teddlie, 2008; Venkatesh et al., 2013). For example, if researchers encounter errors in one type of data, such errors can be reduced by using another method (Tashakkori & Teddlie, 2008). Unlike the corroboration purpose, which we discuss next, the compensation purpose does not require qualitative and quantitative methods be implemented equally (Greene et al., 1989). Instead, when the purpose of the study is compensation, one is likely to use a sequential mixed-methods approach in which the second strand of the study is conducted after the findings from the previous strand of the study are known, and the second study is explicitly used due to the weaknesses associated with the method used or data collected in the first study.

To illustrate a mixed-methods research study with a compensation purpose, we use the study reported in Wisler (2018). The goal of the study was to focus on leaders' ethical decision-making process within the luxury goods industry. The research purpose was to determine if there was a difference between two leaders (CEOs) types: CEOs leading U.S. strategic business units (SBUs) and CEOs leading non-U.S. SBUs of luxury goods organizations in ethical decision-making processes. Factors associated with the decision-making processes include economic egotism, reputation egoism, rule utilitarianism, act utilitarianism, virtue of self, virtue of others, act deontology, and rule deontology. The author used an online survey to collect the quantitative data followed by a series of phenomenological interviews with key survey participants. The relationship between the qualitative study and quantitative study is shown in Figure 4-1. The author acknowledged that there was a challenge in gathering a large sample size to satisfy the minimum number of participants required for the quantitative phase of the study. To compensate for this small sample size, the author gathered qualitative data. The qualitative data not only compensated for the small sample size in the quantitative study, but also enabled the researcher to gain an in-depth understanding of the problem. By comparing the results from both methods, the researcher was more confident in generating valid inferences.

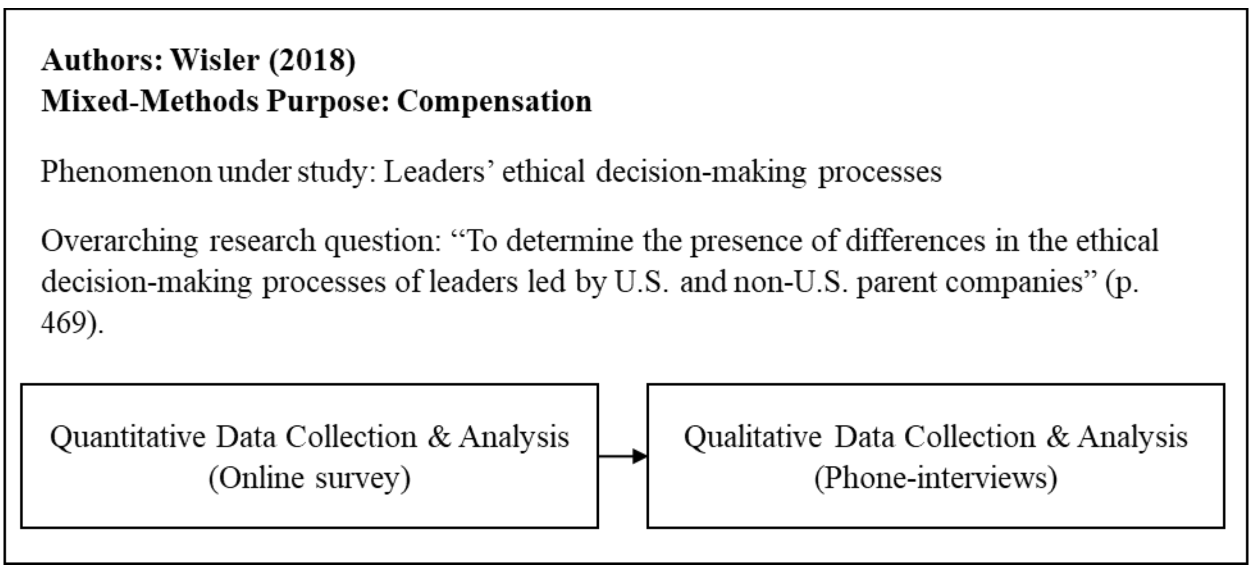

Figure 4-1. Mixed-Methods Research with a Compensation Purpose

4.2.2. Corroboration Purpose

A mixed-methods study with a corroboration purpose aims to assess the credibility of inferences obtained from one approach of the study using another approach of the study (Tashakkori & Teddlie, 2008; Venkatesh et al., 2013). To achieve this purpose, it is important for researchers to counteract or maximize the heterogeneity of irrelevant sources of variance attributable to different types of bias, such as method bias, inquirer bias, and theory bias (Greene et al., 1989). A corroboration purpose differs from a complementarity purpose, which we discuss in section 4.2.5, in that the logic of the corroboration purpose requires different methods to assess the same conceptual phenomenon (Greene et al., 1989). In a classic sense, a corroboration purpose seeks convergence, triangulation, and correspondence of findings across different methods (Caracelli & Greene, 1993; Greene et al., 1989). A mixed-methods study with a corroboration purpose usually consists of both exploratory and explanatory/confirmatory questions (Tashakkori & Teddlie, 2008).

The idea of a corroboration purpose can be traced back to the idea of triangulation proposed by Campbell and Fiske (1959) in which more than one method is used in the validation process to ensure that the explained variance in quantitative analysis is the result of the underlying phenomenon and not the method (Johnson et al., 2007; Teddlie & Tashakkori, 2003). Although the use of multiple qualitative or quantitative approaches is considered triangulation by Campbell and Fiske, their type of triangulation has limited value here because essentially only one paradigm is used in the study and any inherent weaknesses associated with that single paradigm and concomitant methods cannot be addressed by using multiple approaches within the same methodological paradigm (Johnson et al., 2007). The idea of corroboration in mixed-methods research is intended to address this methodological limitation of one type of method by intentionally using both quantitative and qualitative approaches to study a phenomenon and be implemented independently and concurrently to preserve their counteracting biases (Greene et al., 1989). Thus, a concurrent mixed-methods design is well suited for a study with this purpose.

To illustrate, we use the study reported in Brickson (2005). The author used a mixed-methods approach to understand the relationship between organizational identity and how organizations relate to their stakeholders. The author introduced a new construct called “identity orientation.” To assess the construct’s viability, explore its properties, and analyze its predictors at multiple levels of analysis, the author collected data using both qualitative and quantitative methods in a field study. The qualitative measures were implicit (e.g., the author used the Troubling-event question, resting on the assumption that organizational identities determine what aspects of issues are threatening) and elicited general perceptions of the organization’s identity, whereas the quantitative measures explicitly assessed identity orientation. The relationship between the qualitative study and quantitative study is shown in Figure 4-2. By using both methods in the same study, the author was able to triangulate the findings and identify properties and predictors of organizational identity orientation.

Authors: Brickson (2005)
Mixed-Methods Purpose: Corroboration

Phenomenon under study: Organizational identity orientation

A general, overarching research question in terms of an objective: to explore "the general properties of the organization-level construct of identity orientation and assesses its antecedents" (p. 578).

The specific research questions were: "How and with what frequency relations with stakeholders are reflected in organizational identity more broadly?"
"How [are] organizations ... oriented toward stakeholders"?
What are "the possible antecedents of identity orientation"? (p. 578)
Note: The author did not differentiate between quantitative and qualitative research questions.

Qualitative Data Collection & Analysis (Open-ended questions in a survey)

+

Quantitative Data Collection & Analysis (Close-ended questions, standardized scales)

Figure 4-2. Mixed-Methods Research with a Corroboration Purpose

4.2.3. Diversity Purpose

A mixed-methods study with a diversity purpose serves to obtain divergent views of the same phenomenon (Venkatesh et al., 2013). A study with this purpose is used to find "new and better explanations for the phenomena under investigation" (Erzberger & Kelle, 2003, p. 475). The divergent findings will ideally be compared and contrasted to generate stronger (or better) inferences, and the balance in results can be achieved when differences between the qualitative and quantitative findings are properly reconciled (Tashakkori & Teddlie, 2008). Pluye et al. (2009) suggested four strategies that can be used to take into account divergence in mixed-methods research: *reconciliation*, *initiation*, *bracketing*, and *exclusion*. *Reconciliation* may occur when the divergent results can be interpreted in a sense-making plausible manner, which may lead researchers to reanalyze existing data. This strategy may also lead to a new perspective or a new framework but does not lead researchers to ask a new research question. *Initiation* takes place when new frameworks or perspectives that emerge from conflicting results lead to two additional steps: (1) asking new research questions; and (2) collecting and analyzing new data to further examine the new perspective or framework (Caracelli & Greene, 1993). *Bracketing* is appropriate when qualitative and quantitative findings are irreconcilable and suggest extreme results (e.g., best-case versus worst-case scenarios). Lastly, *exclusion* may occur when (1) qualitative inferences contradict quantitative inferences; (2) the results of mixed-methods research are incomplete; and (3) one type of data or results lacks validity.

One can use either a sequential or a concurrent mixed-methods research design when diversity is the purpose. This decision depends on the research questions being addressed. If the time order is considered a critical variable (e.g., how does trust influence brand loyalty among different groups of customers in different stages of product lifecycle?), researchers should use a sequential mixed-methods design. In contrast, if researchers are interested in investigating differences among populations in the same period of time, they can use a concurrent mixed-methods design.

To illustrate mixed-methods research with a diversity purpose, we use the study reported in Chang (2006). This study compared information systems (IS) integration in high-tech organizations from the technology and general management perspectives. Specifically, the author compared the IT and management perceptions of the enterprise resource planning (ERP) system scope, importance, benefits, and implementation success factors. The author gathered both qualitative and quantitative data using interviews from multiple case studies and a survey, respectively. The relationship between the qualitative study and quantitative study is shown in Figure 4-3. The interview results from the case studies were used to develop a questionnaire to compare IT and general management perceptions. In the qualitative phase of the study, there was some evidence of divergence in views between IT and general management. However, in the quantitative phase of the study, where the author focused more narrowly on specific aspects of IS functionality, implementation and benefits showed very similar perceptions by IT and general management staff, with only a small degree of inconsistency between these two groups. For example, IT management’s overall assessments of business functions were more strongly correlated with their overall level of implementation and they tended to rate system benefits and system reliability more highly than that of general management. Taken together, the mixed-methods research results allowed the researcher to obtain divergent views of the same phenomenon by comparing perceptions across different types of participants.

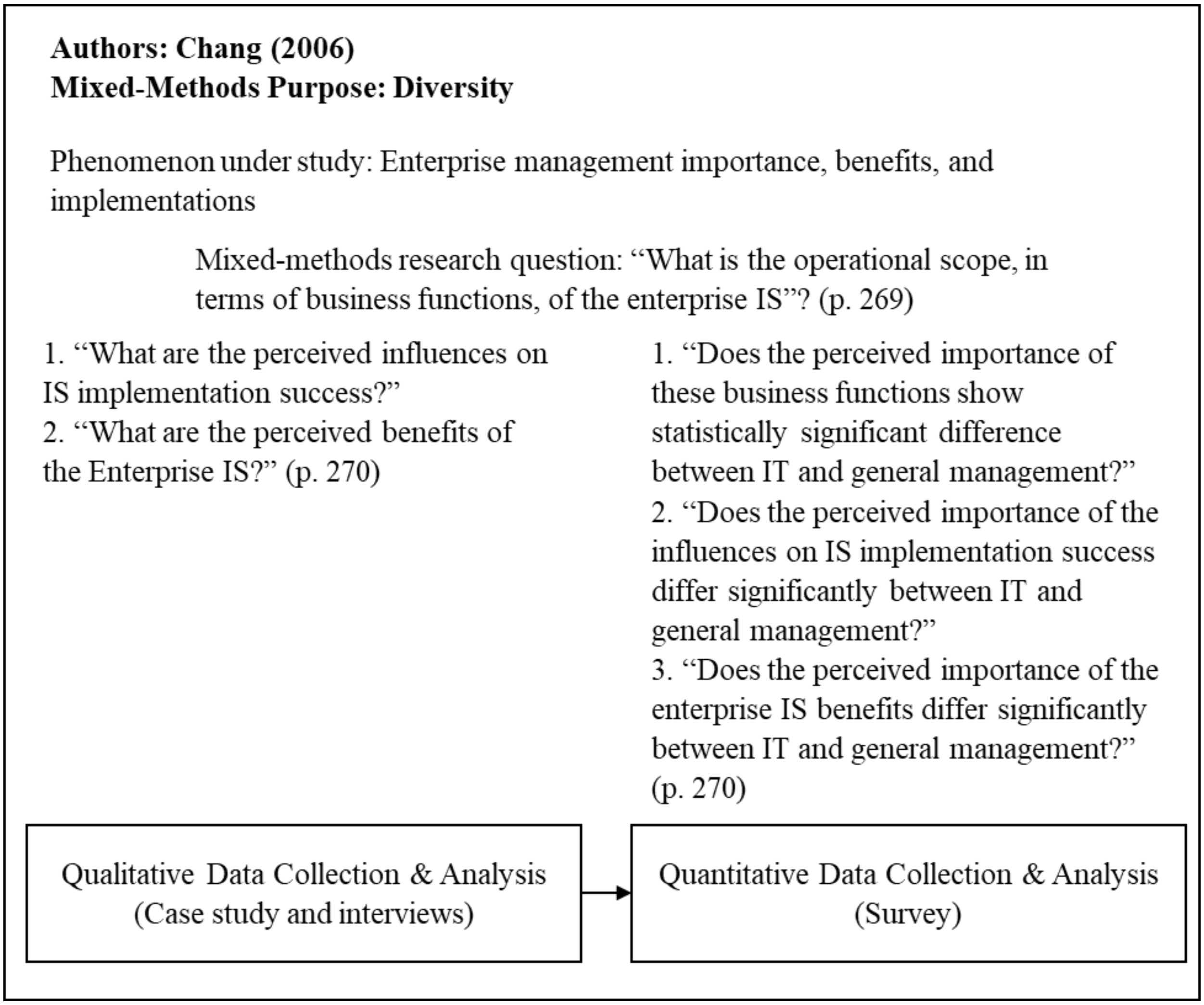

Figure 4-3. Mixed-Methods Research with a Diversity Purpose

4.2.4. Developmental Purpose

In a mixed-methods study with a developmental purpose, the results from one method are used to help develop or inform the design and development of the subsequent study using the other type of method, where development is broadly construed to include sampling designs as well as measurement decisions (Greene et al., 1989; Tashakkori & Teddlie, 2008). The goal of a mixed-methods study with a developmental purpose is to increase the validity of constructs and inquiries by combining both qualitative and quantitative methods so that researchers can compensate the weaknesses of one method with the strengths of another method (Greene et al., 1989; Venkatesh et al., 2013).[2] All studies with a developmental purpose involve the sequential use of qualitative and quantitative methods, where the first method/study (could be a qualitative or quantitative method) is used to help inform the design and development of the second method/study (Greene et al., 1989).

[2] Here, compensation refers to more than just addressing methodological weaknesses.

To illustrate a mixed-methods research with a developmental purpose, we use the study reported in Koh et al. (2004). In this study, they addressed two research questions: (1) what are the critical customer-supplier obligations in an IT outsourcing relationship?; and (2) what is the impact of fulfilling these obligations on success? They used a qualitative study to develop and identify the critical customer-supplier obligations in an IT outsourcing relationship and then used a quantitative study to test the impact of these obligations on success. The relationship between qualitative and quantitative studies is shown in Figure 4-4. In the qualitative part of the study, they conducted in-depth interviews. The results of content analysis of the interview transcripts showed that both customers and suppliers identified six obligations that are critical to success. In the quantitative part of the study, they tested their hypotheses using a survey of 370 managers. In this example, qualitative data were used to develop the focal constructs and quantitative data were used to empirically test the effects of these focal constructs on the dependent variable. Researchers have also been inspired by the developmental purpose to generate more complete, cohesive and accurate set of predictors that complement literature reviews, even though the purpose (developmental) has not been stated as such—for examples, see Venkatesh et al. (2023) and Zhang and Venkatesh (2017).

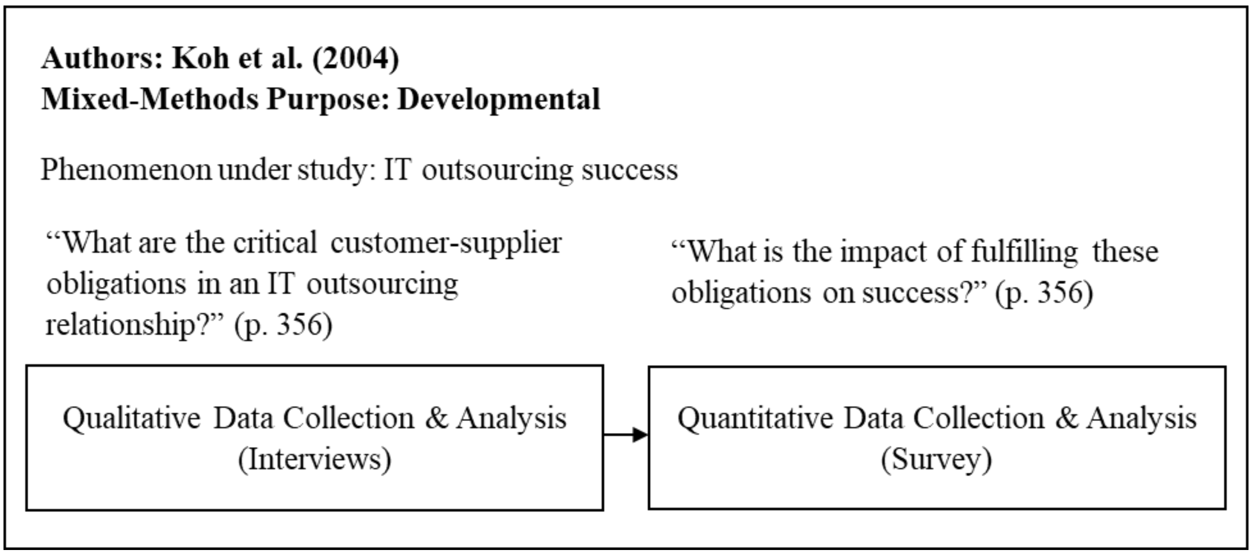

Figure 4-4. Mixed-Methods Research with a Developmental Purpose

4.2.5. Complementarity Purpose

Mixed-methods research with a complementarity purpose seeks elaboration, enhancement, illustration, and clarification of the findings from one method with the results from the other method (Collins et al., 2006), especially by focusing on related by distinct aspects of the same phenomenon or relationship (Greene, 2008). When the purpose in a mixed-methods study is complementarity, qualitative and quantitative methods are used to measure “overlapping but also different facets of a phenomenon, yielding an enriched, elaborated understanding of that phenomenon” (Greene et al., 1989, p. 258). Thus, research questions for the qualitative and quantitative components of a mixed-methods study with complementarity as the purpose should address related aspects of the same phenomenon (Tashakkori & Teddlie, 2008; Venkatesh et al., 2013). Because the qualitative and quantitative methods are used to determine the degree to which each method yields complementary results regarding the same phenomenon, complementarity is generally pursued using a concurrent mixed-methods design—i.e., qualitative and quantitative studies are conducted simultaneously (Teddlie & Tashakkori, 2009). However, a sequential mixed-methods design—i.e., qualitative and quantitative studies are conducted one after another—is also possible (e.g., Tiwana & Bush, 2007).

To illustrate mixed-methods research with a complementarity purpose, we use the study reported in Sonenshein et al. (2014). The goal of their study was to understand the role of self-evaluations in explaining the support for environmental issues. The relationship between the qualitative study and quantitative study is shown in Figure 4-5. They started with a qualitative study followed by a quantitative, observational study. The goal of the qualitative study (study 1) was to develop theory about how environmental issue supporters evaluated themselves in a mixed fashion, positively around having assets (self-assets) and negatively around questioning their performance (self-doubts). They explained how these ongoing self-evaluations (labeled, situated self-work) were shaped by cognitive, relational, and organizational challenges individuals interpreted about an issue from a variety of life domains (work, home, or school). In the quantitative study (study 2), they derived three main profiles of environmental issue supporters (i.e., self-affirmers, self-critics, and self-equivocators) and showed how these profiles related to real issue-supportive behaviors. A mixed-methods approach allowed them to investigate two different but complementary aspects of the same phenomenon—examine how social issue supporters' everyday experiences influenced their self-evaluations (study 1) and why these self-evaluations mattered through their ability to predict issue-related actions (study 2).

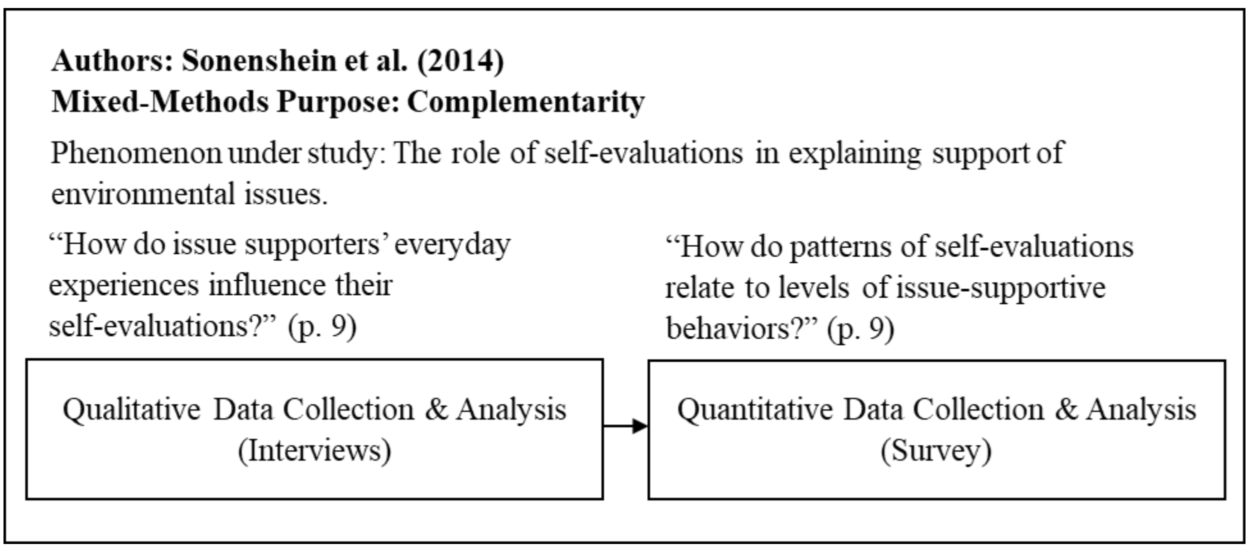

Figure 4-5. Mixed-Methods Research with a Complementarity Purpose

4.2.6. Completeness Purpose

The notion of completeness has been discussed by researchers using both qualitative and quantitative approaches (Teddlie & Tashakkori, 2009). For example, Tobin and Begley (2004) suggested that "completeness is important to qualitative inquiries, as it allows for recognition of multiple realities" (p. 393). Completeness is viewed as "a process whereby different theoretical and substantive components come together to ensure that all aspects of the phenomenon being researched are examined" (Twinn, 2003, p. 546). In this case, a mixed-methods approach is not used to confirm existing data but to make sure a complete picture of the phenomenon is obtained (Tashakkori & Teddlie, 2008; Teddlie & Tashakkori, 2003). A study with a completeness purpose provides a holistic view of the phenomenon that cannot be achieved by one approach only, and the picture is more meaningful than the findings from either a qualitative or quantitative method alone (Teddlie & Tashakkori, 2009). Given the goal of mixed-methods research is to use different theoretical views to study all aspects of a phenomenon, a study with a completeness purpose is generally conducted using a concurrent mixed-methods approach. Conducting both qualitative and quantitative studies simultaneously enables researchers to discover different aspects of the same phenomenon and integrate these aspects to gain a complete picture. Researchers can think of this process using a metaphor of putting a puzzle together—solving the puzzle is best achieved when different pieces of the puzzle are presented at the same time.

To illustrate mixed-methods research with a completeness purpose, we use the study reported in Stewart et al. (2017). As discussed in Chapter 3, the goal of their study was to explore barriers to the successful implementation of a team-based empowerment initiative within the Veterans Health Administration (VHA). They used a concurrent mixed-methods approach to explore the paradox of why leaders resist the implementation of team-based empowerment although such implementation holds promise for improving both personal and organizational outcomes. The relationship between the qualitative and quantitative studies is shown in Figure 4-6. Quantitative and qualitative data were collected independently but simultaneously in the VHA setting during the period or transition. In the quantitative study, they analyzed longitudinal data to test the hypothesis that teams with high-status leaders (i.e., physicians) were less effective in implementing team-based empowerment than were teams with lower-status leaders (e.g., nursing practitioner, physician assistants). However, this quantitative study alone did not allow them to explain the processes that underlie the moderating effect of team leader status (i.e., high-status vs. low status). They complemented the quantitative data with the qualitative data. They used interviews to gather qualitative data. The goal of their qualitative study was to develop theory related to the processes of why high-status leaders resist the implementation of team-based empowerment.

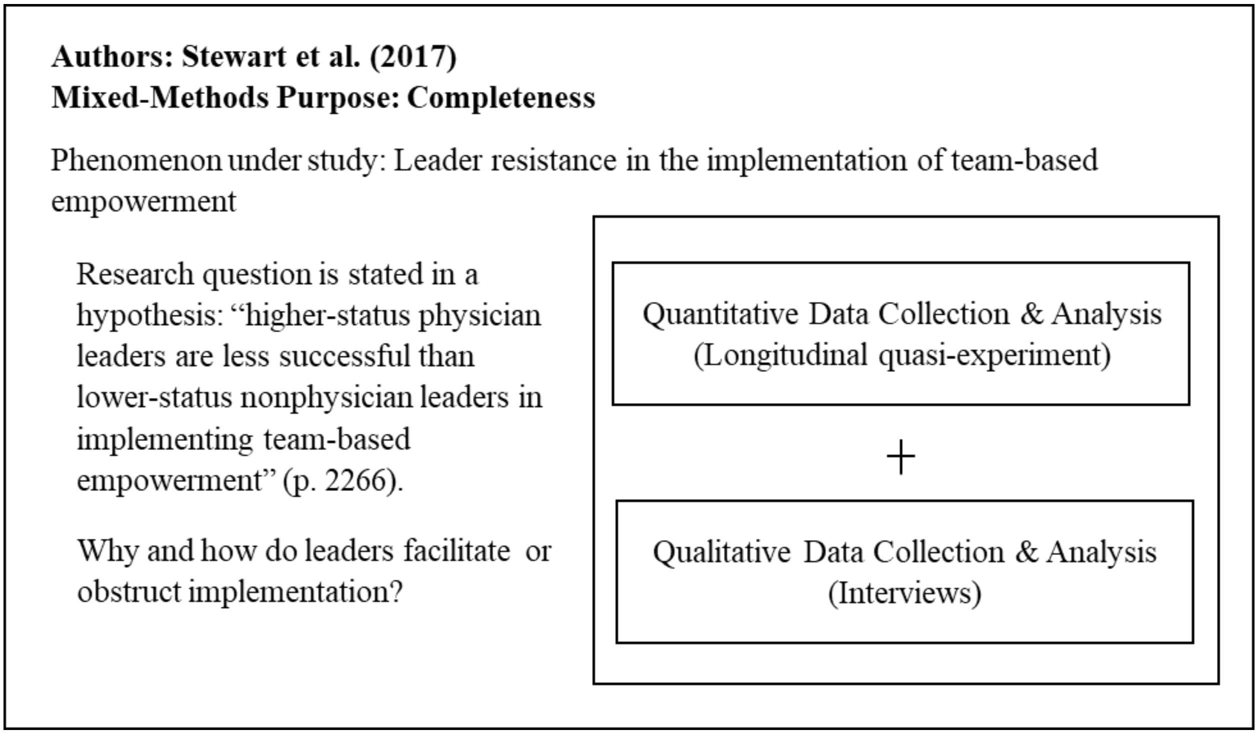

Figure 4-6. Mixed-Methods Research with a Completeness Purpose

4.2.7. Expansion Purpose

A mixed-methods study with an expansion purpose seeks to extend the breadth and range of the phenomenon by using different methods for different components of the phenomenon. The goal of a mixed-methods study with an expansion purpose is to enrich the understanding obtained in a previous strand of the study with the findings obtained in the next strand of the study (Teddlie & Tashakkori, 2009; Venkatesh et al., 2013). For example, in an evaluation study, quantitative methods frequently play a leading role in assessing program outcomes, whereas qualitative methods are used to assess program processes (Caracelli & Greene, 1993; Greene et al., 1989). One is likely to use a sequential mixed-methods design in a study with an expansion purpose because the qualitative study will expand on the initial findings resulting from the quantitative study or vice versa (Teddlie & Tashakkori, 2009).

To illustrate mixed-methods research with an expansion purpose, we use the study reported in Battilana et al. (2015). In this study, they examined the factors that influence social performance of hybrid organizations that pursue a social mission and sustain their operations through commercial activities by studying work integration social enterprises (WISEs). They predicted that both social imprinting, i.e., a founding team's early emphasis on accomplishing the organization's social mission, and economic productivity were important drivers of a WISE's social performance. However, there was a paradox inherent in the social imprinting of WISEs. Although it directly enhanced a WISE's social performance, it also indirectly weakened social performance by negatively influencing economic productivity. To test their predictions regarding the paradoxical nature of the relationship between social imprinting and social performance in WISEs, they used data from surveys administered annually between 2003 and 2007 to a large panel of WISEs operating in France.

In the second stage of the study, they explored a different aspect of the same phenomenon. Whereas the first study focused on testing the paradoxical relationship between social imprinting and social performance, the second study focused on exploring how socially imprinted WISEs might be able to resolve the paradox tested in the first study. The relationship between the qualitative study and quantitative study is shown in Figure 4-7. In the second study, they conducted an in-depth longitudinal qualitative comparative case study of two WISEs: one that successfully attenuated this relationship and one that was unsuccessful in addressing the paradox. The qualitative data were from thirty-five interviews and a wide range of archival materials for each case. The results suggested that a structural differentiation approach that assigns responsibility for social and commercial activities to distinct groups may allow hybrid organizations to mitigate the negative effect.

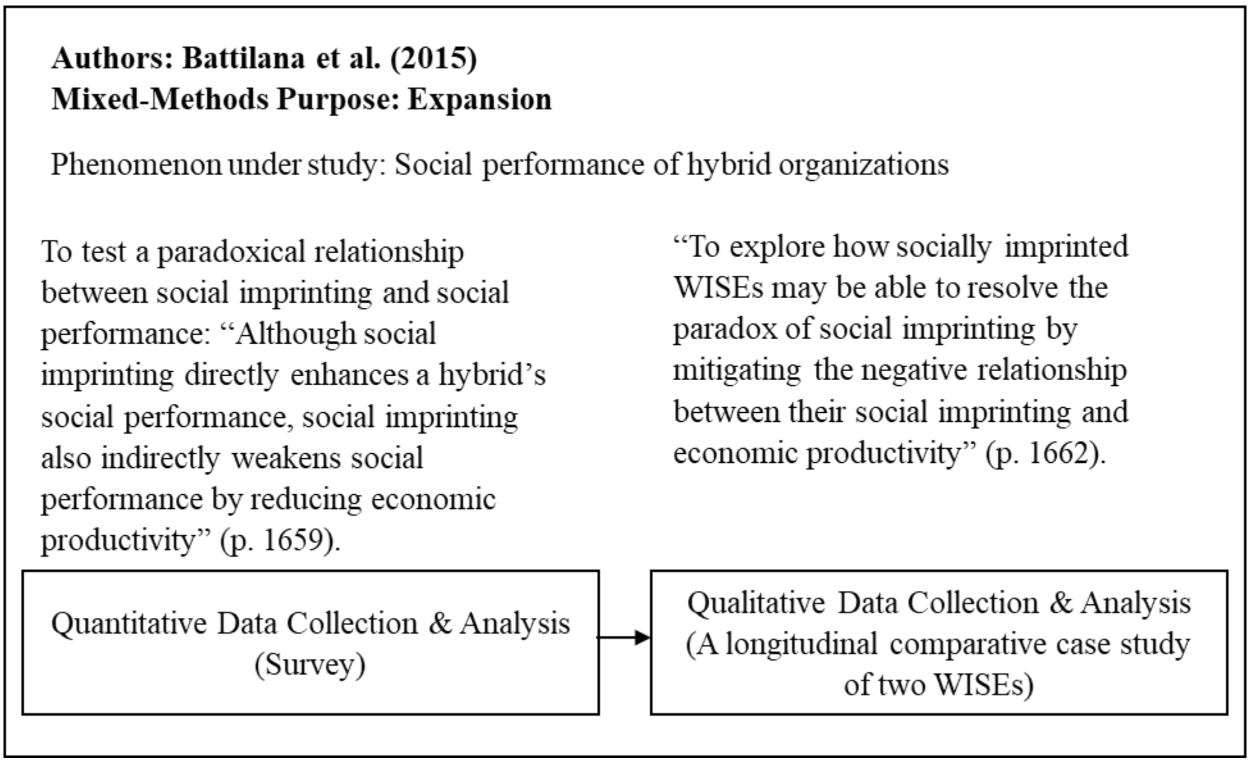

Figure 4-7. Mixed-Methods Research with an Expansion Purpose

4.2.8. Summary

Researchers should clearly specify and/or acknowledge the rationale or justification for using a mixed-methods approach (Newman et al., 2003; Teddlie & Tashakkori, 2009). Although the seven purposes of mixed-methods research we discussed here are not exhaustive, they can be used as a conceptual tool to systematically identify the most appropriate research design (Greene et al., 1989). Identifying the research purpose also helps researchers refine their research question(s)—e.g., if the research purpose is developmental, then the quantitative research question should be conditional on the qualitative research question or vice versa (Onwuegbuzie & Leech, 2006). Examining research questions from the perspective of the mixed-methods purpose may clarify the need for using mixed-methods research. Thus, explicitly identifying the purpose(s) of a mixed-methods research study will improve the likelihood of doing research that has greater meaning and is more likely to lead to valuable implications (Newman et al., 2003).

Summary

- Research questions and purposes of mixed-methods research, together with theoretical perspectives and paradigms, make up the foundation of design decisions that researchers need to make in the course of their mixed-methods studies.
- Mixed-methods research questions include a quantitative research question, a qualitative research question, and sometimes a mixed-methods research question.
- Four dimensions of mixed-methods research questions are: (1) rhetorical style—question format; (2) rhetorical style—level of integration; (3) relationships among research questions; and (4) relationships between research questions and the research process.
- Purposes of mixed-methods research should provide the rationale for conducting mixed-methods research. Seven possible purposes are: (1) compensation; (2) corroboration; (3) diversity; (4) developmental; (5) complementarity; (6) completeness; and (7) expansion.

Exercises

1. Select a research topic of interest to you and create a qualitative research question, a quantitative research question, and a mixed-methods research question.
2. Based on the above research questions, determine the purpose of your mixed-methods research. Explain how mixed-methods research can help answer your research questions.
3. Select an article that uses mixed-methods research in your field or topic of interest and review the research questions and purposes of mixed-methods research. Based on the guidelines discussed in this chapter, did the article specify a clear rationale or justification for using mixed-methods research? Did the article provide a mixed-methods purpose? Explain your answer.

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CHAPTER 5

BASIC STRATEGIES FOR MIXED-METHODS RESEARCH

We reviewed and discussed the appropriateness of using mixed-methods research in the previous chapter. In this chapter, we focus on mixed-methods research design strategies. Once researchers specify the purpose for using a mixed-methods research approach and justify the value it will bring to the study, they then need to decide which mixed-methods design to use. Before deciding which strategy is the most suitable for their mixed-methods purpose, researchers should review and consider various alternative design strategies. To help researchers understand how to select the best design strategy for their study, we discuss five aspects of design: design investigation strategies, strands of the study, time orientation, priority of methodological approach, and mixing strategies. As researchers make their design decisions, the purpose of mixed-methods research should be kept connected with the design strategies because it provides the key reason for conducting mixed-methods research.

5.1. General Properties of Mixed-Methods Research

As there are numerous design strategies and a variety of ways in which these strategies can be implemented, the issue of mixed-methods design involves primarily asking the question of "how do we determine the most appropriate design strategies to use?" We discuss a number of general properties of mixed-methods research that researchers must consider and then demonstrate how the purposes of mixed-methods research, discussed in Chapter 4, are linked to these design decisions. The properties discussed in this chapter were drawn from existing typologies of mixed-methods research from various fields. For example, based on the strands/phases of research, Teddlie and Tashakkori (2006) proposed two types of mixed-methods research designs: (1) monostrand; and (2) multistrand, which can be divided into four types of design: (1) concurrent; (2) sequential; (3) conversion; and (4) fully integrated. Using a similar typology, but from a time orientation perspective, Creswell et al. (2003) proposed two types of mixed-methods designs: (1) concurrent; and (2) sequential. Each typology typically focuses on different features or aspects of mixed-methods design, and these typologies do overlap with each other, depending on the field orientation of the authors (e.g., an "equal status design" in Johnson et al. (2007) is the same as an "equivalent status design" in Tashakkori & Teddlie, 1998). Thus, we argue that researchers need to understand the similarities and differences across typologies, eliminate the redundancy, and focus on key features of mixed-methods designs in order to design their mixed-methods research study.

Design decisions, discussed in this chapter, are summarized in Table 5-1, which are adapted from Venkatesh et al. (2016) and other sources noted above. These properties work in tandem rather than independently in helping researchers address their research questions using the most appropriate mixed-methods designs.

Table 5-1. General Properties of Mixed-Methods Research

Mixed-Methods Property	Key References	Key Design Questions	Possible Dimensions
Design investigation strategies	Tashakkori and Teddlie (1998)	What is the goal of the mixed-methods study? Does the study attempt to develop a theory or test a theory?	• Exploratory • Confirmatory • Both
Strands/phases of research	Teddlie and Tashakkori (2006)	How many phases/strands of research does the study need to answer the research questions?	• Single phase (or single study) or monostrand • Multiple phases (or research program) or multistrand
Time orientation	Creswell (1995); Creswell et al. (2003); Tashakkori and Teddlie (1998)	What is the order of the qualitative and quantitative components of the study?	• Sequential • Concurrent
Priority of methodological approach	Johnson et al. (2007); Tashakkori and Teddlie (1998)	Are the qualitative and quantitative components of the study equally important?	• Equivalent/equal status • Dominant-less dominant (i.e., qualitative dominant or quantitative dominant)
Mixing strategies	Teddlie and Tashakkori (2009)	When does the mixing take place?	• Fully mixed • Partially mixed

5.1.1. Design Investigation Strategies

From the design investigation perspective, mixed-methods research can be categorized into three types of design: *exploratory*, *confirmatory*, or *both* (Tashakkori & Teddlie, 1998). In mixed-methods research with an exploratory design, researchers seek to develop or generate a new theory. Taking into account the discussion about research questions in the previous chapter, research questions in a mixed-methods study with an exploratory design need not necessarily be specified in advance and often unfold as researchers learn more about the phenomenon being investigated (Nastasi et al., 2010). Although confirmatory questions are often associated with quantitative research, there are confirmatory questions in qualitative research and exploratory questions in quantitative research (Maxwell, 2004; Nastasi et al., 2010). Crede and Borrego (2013) is an example of an exploratory mixed-methods study. A mixed-methods research approach was used to "narrow the gap in the literature by addressing the relative lack of research focused on the graduate engineering student experience in research groups, and including the influence of international diversity" (p. 63). The purpose of their mixed-methods research was developmental. The authors conducted ethnographically guided observations and interviews in their qualitative study and used the results to develop a survey that examined graduate engineering student retention in their quantitative study.

In a confirmatory mixed-methods research design, researchers test an existing theory using hypotheses established a priori (Venkatesh et al., 2016). Unlike exploratory mixed-methods research, research questions in a confirmatory study are generally determined at the beginning of the study. A confirmatory study largely follows a traditional scientific method where theory informs hypotheses that in turn are tested using data analysis (Nastasi et al., 2010). For example, Bhattacherjee and Premkumar (2004) conducted a confirmatory mixed-methods study to test a hypothesis that a change in users' beliefs and attitudes toward a system over time could explain why users form intentions to continue using that system. The primary purpose of their mixed-methods research was corroboration in which they used the qualitative study to add further credibility to the findings from the quantitative study. The qualitative data from the open-ended section of the survey were used to test the same hypotheses as those tested using the quantitative data.

The most common type of mixed-methods research from the design investigation perspective is the integration of exploratory and confirmatory designs. One of the strengths of mixed-methods research is the ability to address both exploratory and confirmatory research questions in the same study or research program. The study reported in Stewart et al. (2017), discussed in Chapter 4, is a good example of mixed-methods research that combines exploratory and confirmatory design elements in the same research program. They tested the hypothesis that higher-status (physician) leaders are less successful than lower-status (non-physician) leaders in implementing team-based empowerment, and then sought to explain why and how leaders facilitated or obstructed the implementation of team-based empowerment.

5.1.2. Strands of the Study

Following Teddlie and Tashakkori (2009), we define strands or phases as encompassing three stages: (1) *conceptualization* (i.e., consisting of theoretical foundations, purposes, and research methods); (2) *experiential* (i.e., consisting of data collection and analysis); and (3) *inferential* (i.e., consisting of data interpretation and application). From a research strand perspective, mixed-methods research designs can be classified into two types: *mixed-methods monostrand designs* and *mixed-methods multistrand designs* (Tashakkori & Teddlie, 2003; Teddlie & Tashakkori, 2006; Venkatesh et al., 2016).

5.1.2.1. Monostrand Design

A monostrand design consists of a single phase of conceptualization-experiential-inferential process, yet the study has both qualitative and quantitative components (Teddlie & Tashakkori, 2006; Venkatesh et al., 2016). This design is also called quasi-mixed design because only one type of data is analyzed and only one type of inference is made (Teddlie & Tashakkori, 2006). An example of this design is a *monostrand conversion design*. Figure 5-1 illustrates a mixed-methods study with monostrand design (Teddlie & Tashakkori, 2006). Some of the characteristics of a monostrand conversion design are discussed next.

Monostrand conversion designs are used in a single strand study in which research questions are answered through an analysis of transformed data (i.e., quantitized or qualitized data). The mixing of methods takes place in the experiential stage of the study, when data are transformed into another form and then analyzed accordingly. The conversion process of qualitative data to quantitative data is called *quantitizing*. The quantitizing practice provides useful information by obtaining the numerical values of observations in addition to researchers' narrative descriptions (Onwuegbuzie & Johnson, 2006; Sandelowski, 2000; Venkatesh et al., 2016). The conversion process of quantitative data to qualitative data is called *qualitizing* (Teddlie & Tashakkori, 2006). This conversion process should only be conducted if researchers aim to extract more information from quantitative data or to confirm interpretations of those data (Sandelowski, 2000; Venkatesh et al., 2016; for an example, see Raman et al., 2022). In the experiential stage, data are converted into another form and the transformed data are suitably analyzed. The results are then used to develop inferences.

Monostrand conversion designs may be planned before the study actually occurs, but researchers usually make the decision to transform their data when necessary as the study unfolds (Teddlie & Tashakkori, 2006). For example, researchers may discover unexpected patterns in their interview data and decide that the data should be converted into numerical form to allow for a more thorough analysis of the data.

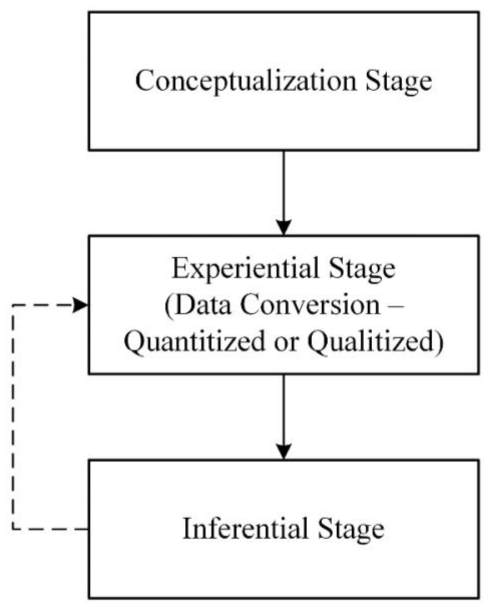

Figure 5-1. Monostrand Conversion Design

Although a monostrand conversion design offers several benefits, such as providing more insights into the phenomenon under investigation, it also comes with some limitations including:

1. When converting qualitative data into quantitative data, the numerical data may not satisfactorily capture enough of the complexity of the qualitative data both to understand and communicate it (Sandelowski et al., 2009). Thus, it is recommended that researchers only perform quantitizing if it will add value.
2. Quantitizing may also cause the loss of depth and flexibility of the qualitative data (Driscoll et al., 2007). Whereas qualitative codes are generally multi-dimensional (i.e., they can and do provide insights into a host of interrelated conceptual themes during analysis), quantitative data are usually fixed and one-dimensional (i.e., they are composed of a single set of responses

representing a conceptual category that is predetermined prior to data collection). Dichotomizing qualitative data into a single dimension of quantitative data may reduce the richness of qualitative data (Driscoll et al., 2007).
3. When converting quantitative data into qualitative data, the results may represent an overgeneralization of the observed numeric data (Teddlie & Tashakkori, 2009; Venkatesh et al., 2016). It is also possible that profiles emerging from the qualitizing technique yield an unrealistic representation and thus could lead to incorrect inferences (Venkatesh et al., 2016).
4. Quantitized data are vulnerable to the problem of multicollinearity, wherein response categories are themselves linked as a consequence of the coding strategy (Driscoll et al., 2007). Further, the need to collect qualitative data may force researchers to reduce the sample size, which can lead to low statistical power (Driscoll et al., 2007).

An example of a study with a monostrand design is reported in Hahs-Vaughn and Onwuegbuzie (2010). They gathered qualitative data (i.e., abstracts of empirical research articles published in *Research in the Schools* journal) to study the quality of abstracts in empirical papers. All abstracts were quantitized by assigning "1" to abstracts that were classified as being developed and "0" to abstracts that were classified as being underdeveloped. They noted that this "dichotomization allowed the researchers to correlate the quality of abstracts (originally representing qualitative data that were converted to quantitative data) with selected nominal-level (i.e., decision made by the editor regarding the manuscript, type of institution to which the first author belonged, and gender of the first author) and ratio-level (i.e., number of authors of each article and length of article) quantitative variables" (p. 56). Quantitized data can be subjected to statistical analyses and associated interpretation (Onwuegbuzie & Teddlie, 2003).

Another example is the first stage of the illustrative study discussed in Venkatesh et al. (2016). In that study, they converted the interview data into numerical data. When the investigators collected the qualitative data, they asked respondents to identify factors that influenced their decision to purchase a personal computer (PC), and then the interviewers asked them to indicate the degree to which that factor was important in their decision to adopt or not to adopt a PC for household use (see Venkatesh et al., 2016 for details). This technique provides not only the factors that the coders derived from coding the qualitative data, but also the associated magnitude of importance (Venkatesh et al., 2016). For an example that extracts sentiments from news articles, see Raman et al. (2022).

5.1.2.2. Multistrand Design

Mixed-methods research with a multistrand design contains at least two research strands (Teddlie & Tashakkori, 2006). In this design, one can mix the quantitative and qualitative components in or across all stages of the study. Multistrand designs can also contain data conversion in which data are transformed and analyzed both qualitatively and quantitatively. Most published mixed-methods articles have adopted a multistrand design. For example, Sonenshein et al. (2014), discussed in Chapter 4, gathered qualitative data using interviews in the first strand of their study and gathered quantitative data using a survey in the second strand of their study; Koh et al. (2004) gathered qualitative data in the first strand of their study and then tested their hypotheses using quantitative data gathered in the second strand of their study; and Stewart et al. (2017) gathered both qualitative and quantitative data concurrently. If a researcher adopts this design, decisions must be made about other design properties, including time orientation, mixing strategies, and the priority of methodology approaches (Venkatesh et al., 2016).

5.1.3. Time Orientation

From a time orientation perspective, mixed-methods research can be categorized into two types: *concurrent* and *sequential* mixed-methods designs.

5.1.3.1. Concurrent Mixed-Methods Design

A concurrent mixed-methods design is characterized by conducting the qualitative and quantitative components of the study at the same time (Venkatesh et al., 2013, 2016). In this type of design, researchers gather both qualitative and quantitative data, analyze them separately, and then compare the results (Creswell & Creswell, 2018). This type of design has been used to validate one form of data with the other form, to transform the data for comparison, and to address different types of questions (Creswell & Plano Clark, 2018; Driscoll et al., 2007). In some cases, the same individuals provide both qualitative and quantitative data so that the data can be easily compared (Driscoll et al., 2007). There are three types of concurrent mixed-methods designs (Creswell et al., 2003).

5.1.3.1.1. Concurrent Triangulation Design

In this design, both the qualitative and quantitative components of the study are conducted concurrently in the same phase. Qualitative and quantitative strands of the study are usually given equal weight in a concurrent triangulation design, although it is not always the case. A graphical representation of a concurrent mixed-methods design is shown in Figure 5-2 (Teddlie & Tashakkori, 2006).

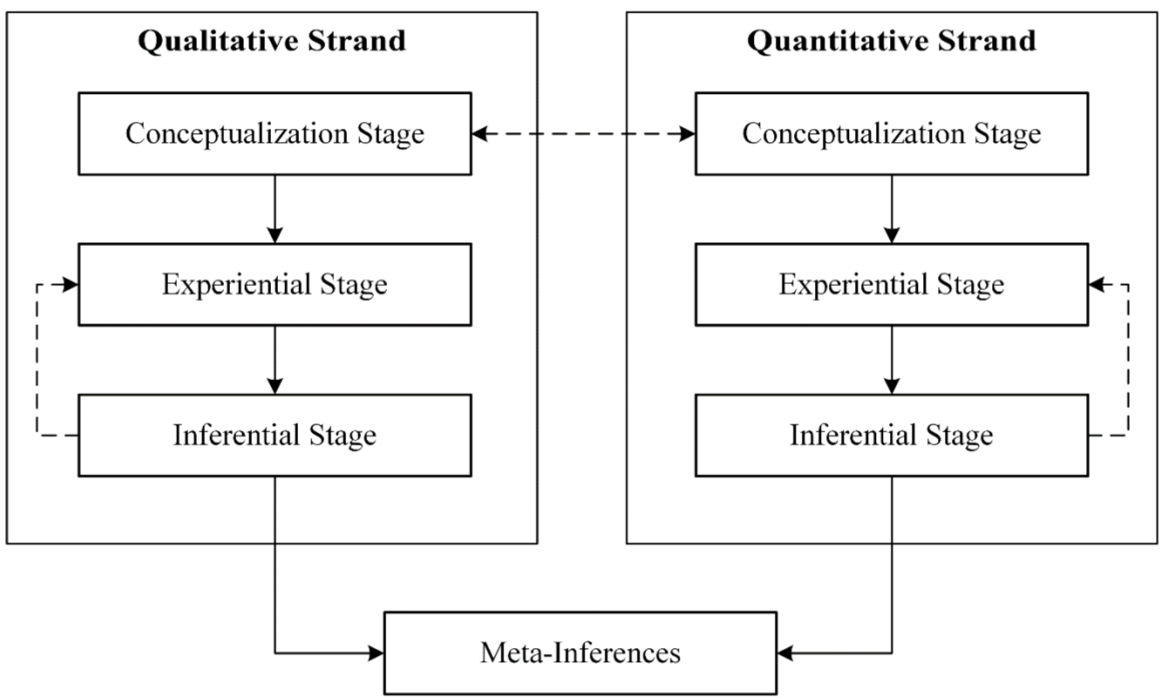

Figure 5-2. Concurrent Mixed-Methods Design

For example, in a study of the implementation of a team-based empowerment initiative within the Veterans Health Administration by Stewart et al. (2017), which is discussed in Chapters 3 and 4, both qualitative and quantitative data were collected concurrently, and equal status was given to both approaches. Specifically, at the conceptualization stage, the quantitative research questions and hypotheses were formulated independently from the qualitative research questions. However, they were interrelated as the purpose of the study was completeness—it addressed different aspects of the same phenomenon. In the quantitative strand of the study, they hypothesized that teams with high-status leaders were less effective in implementing team-based empowerment than were teams with lower-status leaders. In the qualitative strand of the study, they explored the moderating role of team-status leader by identifying differences in identity as the underlying explanation for the differing reactions between physicians and non-physicians. At the experiential stage, quantitative data and qualitative data were analyzed separately, and the results were used to derive quantitative and qualitative inferences at the inferential stage, respectively. Meta-inferences or the integration of qualitative and quantitative inferences took place at the end of the study.

5.1.3.1.2. Concurrent Nested Design

In a concurrent nested design, both the qualitative and quantitative components of the study are conducted at the same time, but one form of data is given more weight than the other (Creswell et al., 2003). A study strand that receives less priority is embedded or nested in the research to provide a supporting role. Mixing usually takes place during the analysis or experiential phase (Kroll & Neri, 2009). An example of mixed-methods research with a concurrent nested design is the study of psychological contract violation reported in Robinson and Rousseau (1994). At the conceptualization stage of the quantitative strand, they formulated the research question (i.e., to investigate the impact of violations on employee trust, satisfaction, and retention). At the experiential stage, they conducted a two-stage survey. In the second stage survey, they also gathered qualitative data via open-ended responses to identify how employees experienced psychological contract violations. In their work, the qualitative data received less weight than the quantitative data and was used to provide additional explanations for the hypotheses tested using the quantitative analysis. A graphical representation of a concurrent nested design is shown in Figure 5-3 (Teddlie & Tashakkori, 2006).

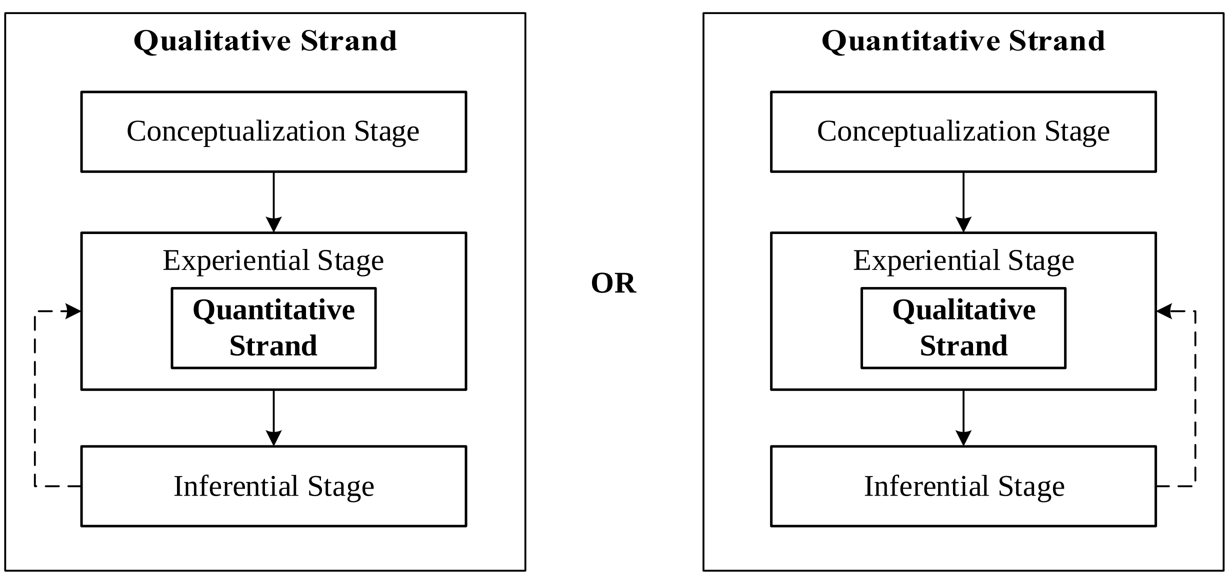

Figure 5-3. Concurrent Nested Design

5.1.3.1.3. Concurrent Transformative Design

A concurrent transformative design combines the features of both concurrent triangulation and concurrent nested designs (Creswell et al., 2003; Venkatesh et al., 2016). It may involve triangulation of qualitative and quantitative components that are equally important. It may also have a predominant method that guides the project (Creswell et al., 2003). In this design, researchers use a specific theoretical perspective that can be based on certain ideologies, such as critical theory, advocacy, and participatory research. This perspective reflects researchers' personal stance toward the topic they are studying and is reflected in the purpose or research questions of the study (Creswell et al., 2003). The choice of a concurrent transformative design is made to facilitate the chosen theoretical perspective. For example, the design may be nested so that diverse participants are given a voice in the change process of an organization that is studied primarily quantitatively. The design may involve triangulation of quantitative and qualitative data to provide evidence for an inequality of policies in an organization (Creswell et al., 2003). For example, Doyle et al. (2013) examined the relationship between disability and successful transition from sixth year of secondary school to higher education. Their study used a concurrent transformative, triangulation design to address the research question. The transformative emancipatory paradigm that they used was aimed at better understanding life experiences of marginalized groups (i.e., disabled individuals) with the purpose of knowingly investigating and analyzing social inequalities and imbalance (Doyle et al., 2013).

Although concurrent mixed-methods designs are powerful, they are challenging to conduct due to the complexity of running multiple strands of research simultaneously (Teddlie & Tashakkori, 2006). Such a design not only requires considerable expertise to examine the same phenomenon simultaneously and separately using two different approaches, but also involves the integration of findings from simultaneous data analysis into a coherent set of inferences (Teddlie & Tashakkori, 2006). Given the challenges associated with a concurrent design, it is best achieved using a collaborative team approach in which each team member can contribute to the complex, simultaneously evolving research design (Teddlie & Tashakkori, 2006).

5.1.3.2. Sequential Mixed-Methods Design

Sequential mixed-methods designs are "designs in which there are at least two strands that occur chronologically" (Teddlie & Tashakkori, 2006, p. 21). In this design, researchers first collect and analyze one form of data, and then use the conclusions made on the basis of this data analysis to formulate research questions used in the next strand of the study (Teddlie & Tashakkori, 2006; Venkatesh et al., 2013). The final inferences are based on the results of both strands of the study.

Creswell et al. (2003) differentiated sequential mixed-methods designs into three types of designs: (1) a sequential explanatory design (a quantitative followed by qualitative approach); (2) a sequential exploratory design (a qualitative followed by a quantitative approach); and (3) a sequential transformative design. However, as we mentioned in Chapter 1, although quantitative research is generally associated with confirmatory or explanatory questions, there are many quantitative studies that can be classified as exploratory. Similarly, there are many qualitative studies that can be classified as explanatory or confirmatory. For that reason, we do not use the term explanatory to define a quantitative-qualitative mixed-methods research design or the term exploratory to define a qualitative-quantitative mixed-methods design. Instead, we simply refer to the order of the study to describe the types of sequential mixed-methods designs.

5.1.3.2.1. Sequential (Quantitative-Qualitative) Design

In this design, researchers first collect and analyze quantitative data, and then collect and analyze qualitative data to help explain or elaborate the results obtained in the first strand (i.e., quantitative) of the study (Creswell & Plano Clark, 2018). The rationale for this approach is that the quantitative data and their subsequent analysis provide a general understanding of the research problem. The qualitative data and their analysis refine and explain those quantitative findings by allowing researchers to draw on participants' views in more depth (Ivankova et al., 2006). The advantages of this design include being easy to implement (i.e., because all steps fall into clear separate stages) and providing opportunities for the exploration of the quantitative results in more depth (Creswell et al., 2003). However, the weaknesses of this design include the length of time involved in data collection to complete two separate phases and the significant amount of resources required to collect and analyze both types of data sequentially (Creswell et al., 2003; Ivankova et al., 2006). A graphical representation of this type of design is illustrated in Figure 5-4 (Teddlie & Tashakkori, 2006).

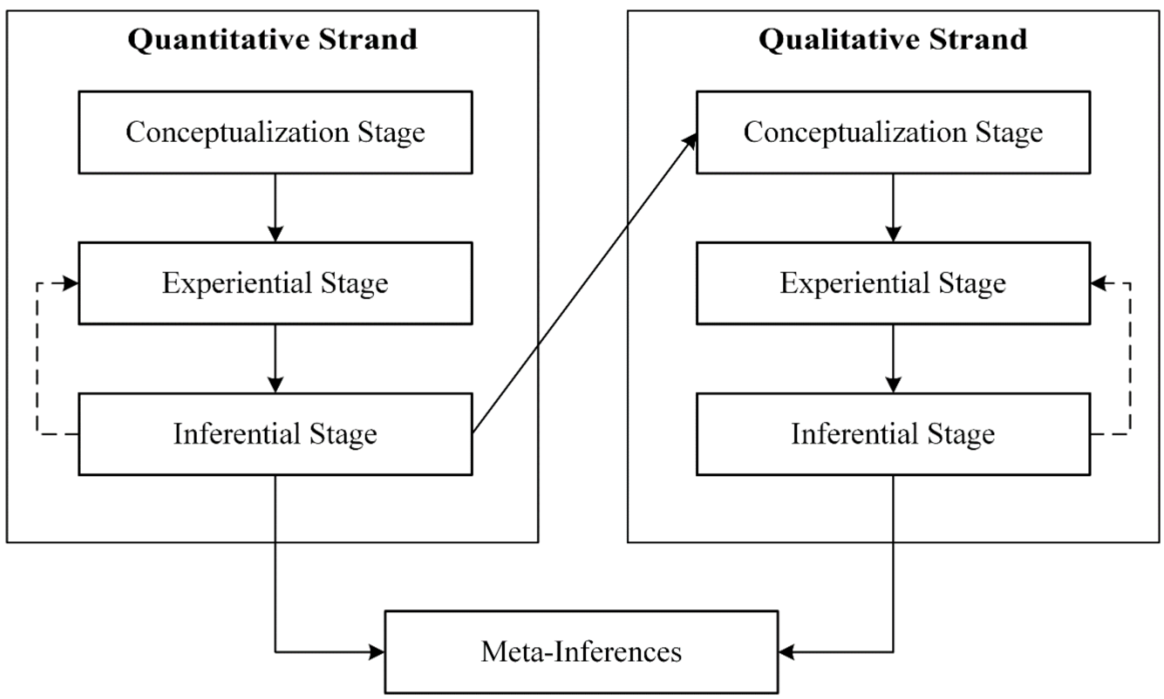

Figure 5-4. Sequential (Quantitative-Qualitative) Design

As an example, in examining the factors that influence social performance of hybrid organizations that pursue a social mission and sustain their operations through commercial activities by studying work integration social enterprises (WISEs), Battilana et al. (2015) first gathered and analyzed quantitative data. They conducted regression analyses to test the existence of the hypothesized paradox—although social imprinting directly enhanced WISE's social performance, it also indirectly weakened social performance by negatively influencing economic productivity. During the inferential stage, the quantitative results led them to conclude that the paradoxical relationship between social imprinting and social performance in WISEs was significant. Using this quantitative inference, they developed the rationale for conducting a qualitative study during the conceptualization stage of the qualitative strand. They noted that "although social imprinting enhances a WISE's social performance by keeping it from neglecting its beneficiaries, social imprinting also indirectly weakens social performance through the negative relationship that social imprinting has with economic productivity" (p. 1670). They then gathered and analyzed qualitative data to explore how socially imprinted WISEs may be able to resolve the paradox of social imprinting by mitigating the negative relationship between social imprinting and economic productivity.

5.1.3.2.2. Sequential (Qualitative-Quantitative) Design

This design begins with the collection and analysis of qualitative data in the first strand of the study (Creswell & Plano Clark, 2018). Building on the findings from the qualitative strand of the study, researchers conduct a developmental phase by designing quantitative features (e.g., generating new variables, designing instruments or scales, developing intervention plans). In the inferential stage, researchers interpret how the quantitative results build on the initial qualitative findings or how the quantitative findings provide a clear understanding because they are based on the qualitative findings. A graphical representation of a sequential exploratory design is shown in Figure 5-5 (Teddlie & Tashakkori, 2006).

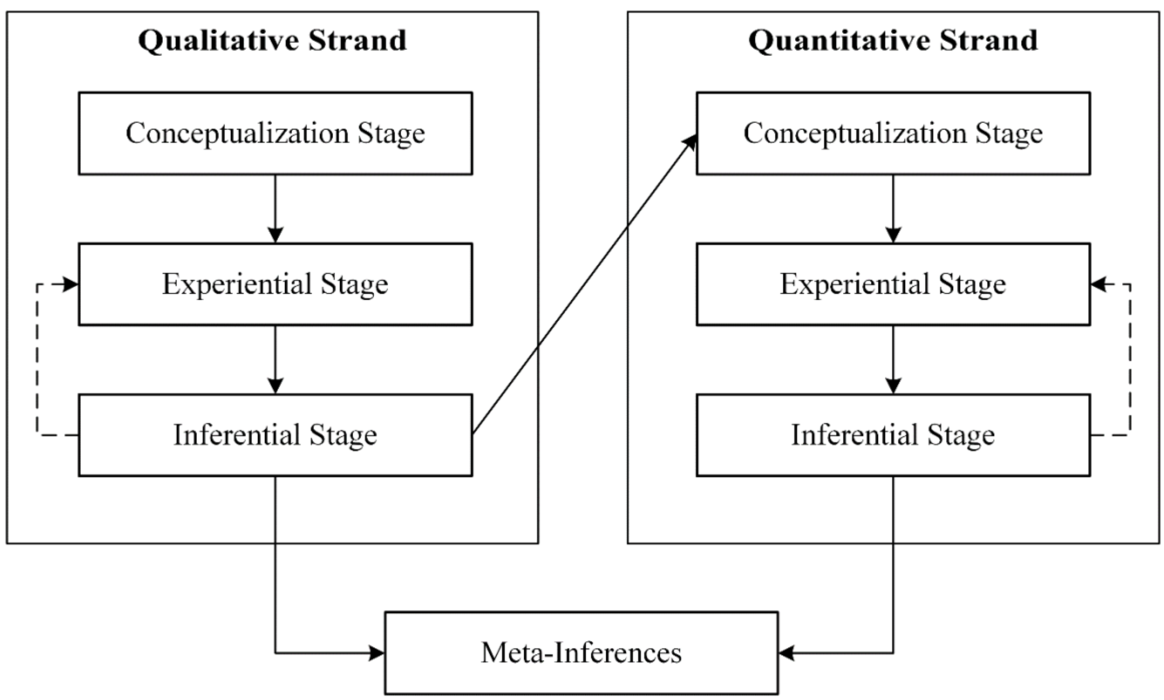

Figure 5-5. Sequential (Qualitative-Quantitative) Design

An example of mixed-methods research with a sequential exploratory design is the study reported in Koh et al. (2004), discussed in Chapter 4. They gathered and analyzed qualitative data (i.e., interview data) in the first strand of the study. This qualitative study was conducted to identify the critical customer-supplier obligations in an IT outsourcing relationship. During the experiential stage of their qualitative study, they used Miles and Huberman's (1994) approach to code and analyze the interview data. The qualitative data analysis led them to identify six major components of supplier obligations in an outsourcing project. They used these obligations to develop a research model in the quantitative strand of the study. They then empirically tested the model using hierarchical regression analysis. Although they did not provide meta-inferences, they did follow the sequential exploratory design, as shown in Figure 5-5. Another example of such a design approach, which was not specifically termed as such (also noted in Chapter 4) is Zhang and Venkatesh (2017).

5.1.3.2.3. Sequential Transformative Design

A sequential transformative design is similar to a concurrent transformative design. Researchers can use either a qualitative or quantitative approach as the first strand for their study, but they must use a theoretical perspective to guide the study (Creswell et al., 2003; Venkatesh et al., 2016). The aim of this theoretical perspective, whether it be a conceptual framework, a specific ideology, or advocacy, is more important in guiding the study than the use of methods alone. By using a mixed-methods approach, a researcher may be able to amplify diverse perspectives, to better advocate for participants, or to better understand a phenomenon or process that is changing as a result of being studied (Creswell et al., 2003). For example, Ray-Bennett et al. (2010) studied the meaning of health security for disaster resilience through people's perspectives in Bangladesh. Mixed-methods research with a sequential transformative design was used to identify local perspectives on how health affected vulnerability to disasters alongside local health security indicators. They used two approaches: (1) *the capability approach*—an approach that considers health as an integral part of good development; and (2) *the dominant paradigm*—a perspective that considers health as a means to achieve development. To understand how the definitions and explanations of health are socially, politically, economically, and culturally lived and constructed by people in different societies, they also studied the phenomenon from a *people perspective*. In this example, they used various qualitative and quantitative techniques, including focus group discussions (FGD), household survey questionnaires, one-to-one and group interviews (formal and informal), and household monitoring. A mixed-methods research approach allowed them to attend to, consider, and incorporate different perspectives that guide the research process.

5.1.4. Priority of Methodological Approach

Based on the priority of the methodological approach, mixed-methods research can be categorized into two types: (1) *equivalent status* or *equal status designs* (we use the term equal status designs throughout this book for consistency); and (2) *dominant-less dominant status designs*.

5.1.4.1. Equal Status Design

In an equal status design, researchers placed equal weight on both the qualitative and quantitative strands (Tashakkori & Teddlie, 1998). In a concurrent design, an equal status design has to be implemented using a concurrent triangulation design, whereas in a sequential status design, equal weight can be given to both qualitative and quantitative approaches, regardless of whether it is an exploratory or explanatory study. For example, Battilana et al. (2015), discussed in Chapter 4, emphasized the qualitative and quantitative strands of their study equally. In the first strand of the study, they tested the hypothesized paradox (i.e., social imprinting had a positive effect on social performance, but it could have a negative effect through the mediation of economic productivity). They then analyzed their qualitative data by conducting an in-depth comparative case analysis to explore how socially imprinted WISEs can resolve the paradox of social imprinting. By adopting an equal status design, they were able to develop and validate their hypothesis that the relationship between social imprinting and social performance was paradoxical, and that the paradox can be resolved using a qualitative study.

5.1.4.2. Dominant-Less Dominant Status Design

In a dominant-less dominant status design, researchers conduct a study in a single dominant strand with a small component of the overall research project drawn from an alternative strand (Tashakkori & Teddlie, 1998). There are two types of dominant-less dominant status designs: (1) *quantitative-dominant mixed-methods designs*; and (2) *qualitative-dominant mixed-methods designs* (Johnson et al., 2007). Such a strategy may also be preferable for those who are still learning the *other* type of method (the one different from their core, general method expertise).

In a *quantitative-dominant mixed-methods design*, quantitative data are used to provide an additional view that may benefit or fill a gap that exists in the entire research project. For example, in the study by Robinson and Rousseau (1994) on psychological contract violation, which was discussed previously, the quantitative study was the dominant strand. The quantitative data were used to test the relationship between psychological contract violations and employee trust, satisfaction, and retention, whereas the qualitative data were used to identify how employees experienced psychological contract violations. They conducted a longitudinal study to gather quantitative data in two stages of a survey. However, the qualitative data were only collected at the end of the second stage of the survey. Participants were only asked two questions (i.e., they were asked if their employer had ever failed to meet the obligation(s) that were promised to them, and if so, they were asked to explain that experience). They analyzed the quantitative data using regressions. The qualitative responses were analyzed using a simple coding scheme (i.e., the responses were coded into categories by the individuals). When the authors discussed the findings, they placed greater emphasis on the quantitative findings than on the qualitative findings. The qualitative findings were used to enhance the findings of the quantitative strand of the study by revealing different types of psychological contract violations found to be significant in the quantitative phase of the study.

In a *qualitative-dominant mixed-methods design*, researchers rely on qualitative data to answer their research questions, whereas concurrently recognizing that the addition of quantitative data and approaches is likely to benefit some parts of the research (Johnson et al., 2007). For example, in the study reported in Barley (1986) using an ethnographic method, his primary data (e.g., text of field notes, tape recordings) were gathered using qualitative techniques. However, in the research process, he also used some quantitative techniques to test a number of predictions derived from the qualitative data analysis. For example, the findings from analyzing the qualitative data suggested that institution and action in the areas where the CT scan was taken were linked via a structuring process. He argued that if this is the case, the shape of each department's centralization profile should parallel trends revealed by a chronological analysis of scripts. Thus, he tested his prediction by regressing each department's centralization scores (linear, squares) on the day of operation on which the scans took place to test for both linear and curvilinear trends. In this example, the quantitative data were used to provide additional support for the findings and they received less weight than the qualitative data.

5.1.5. Mixing Strategies

True mixed-methods research includes an integration of qualitative and quantitative methods. The decision on when and how to integrate the data should be traced back to the research questions, including how they are formulated and whether secondary questions have equal weight as the primary questions. This integration or mixing can occur at various stages of the research process

(Teddlie & Tashakkori, 2009), either at all stages of the study (i.e., *fully mixed-methods design*) or at a specific stage of the study (i.e., *partially mixed-methods design*) (Teddlie & Tashakkori, 2009).

5.1.5.1. Fully Mixed-Methods Design

In a fully mixed-methods design, mixing of qualitative and quantitative approaches occurs in an interactive manner in all stages of the study (Teddlie & Tashakkori, 2006). Although it is not always the case, a fully mixed-methods design is commonly associated with an equal status design in which both qualitative and quantitative strands of the study are conducted concurrently. Given that at each stage the qualitative and quantitative strands are intertwined (Teddlie & Tashakkori, 2009), a side-by-side comparison of research questions, data, findings, and inferences that take place in the concurrent design is favorable for the researchers who adopt a fully mixed-methods design. A concurrent design allows researchers to compare and contrast the conceptualization of qualitative and quantitative research questions, analyze both qualitative and quantitative data simultaneously, and derive quantitative and qualitative inferences at the same time. A graphical representation of a fully mixed-methods design is shown in Figure 5-6 (Teddlie & Tashakkori, 2006).

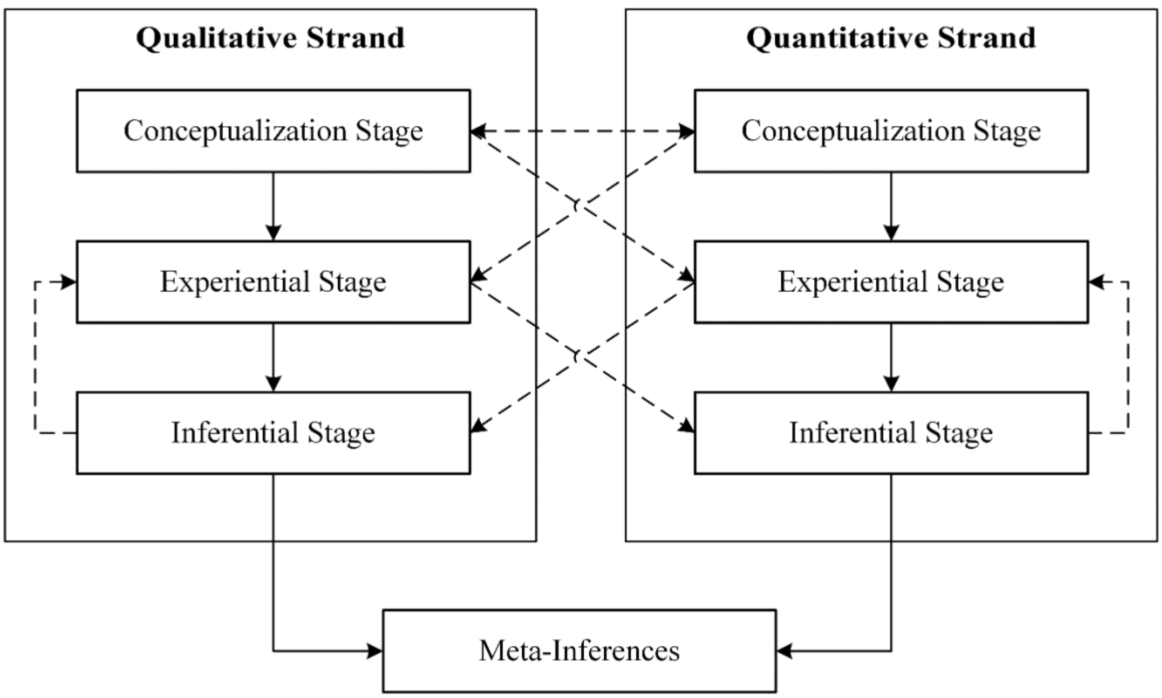

Figure 5-6. Fully Mixed-Methods Design

An example of a fully mixed-methods design is the study reported in Amabile et al. (2005). They used both quantitative and qualitative longitudinal data from daily diaries of individuals working on organizational projects to examine the nature, form, and temporal dynamics of the affect-creativity relationship. The purpose of the study was *completeness*—to provide a holistic view of the phenomenon. The data included multiple measures of affect, as well as multiple measures of creativity. The qualitative and quantitative data were collected simultaneously. Some measures were scale-rated responses to specific questions, whereas others were open-ended descriptions of participants' day-to-day experiences at work. This study employed a fully mixed-methods design.

At the conceptualization stage, the quantitative research questions were related to the qualitative research questions. Using both qualitative and quantitative methods, they delved deeply into the affect-creativity relationship. They initially formulated four quantitative research questions: "Is there a positive or a negative linear relationship? Is creativity facilitated by fluctuation across the range from negative to positive affect? Might creativity be higher on days of mixed emotion, when both positive and negative emotions occur? And is there a curvilinear relationship, whereby creativity is highest at some optimal level of affect along a continuum from extremely negative to extremely positively?" (p. 376). Whereas these questions can be answered using a qualitative method, they also intended to further explore the relationship between affect and creativity by examining possible temporal patterns (e.g., whether affect precedes creative thought or whether affect co-occurs with creative thought). This research objective was addressed using both quantitative and qualitative analyses.

At the experiential stage, the quantitative and qualitative data were collected concurrently. A daily questionnaire using an electronic event sampling methodology and content coding of narratives from the daily questionnaire were used to collect quantitative and qualitative data, respectively. The qualitative data were also quantitized and analyzed.

At the inferential stage, the results of qualitative and quantitative data analyses were integrated and interpreted simultaneously. For example, the authors noted that "our quantitative and qualitative data, collected over long periods of time from people doing creative work in organizations, afforded an unusual opportunity to understand the affect-creativity relationship…, we found consistent evidence of a positive relationship between positive affect and creativity and no evidence of a negative relationship" (pp. 389-390).

5.1.5.2. Partially Mixed-Methods Design

A partially mixed-methods design is popular among researchers simply because this design and its examples have been well described in the literature (Teddlie & Tashakkori, 2006). Further, using this design, researchers do not have to integrate the qualitative and quantitative approaches across all stages (Teddlie & Tashakkori, 2006). Mixing in a partially mixed-methods design takes place at specific stages in the research process. The most common stages of integration in a partially mixed-methods design are the experiential (i.e., data collection and analysis) and inferential stages. An example of a partially mixed-methods design is the study reported in Battilana et al. (2015). They first conducted a quantitative study by testing the hypothesis that both social imprinting and economic productivity were positively associated with WISEs' social performance. In the qualitative study, they examined the mechanisms underlying those relationships. The integration took place at the inferential stage. For example, the authors noted that they "hypothesized, and validated through regression analyses, that the relationship between social imprinting and social performance is paradoxical . . . also uncovered, through our longitudinal comparative case analysis, that socially imprinted WISEs may resolve this paradox" (p. 1678).

5.2. Relationships between Purposes and Mixed-Methods Designs

Design decisions depend on the mixed-methods properties, as discussed previously. We present a model of decision choices based on the three general properties of mixed-methods research—*time orientation*, *priority of methodological approach,* and *mixing strategies* (see Figure 5-7). The other two properties—*design investigation strategies* and *strands/phases of research*—are not included in this decision model for two reasons. First, although mixed-methods research can address either exploratory or confirmatory questions, we encourage researchers to address both questions in a mixed-methods study because addressing both types of questions in a single study or a program of research is the primary strength of mixed-methods research. Second, with regard to the strands/phases of research, we encourage researchers to adopt a multistrand design to fully harness the advantages of mixed-methods research. A decision to transform one type of data to another (i.e., quantitizing or qualitizing), which is a major element of a monostrand conversion design, should be done only if researchers believe that doing so will bring additional value.

As shown in Figure 5-7, we argue that the purpose of mixed-methods research plays a major role in guiding design decisions. Ideally, we recommend researchers use a concurrent design if the purpose of their mixed-methods research is *corroboration* or *complementarity*. For a study with a corroboration purpose, both qualitative and quantitative strands of the study can be executed independently and concurrently to preserve their counteracting biases (Greene et al., 1989). Thus, concurrent designs are the most suitable design to accommodate a corroboration purpose. When the purpose is complementarity, a concurrent design allows researchers to measure overlapping but different aspects of the same phenomenon. They can conduct a qualitative study and quantitative study simultaneously because the findings from one strand of the study are independent from those from the other strand of the study and they can be integrated at the inferential stage. Thus, a complementarity purpose is readily achieved using a concurrent design.

If the purpose is *compensation, developmental*, or *expansion*, we suggest researchers use a sequential design. Mixed-methods research with a compensation purpose is also best achieved using a sequential design because the next strand of the study aims to overcome the limitations and weaknesses associated with the previous strand of the study including those that emerge in the first strand (e.g., small sample size, too much missing data) wherein some of the issues may not be known until after the first strand has concluded and results known. Likewise, mixed-methods research with a developmental purpose seeks to use the results from one approach to help develop the research questions that will be addressed using another approach. Thus, a sequential design is appropriate and more appropriately, necessary to achieve this purpose. Similarly, mixed-methods research with an expansion purpose is best achieved using a sequential design because a qualitative study is needed to expand on the initial findings from the quantitative study, or vice versa (Teddlie & Tashakkori, 2009).

Lastly, if the purpose is *diversity* or *completeness*, researchers can use both types of designs. Mixed-methods research with diversity as the purpose can be conducted using either sequential or concurrent designs because the diverse findings can emerge at any stage in the research process. When the purpose is completeness, researchers can either use a concurrent or sequential design. A concurrent design allows researchers to examine different aspects of the same phenomenon. Because qualitative and quantitative strands of the study are used to answer different research questions that are related to different aspects of the same phenomenon, a concurrent research design can help researchers shorten the length of time needed in data collection. However, a sequential design could also be used to achieve a completeness purpose. A sequential design will allow researchers to use the findings from the first strand of the study to further develop the research questions in the second strand of the study. The combination of qualitative and quantitative methods provides richness and a more complete picture of the phenomenon under study that one method alone would not yield.

Although there are different types of concurrent and sequential designs, we do not show these design types in the decision model in order to maintain simplicity and reduce redundancy in designing mixed-methods research. For example, a nested concurrent mixed design is typically associated with a dominant-less dominant mixed design. Thus, if a researcher adopts a nested concurrent design, then one will typically employ a dominant-less dominant mixed design. Further, because the difference between the two primary sequential designs discussed previously is only in the order of qualitative and quantitative strands of the study, we argue that this decision should be straightforward to researchers who adopt a sequential design and, hence, is not included in the decision model. We also propose that the most suitable way to execute a fully mixed-methods design is to use an equal status design in which qualitative and quantitative strands of the study are given the same priority and mixed across all stages of the study.

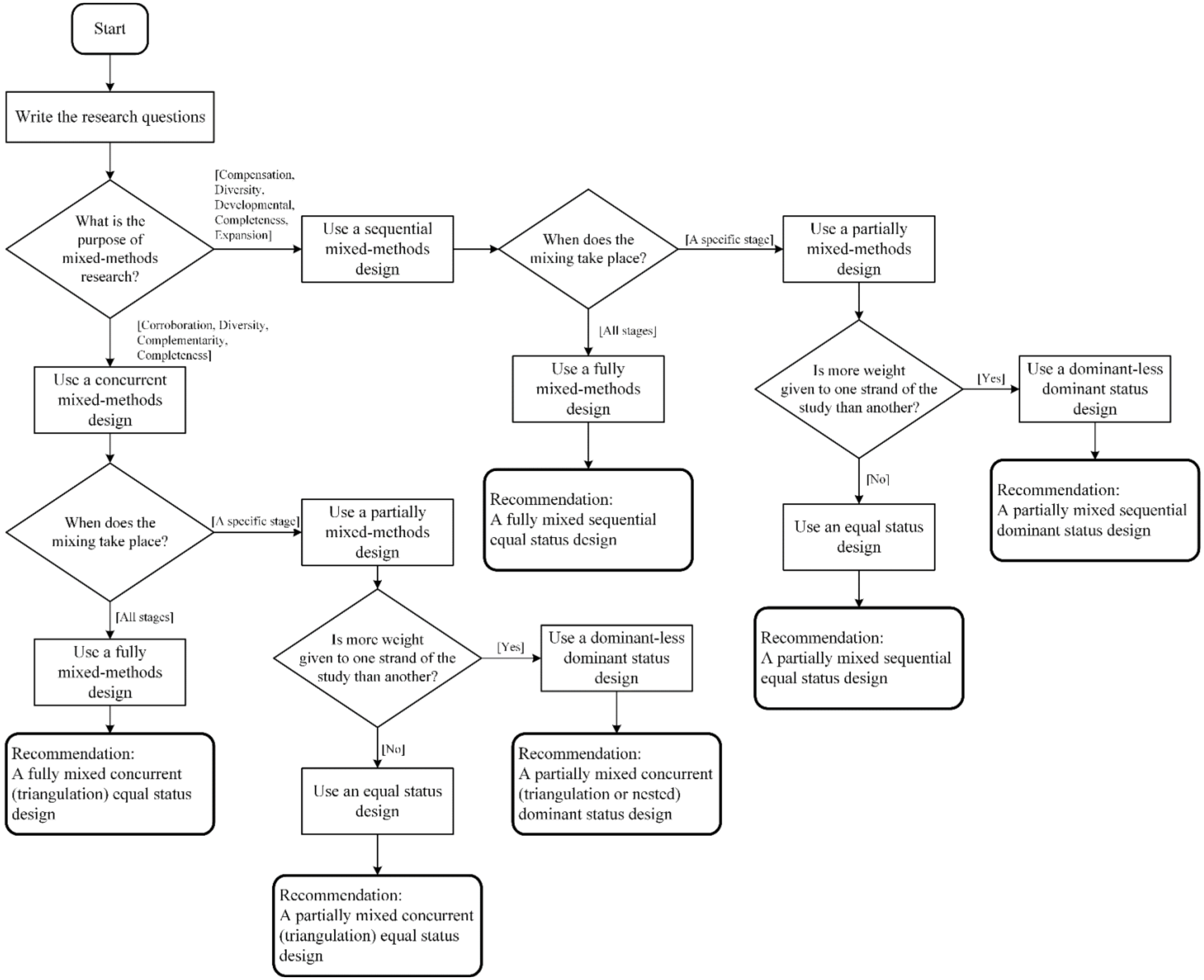

Figure 5-7. Model of Decision Choice for Basic Strategies for Mixed-Methods Research

Based on the combination of purposes, time orientation, priority of methodological approach, and mixing strategies, we summarize the design recommendations for mixed-methods research in Tables 5-2, 5-3, 5-4, 5-5, 5-6, 5-7, and 5-8. As presented in the tables, we suggest researchers use *a partially mixed concurrent equal status design*, *a partially mixed concurrent dominant status design*, or *a fully mixed concurrent equal status design* if the purpose of mixed-methods research is corroboration, complementarity, or completeness. If the purpose of mixed-methods research is compensation, developmental, or expansion, we recommend the use of *a partially mixed sequential equal status design*, *a partially mixed sequential dominant status design*, or *a fully mixed sequential equal status design*. Researchers can use any of the possible design options if the purpose is developmental. We also offer an example for each mixed-methods purpose using one of the possible design options.

Table 5-2. Design Recommendation for Mixed-Methods Research with Compensation Purpose

Possible Design Options	Example
• A partially mixed sequential equal status design • A partially mixed sequential dominant status design • A fully mixed sequential equal status design	Wisler (2018) The author used a *partially mixed sequential dominant status design* to determine the presence of differences in the ethical decision-making process of leaders led by U.S. and non-U.S. leaders. The design decisions included: • The purpose of the study was *compensation*—the author compensated for the weaknesses associated with the small sample size of the quantitative study with qualitative data. • From the time orientation perspective, the design was a *sequential (quantitative-qualitative) mixed-methods design*—a quantitative study followed by a qualitative study. • The quantitative strand received more weight than the qualitative study (i.e., *dominant-less dominant status design*). The study supplemented the quantitative data with a sample of phenomenological qualitative interviews with key survey participants to add clarity to the interpretations of the survey questions. • The mixing took place at the interpretation stage. For instance, the author noted that “results of the study show no evidence of difference in the ethical decision-making profiles between the two groups of leaders. The themes and emergent findings resulting from the qualitative analysis indicate a profound incompatibility between the values informing decision-makers using the luxury strategy and those employed by leaders operating within the principles and parameters of responsible leadership and conscious capitalism” (p. 443).

Table 5-3. Design Recommendation for Mixed-Methods Research with Corroboration Purpose

Possible Design Options	Example

• A partially mixed concurrent equal status design
• A partially mixed concurrent dominant status design
• A fully mixed concurrent equal status design
	Brickson (2005)
	The author sought to better understand the connection between organizational identity and how organizations relate to their stakeholders. The author used a *fully mixed concurrent equal status design*. The design decisions included:
	• The purpose of mixed-methods research was *corroboration*. The qualitative data projected the general perceptions of the organization's identity, whereas the quantitative data measured identity orientation.
	• A *fully mixed design* was reflected in all stages of the study.
	    ○ At the conceptualization stage, the qualitative and quantitative research questions informed one another (e.g., how and with what frequency relations with stakeholders are reflected in organizational identity more broadly; how organizations are oriented toward stakeholders).
	    ○ At the experiential stage, the quantitative data were qualitized and the qualitative data were quantitized. Both the original data and transformed data were analyzed and compared simultaneously. For example, the score for the organizational identity was computed by summing codes across both qualitative and quantitative measures and each approach was given equal weight (i.e., *equal status design*).
	    ○ At the inferential stage, the findings from qualitative and qualitative studies complemented each other and interpretations of qualitative findings were dependent on quantitative findings, and vice versa.
	• The qualitative and quantitative studies were conducted *concurrently*. Specifically, the study used a *concurrent triangulation design* in which both approaches received equal weight. Both qualitative and quantitative data were collected in the same survey.

Table 5-4. Design Recommendation for Mixed-Methods Research with Diversity Purpose

Possible Design Options	Example
• A partially mixed concurrent equal status design • A partially mixed concurrent dominant status design • A fully mixed concurrent equal status design • A partially mixed sequential equal status design • A partially mixed sequential dominant status design • A fully mixed sequential equal status design	Chang (2006) The author used a *partially mixed sequential equal status design*. The author first conducted interviews followed by surveys. The design decisions included: • The purpose of mixed-methods research was *diversity*. The qualitative strand of the study focused on investigating the operational scope, in terms of business functions, of the enterprise IS in the organization, and identifying implementation success factors and benefits of the enterprise IS. The quantitative study focused on identifying the differences between IT and general management regarding the perceived importance of business functions and perceived implementation success factor and benefits. • There was also an element of a *developmental purpose*, where case study results were used to develop a questionnaire to compare IT and general management perceptions of the operational scope, implementation influences and benefits. • A *sequential (qualitative-quantitative) design*, with a qualitative study conducted first followed by a quantitative study. Each study received equal weight (i.e., *equal status design*). • Although meta-inferences were not provided, a degree of mixing was observed at the interpretation stage. For example, they noted that "despite this 'anecdotal' divergence of views expressed in the interview phase, quantitative comparison of the rather more narrowly focused specific aspects of IS functionality, implementation and benefits showed very similar perceptions by IT and general management staff, and the few significant individual differences observed show no particular pattern" (p. 283).

Table 5-5. Design Recommendation for Mixed-Methods Research with Developmental Purpose

Possible Design Options	Example
• A partially mixed sequential equal status design • A partially mixed sequential dominant status design • A fully mixed sequential equal status design	Koh et al. (2004) In this study, they used a *partially mixed sequential (qualitative-quantitative) equal status design*. The design decisions included: • The purpose of mixed-methods research was *developmental*. In the qualitative study, they identified customer-supplier obligations in the outsourcing context and in the quantitative study, the authors assessed the impact that fulfilling these obligations had on success. • They used a *sequential exploratory design* (i.e., a qualitative study was conducted to develop the model and a quantitative study was conducted to test the model). Both approaches were given equal weight (i.e., *equal status design*). • The mixing took place at the interpretation stage (*partially mixed-methods design*). Although meta-inferences were not explicitly stated, they noted that "results from our study showed the existence of a psychological contract between outsourcing customers and suppliers, and that fulfilling these obligations explained a significant amount of the variance in outsourcing success" (pp. 370-371).

Table 5-6. Design Recommendation for Mixed-Methods Research with Complementarity Purpose

Possible Design Options	Example
• A partially mixed concurrent equal status design • A partially mixed concurrent dominant status design • A fully mixed concurrent equal status design	Ruderman et al. (2002) They used a *partially mixed concurrent equal status design*. The design decisions included: • The purpose of mixed-methods research was *complementarity*—the second (i.e., quantitative) study was conducted to provide additional perspective on the first (i.e., qualitative) study. The qualitative study explored the transfer of skills and perspectives developed in women's personal roles to the managerial role. They used the quantitative study to further examine this relationship from a different perspective. • They used a *concurrent (triangulation) design*—both qualitative and quantitative data were collected simultaneously but using different samples. • Both strands of the study received equal weight (i.e., *equal status design*). The qualitative results suggested that the roles women play in their personal lives provide various benefits, including psychological benefits, emotional advice and support, and practice at multitasking. The quantitative results suggested that multiple role commitment positively related to life satisfaction, self-esteem, and self-acceptance. • Mixing took place at the interpretation stage. For example, they noted that "both studies support the role accumulation perspective that multiple roles can be enriching rather than depleting" (p. 380).

Table 5-7. Design Recommendation for Mixed-Methods Research with Completeness Purpose

Possible Design Options	Example
• A partially mixed concurrent equal status design • A partially mixed concurrent dominant status design • A fully mixed concurrent equal status design • A partially mixed sequential equal status design • A partially mixed sequential dominant status design • A fully mixed sequential equal status design	Stewart et al. (2017) They used a *partially mixed concurrent equal status design* to explore barriers to the successful implementation of a team-based empowerment initiative within the Veterans Health Administration (VHA). The design decisions included: • The purpose of mixed-methods research was *completeness*. Each strand of the study was used to investigate different aspects of the same phenomenon. • Quantitative and qualitative data were collected independently but simultaneously (i.e., *concurrent mixed-methods design*) as part of a large-scale study of VHA teams, and each strand of the study received equal weight (i.e., *equal status design*). • Mixing took place at the interpretation stage (i.e., *partially mixed design*). For example, they noted that “leader status was supported as a moderator of the relationship between team-based empowerment and team effectiveness. We supplemented this quantitative finding with qualitative analysis that provides evidence of identity and delegation as mediators explaining the ‘why’ and ‘how’ of the conditional relationship” (p. 2281).

Table 5-8. Design Recommendation for Mixed-Methods Research with Expansion Purpose

Possible Design Options	Example
• A partially mixed sequential equal status design • A partially mixed sequential dominant status design • A fully mixed sequential equal status design	Battilana et al. (2015) They used a *partially mixed sequential equal status design* to understand the relationship between social imprinting and social performance. The design decisions included: • The purpose of mixed-methods research was *expansion*. They used a quantitative approach to test the existence of the hypothesized paradox that social imprinting had a positive effect on social performance, but it also indirectly weakened social performance through its negative relationship with economic productivity. They then used a qualitative approach to explore how socially imprinted WISEs may be able to resolve the paradox of social imprinting by mitigating the negative relationship between their social imprinting and economic productivity. • To achieve the purpose of mixed-methods research, they first conducted a quantitative study followed by a qualitative study (i.e., *sequential (explanatory) mixed-methods design*) and each study was emphasized equally (i.e., *equal status design*). • The mixing took place at the interpretation stage (i.e., *partially mixed-methods design*). For example, they argued that "although social imprinting enhances a hybrid's social performance, social imprinting also indirectly weakens social performance through the negative relationship that social imprinting has with economic productivity . . . our qualitative findings suggest that a critical condition to overcome this paradox is the partial unfreezing of the hybrid's social imprint, which opens the possibility for it to manage its imprinting legacy" (p. 1679).

Note that the possible design options discussed in this chapter are not exhaustive and are recommendations based on most likely scenarios we foresee. Researchers are welcome to use other types of designs not listed as the possible design options for a specific mixed-methods research purpose. For example, although a complementarity purpose is best achieved using a concurrent design, researchers can use a sequential design to achieve this purpose, as long as they can justify why such design is useful and/or appropriate for the given context. An example of a study with a complementarity purpose that uses a sequential design is Sonenshein et al. (2014) that examines the role of self-evaluations in explaining support of environmental issues. Specifically, they used a *partially mixed sequential equal status design*—they started with a qualitative study followed by a quantitative, observational study. Such a design allowed them to investigate two different, but complementary aspects of the same phenomenon—examine how social issue supporters' everyday experiences influenced their self-evaluations (study 1) and why these self-evaluations mattered through their ability to predict issue-related actions (study 2).

Summary

- We discuss five mixed-methods properties that should be considered by researchers in designing a mixed-methods study. These are design investigation strategies, strands of the study, time orientation, priority of methodological approach, and mixing strategies.
- From a design investigation perspective, mixed-methods research can be categorized into three types: exploratory, confirmatory, or both.
- From a research strand perspective, mixed-methods research can be categorized into two types: monostrand and multistrand.
- From a time orientation perspective, mixed-methods research can be categorized into two types: concurrent and sequential.
- Based on the priority of the methodological approach, mixed-methods research can be categorized into two types: equivalent/equal status and dominant-less dominant status.
- Based on the mixing strategies, the integration in mixed-methods research can take place at all stages of the study (i.e., fully mixed-methods design) or at a specific stage of the study (i.e., partial mixed-methods design).
- We recommend researchers use the model of decision choices proposed in this chapter to help them make design decisions. In this model, the purpose of mixed-methods research plays a major role in guiding the design decisions. Figure 5-7 and Tables 5-2 through 5-8 provide key information.
- We suggest researchers use a partially mixed concurrent equal status design, a partially mixed concurrent dominant status design, or a fully mixed concurrent equal status design if the purpose of mixed-methods research is corroboration or complementarity, and to use a partially mixed sequential equal status design, a partially mixed sequential dominant status design, or a fully mixed sequential equal status design if the purpose of mixed-methods research is compensation, developmental, or expansion. Researchers can use any of the possible design options if the purpose is diversity and completeness.

Exercises

1. Select a topic from your field and develop two to three research questions that can be studied using a mixed-methods research approach.
2. Based on your response to the previous question, determine the purpose of the proposed mixed-methods research. Identify different design strategies that you can use in your study and justify your decisions. Describe these designs and discuss how they can be used to address your research questions and to achieve your mixed-methods research purpose.
3. Select an article in your field that uses a mixed-methods research approach. What was the purpose of mixed-methods research? Review the design decisions in the article, namely design investigation strategies, strands of the study, time orientation, priority of methodological approach, and mixing strategies. Critique the decisions they made and wherever you disagree, indicate what decisions you would have made and why?

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CHAPTER 6

MIXED-METHODS DATA COLLECTION STRATEGIES

A data collection strategy is a detailed plan to collect empirical data using one or more methods. It is how researchers "get" their information (Johnson & Turner, 2003). After researchers have made decisions associated with the general properties of mixed-methods research discussed in Chapter 5, they will then need to develop a strategy for collecting data. Given mixed-methods research involves the use of qualitative and quantitative approaches, the data collection procedures will need to include both types of data. In this chapter, we address:

- Sampling designs and issues in qualitative and quantitative research;
- Mixed-methods sampling strategies; and
- Procedures for qualitative, quantitative, and mixed-methods data collection.

6.1. Sampling Designs in Qualitative and Quantitative Research

Sampling is an important step in the research process because it helps determine the quality of inferences made by the researcher (Collins et al., 2006). In both qualitative and quantitative strands of a mixed-methods study, researchers must decide the sampling strategies, including "how many participants do I need to answer my research questions?" (i.e., sample size) and "how do I select these sample members?" (i.e., sampling schema) (Collins et al., 2007; Onwuegbuzie & Collins, 2007).

6.1.1. Sampling Schema

Prior studies have proposed a number of sampling schemas that can be categorized as either *random sampling* (i.e., *probabilistic sampling*) or *non-random sampling* (*non-probabilistic sampling*). Although probabilistic sampling is generally associated with quantitative research and non-probabilistic sampling is generally associated with qualitative research, researchers can use either sampling method in qualitative and quantitative studies.

6.1.1.1. Probability Sampling

One of the primary goals of using probability sampling techniques is generalizability (external validity) or the ability to extrapolate findings from a subset of a population or a particular setting to a larger defined population of people or setting (Kemper et al., 2003). In order to ensure random selection of participants, researchers must set up a process or procedure that assures that the different units in the population have equal probabilities of being chosen (Trochim, 2006). Table 6-1 summarizes five major probability sampling schemes.

Table 6-1. Major Probability Sampling Schemes

Sampling Scheme	Description
Simple random sampling	Every individual in the desired population has an equal and independent chance of being chosen for the study (Trochim, 2006).
Systematic random sampling	Individuals are chosen from a list by selecting every k^{th} sampling frame member, where k is the population size divided by the sample size (Collins et al., 2006).

Sampling Scheme	Description
Stratified random sampling	The sampling frame is divided into homogeneous subgroups and then each subgroup is randomly sampled (Trochim, 2006).
Cluster random sampling	Intact groups, representing clusters of individuals, are chosen rather than selecting individuals one at a time (Collins et al., 2006).
Multistage random sampling	The first four methods are combined in a variety of useful ways that help researchers address their sampling needs in the most efficient and effective manner possible (Trochim, 2006).

Simple random sampling is a technique in which *n* distinct units are selected from the *N* units in the population in such a way that every possible combination of n units has an equal and independent chance of being selected in the sample (Thompson, 2012). The advantage of this method is that data can, in theory, be generalized from the sample to the entire population with a computable margin of error. However, the selected units might be spread over a large geographic area, making them very difficult to reach (Kemper et al., 2003), although such barriers can be overcome in online studies.

In *systematic random sampling*, the sample is chosen by selecting a random starting point and then picking every k^{th} element in succession from the sampling frame. The sampling interval *k* is determined by dividing the population size *N* by the sample size *n* (Collins et al., 2006). This method has the obvious caveat that it can be used only if the researcher is certain that the population list is not ordered in such a way that every k^{th} unit results in a sample that is systematically different from the population at large (Kemper et al., 2003).

A stratified random sample is obtained by separating the population elements into groups or strata, such that each element belongs to a single group (Kemper et al., 2003). There are two different types of stratified random sampling: (1) *proportional stratified random sampling*—the proportion of each unit randomly selected from each group is the same as the proportion in the target population; and (2) *non-proportional stratified sampling*—the number of units selected from each group is generally the same, regardless of the relative proportion in the population (Kemper et al., 2003).

Cluster sampling is similar to stratified sampling in which we select groups or categories. However, instead of taking a random sample within each group, in cluster sampling, a random sample of groups within the population is first performed (Kemper et al., 2003). This approach is useful when there are resource constraints that preclude developing a complete sampling frame or when it takes a significant effort to collect data..

Multistage random sampling is a combination of two or more methods discussed above in which the samples are selected randomly in each stage from the population (Collins et al., 2006; Trochim, 2006). The process usually starts with random cluster sampling and then applies simple random sampling or stratified random sampling.

6.1.1.2. Non-Probability Sampling

In non-probability sampling, subjective methods are used to decide which elements are included in the sample, and sample members are identified in a way that does not give all participants or units in the population an equal chance of being included (Trochim, 2006). One can divide non-probability sampling methods into two broad categories: *accidental* and *purposive sampling*. In accidental or convenience sampling, members of a target population that meet certain practical criteria, such as easy accessibility, geographical proximity, availability at a given time, and willingness to participate, are chosen. In contrast, purposive sampling involves sampling with a purpose in mind. This will typically be specific pre-defined groups (e.g., women aged 50-60 years; IT professionals) or theoretically based targets of selection (e.g., multiple case studies at different cities) (Yin, 2003). Table 6-2 summarizes major subcategories of purposive sampling methods (definitions are from various sources, including Collins et al., 2007; Onwuegbuzie & Leech, 2007; Trochim, 2006). For instance, one might sample for specific groups or types of people as in modal instance, expert, or quota sampling; alternatively, one might sample for diversity as in heterogeneous sampling. In all of these sampling methods, researchers know what they want—they are sampling with a purpose (Trochim, 2006).

Table 6-2. Major Non-Probability, Purposive Sampling Schemes

Sampling Scheme	Description
Modal instance sampling	Choosing settings, groups, and individuals because they occur most frequently.
Expert sampling	Assembling a sample of persons with known or demonstrated experience and expertise in some area.
Heterogeneous sampling	Choosing groups, settings, or individuals with an intention to include all opinions or views.
Homogeneous sampling	Focus on individuals who share similar traits or specific characteristics.
Snowball sampling	Begins by identifying someone who meets the criteria for inclusion in the sample. Then that person is asked to recommend others who also meet the criteria.
Random purposeful sampling	Researchers first obtain a list of individuals interested in participating in the study using one of the purposive sampling methods and then randomly select a desired number of individuals from the list.
Stratified purposeful sampling	Sampling frame is divided into strata or groups to obtain relatively homogenous subgroups and a purposeful sample is selected from each stratum.
Criterion sampling	Choosing settings, groups, and/or individuals because they fit one or more criteria.
Critical case sampling	Choosing settings, groups, and/or individuals based on specific characteristics because their inclusion provides researchers with compelling insights about the phenomenon of interest.
Quota sampling	Researchers identify desired characteristics and quotas of sample members to be included in the sample.

6.1.2. Sample Size

The number of participants to be recruited for a study is a challenging question (Luborsky & Rubinstein, 1995). There is seldom a simple answer to the question of sample size, especially in qualitative research. Nevertheless, to increase representation, it is essential that a sample size is accurately estimated in both quantitative (e.g., Cohen, 1988) and qualitative (e.g., Onwuegbuzie & Leech, 2007) research (Collins et al., 2007). Drawing on a number of prior studies (e.g., Collins et al., 2006; VanVoorhis & Morgan, 2007; Wolf et al., 2013), we summarize minimum sample sizes for most common quantitative and qualitative research designs (see Table 6-3). Whereas the criteria for sample size in quantitative research are based on probability computations, the criteria in qualitative research are typically based on expert opinions (Collins et al., 2006).

Table 6-3. Minimum Sample Size Recommendations

Research Design	Reasonable Sample Size
Quantitative	
Measuring group differences (e.g., t-test, ANOVA)	Cell size of 30 for 80 percent power, if decreased, no lower than seven per cell (VanVoorhis & Morgan, 2007)
Relationships (e.g., correlations, regression)	~50 (VanVoorhis & Morgan, 2007)
Chi-Square	At least twenty overall, no cell smaller than five (VanVoorhis & Morgan, 2007)
Factor analysis	~300 (VanVoorhis & Morgan, 2007)
Structural equation model	Ranges from thirty cases (for one-factor CFA with 4 indicators loading at .80) to 460 (for two-factor CFA with 3 indicators loading at .50) (Wolf et al., 2013)
Qualitative	
Case study	Three-five participants (Collins et al., 2006)
Phenomenological	Six-ten interviews (Collins et al., 2006)
Grounded theory	Fifteen-twenty cases (Collins et al., 2006)
Ethnography	One cultural group; thirty-fifty interviews (Collins et al., 2006)
Ethological	100-200 units of observations (Collins et al., 2006)

6.2. Sampling Guidelines for Qualitative and Quantitative Research

Sampling issues in qualitative research focus on discovering the scope and the nature of the system to be sampled, whereas quantitative research focuses on determining how many cases or observations are needed to reliably represent the whole system and to minimize falsely identifying or missing existing relationships between factors (i.e., depth/generalizability trade-off) (Luborsky & Rubinstein, 1995). Here, sampling designs play a pivotal role in determining the type of generalization that is justifiable (Collins et al., 2006). Whereas large and random samples tend to support *statistical generalizations* (i.e., making generalizations or inferences on data extracted from a representative statistical sample to the population from which the sample was drawn), small and purposive samples tend to support *analytical generalizations* (i.e., inferences that can be applied to wider theory on the basis of how selected cases fit with general constructs) (Curtis et al., 2000) and *case-to-case transfer* (i.e., making generalizations from one case to another similar case) (Collins et al., 2006). If the goal is not to generalize findings to a population but to obtain insights about a phenomenon, set of individuals, or set of events, then researchers can purposefully select individuals, groups, and/or settings that enhance understanding of that underlying phenomenon, individuals, or events (Onwuegbuzie & Collins, 2007). Lee and Baskerville (2012, pp. 751-752) suggested that a theory that has survived empirical testing in a particular setting (e.g., organizations, countries) may be responsibly generalized to a new setting, without retesting it, only if one is willing to accept four judgment calls: (1) "the 'uniformity of nature' judgment call" (i.e., when sufficiently similar situations occur in the future, similar effects will follow); (2) "the ‘sufficient similarity in relevant conditions’ judgment call” (i.e., the setting that is being generalized from and the setting that is being generalized to are sufficiently similar); (3) “the ‘successful identification of relevant variables’ judgment call” (i.e., the theory, as already empirically tested, indeed contains all the relevant variables that have significant effects in shaping the phenomenon of interest); and (4) “the ‘theory is true’ judgment call” (i.e., in using a theory in a new setting, one may only make a judgment call that it is true). These judgment calls suggest that sampling strategies should be designed carefully because they determine how and where a theory should be tested that in turn affects the type of generalization that can be derived from the theory.

Generally, the decision on sampling designs is determined by research questions. Whether the methodology employed is qualitative or quantitative, sampling methods are intended to maximize efficiency and validity (Palinkas et al., 2015). Nevertheless, sampling must be consistent with the purposes and assumptions inherent in the use of either qualitative or quantitative methods (Palinkas et al., 2015). Qualitative methods place primary emphases on saturation (i.e., obtaining a comprehensive understanding by continuing to sample until no new substantive information is acquired) (Miles et al., 2020). In contrast, quantitative methods place primary emphasis on generalizability (i.e., ensuring that the knowledge gained is representative of the population from which the sample is drawn) (Palinkas et al., 2015), although more recent approaches that focus on contextualization depart from the notion of universal generalization (Johns, 2006, 2017). Thus, each methodology has different expectations and sampling procedures.

A number of researchers, including Glaser and Strauss (1967), Miles et al. (2020), and Patton (1990), have discussed different sampling strategies that can be used in qualitative research. Building on the recommendations of Miles and Huberman (1994) about sampling strategies (see also Miles et al., 2020), Curtis et al. (2000) summarized six criteria for selecting qualitative samples including:

1. A sampling strategy should be relevant to the conceptual framework and the research questions addressed by the study.
2. A sample should generate rich information on the type of phenomenon under investigation.
3. A sample should enhance the generalizability of the findings. For qualitative samples, researchers are more concerned with generalizability at the abstract, conceptual or theoretical level (i.e., applied to wider theory on the basis of how selected cases ‘fit’ with general constructs) than statistical generalizability (i.e., applied to wider populations on the basis of representative statistical samples). The interested reader is referred to one especially interesting discussion of generalizability related to theoretical and empirical generalizations presented in Lee and Baskerville (2003).
4. A sample should produce believable descriptions/explanations.
5. Researchers should consider whether the method of selection permits informed consent where it is required, whether there are benefits or risks associated with selection for and participation in the study, and whether the study will adequately protect the enrolled participants by explicitly addressing potential ethical concerns.
6. Researchers should consider feasibility in terms of the resource costs of money and time, the practical issues of accessibility, and whether the sampling strategy is compatible with the researchers’ work style and competency.

We summarize the principles for selecting quantitative samples as follows:

1. Sampling decisions must be theoretically driven (Osborne, 2008). The sampling choices should be relevant to the research questions and objectives of the study (Daniel, 2012).
2. Given that the decision on design corresponding to the research objectives will have an impact on the sample size (VanVoorhis & Morgan, 2007), the study design should be carefully planned before sampling decisions are made.
3. The identification of the minimum/most appropriate sample size depends on careful and detailed planning of all stages of the research process (Delice, 2010). Decisions on a sampling schema and sample size are typically made at the beginning of the study.
4. A good sampling technique should describe the study population, list the members of the population, identify the sampling type, determine the sample size, and test the representative power of the sample (Delice, 2010).
5. A sample should aim to apply the relationships obtained among variables to a general population (i.e., statistical generalization) (Collins et al., 2006).

6.3. Sampling Strategies in Mixed-Methods Research

Determining issues regarding sampling is also important in designing a mixed-methods study. Although making sampling decisions can be difficult for both qualitative and quantitative research, sampling strategies are even more complex for mixed-methods research. In mixed-methods research, researchers must consider sampling schema and sample size for both the qualitative and quantitative strands of the study (Collins et al., 2006). To help researchers make a sampling design decision, Teddlie and Yu (2007) proposed five mixed-methods sampling strategies: (1) basic, (2) sequential, (3) concurrent, (4) multilevel, and (5) multiple. Similarly, Onwuegbuzie and Collins (2007) developed a framework by integrating the time orientation (i.e., concurrent and sequential) and the relationship between the qualitative and quantitative samples (i.e., identical, parallel, nested, and multilevel). Venkatesh et al. (2016) integrated Onwuegbuzie and Collins' (2007) and Teddlie and Yu's (2007) framework and suggested four sampling designs: basic, sequential, concurrent, and multiple sampling designs, which we describe next:

1. *Basic sampling designs* include all the qualitative and quantitative sampling designs presented in Tables 6-1 and 6-2.
2. *Sequential sampling designs* typically involve some or all of the findings stemming from the sample selected from one phase being used to drive the second phase and subsequently, the sample pertaining to this phase (Collins et al., 2007). Four types of sequential sampling designs include (Onwuegbuzie & Collins, 2007):
    a. *Identical samples*: Both qualitative and quantitative strands of the study use the same sample members.
    b. *Parallel samples*: The samples for the qualitative and quantitative components of the study are different, but they are drawn from the same population.
    c. *Nested samples*: The sample members selected for one phase of the study represent a subset of those participants chosen for the other component of the study.
    d. *Multilevel samples*: Researchers use two or more sets of samples obtained from different levels (e.g., organization, individual).
3. *Concurrent sampling designs* enable researchers to triangulate the results from separate quantitative and qualitative components of their study and confirm, cross-validate, or corroborate their findings in a single study or research program (Creswell et al., 2003;

Venkatesh et al., 2016). Like sequential sampling designs, concurrent sampling designs can be identical, parallel, nested, or multilevel designs.

4. *Multiple sampling designs* typically involve using more than one sampling technique, such as using simple random sampling in the quantitative study and expert sampling in the quantitative study.

Mixed-methods research frequently requires mixed-methods sampling procedures in order to simultaneously increase inference quality and generalizability (Collins et al., 2006; Kemper et al., 2003). To achieve this objective, there is often a need for two types of samples: probability sample (to increase statistical generalizability) and purposive sample (to increase analytical generalizability and case-to-case transfer) (Kemper et al., 2003). Collins et al. (2006) proposed a two-dimensional representation of the types of generalizations made in mixed-methods research (see Figure 6-1). Once again, for a broad discussion of generalizability, the interested reader is referred to Lee and Baskerville (2003).

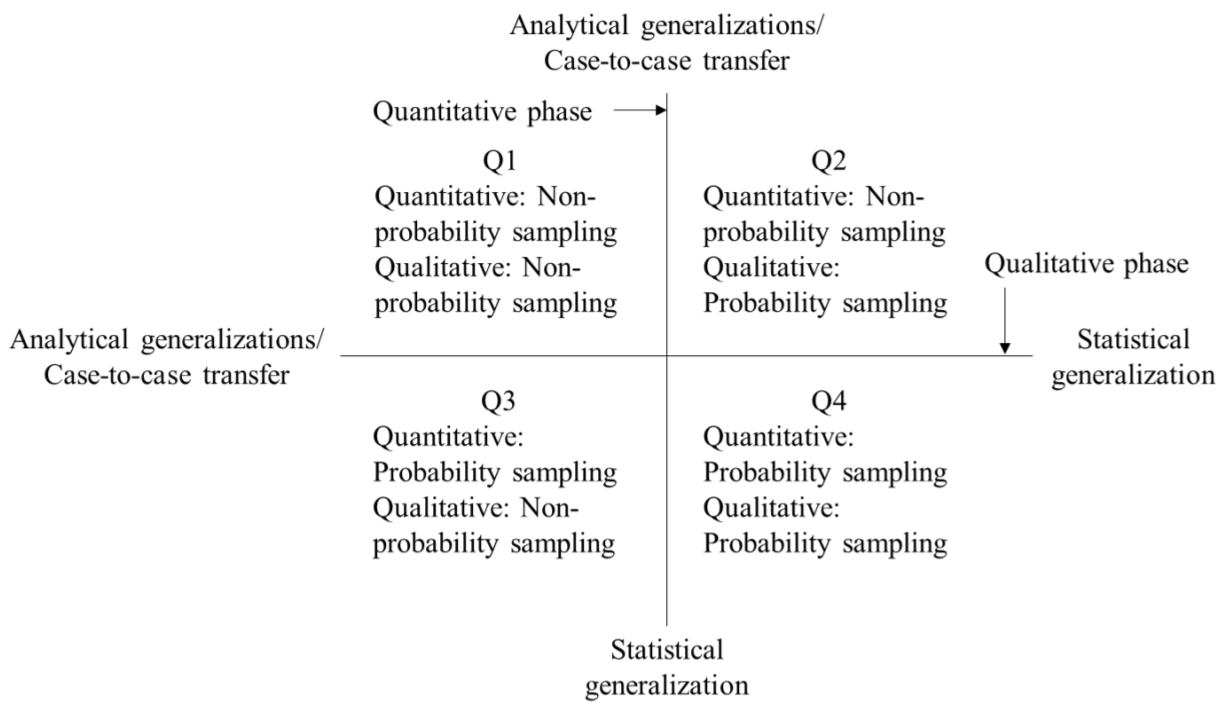

Figure 6-1. Generalizations and Sampling Designs in Mixed-Methods Research

As can be seen in Figure 6-1, the selection of sampling designs determines the types of inferences and generalizations that can be generated from a study. Quadrant 1 represents meta-inferences that involve purely analytical generalization/case-to-case transfers. These types of inferences are usually associated with non-probability sampling in both qualitative and quantitative strands of the study. Quadrant 2 represents meta-inferences that involve a combination of statistical generalization from the qualitative strand and analytical generalization/case-to-case transfer from the quantitative strand. Quadrant 3 represents meta-inferences that involve a combination of statistical generalizations from the quantitative strand and analytical generalization/case-to-case transfer from the qualitative strand. Quadrant 4 represents meta-inferences that involve purely statistical generalizations (Collins et al., 2007).

To determine the most suitable sampling designs for one's research purpose, Collins (2010) proposed five criteria for formulating mixed-methods sampling decisions:

1. The sampling unit selected for each strand of the study should reflect the dependent relationship between the samples selected per phase and the time orientation of the strand (i.e., concurrent or sequential).
2. The sampling unit selected for each strand of the study should reflect the relationship between the quantitative and qualitative samples.
3. The sampling unit selected for each strand of the study should reflect the relationship between the specific combination of the sampling schemes and the chosen type of generalization.
4. The sampling unit selected for each strand of the study should reflect the relationship between the varying types of data collected in terms of addressing the research questions.
5. Researchers should identify the relationship between the emphasis of approach (dominant, less-dominant, equal) and the formulation of appropriate meta-inferences and generalizations based on data collected from both strands of the study.

Using the guidelines for qualitative and quantitative sampling designs discussed earlier and these five criteria of mixed-methods sampling designs should help researchers determine the appropriate sampling designs (i.e., sampling schemes and sample sizes) for each strand of the study.

6.3.1. Sampling Examples in Mixed-Methods Research

To illustrate how sampling decisions are made in mixed-methods research, we use two studies discussed in Chapter 5: Stewart et al. (2017) and Koh et al. (2004). Whereas Stewart et al. used a concurrent mixed-methods design, Koh et al. used a sequential mixed-methods design.

6.3.1.1. Stewart et al. (2017)

The mixed-methods study design was a partially mixed concurrent equal status design. The study aimed to explore barriers to the successful implementation of a team-based empowerment initiative within the Veterans Health Administration (VHA). The mixed-methods sampling design was *nested sampling*—the sample members selected for the qualitative study represented a subset of those participants chosen for the quantitative study. In study 1, they used a longitudinal quasi-experimental design to gather quantitative data, and in study 2, they used an in-depth interview technique to gather qualitative data. In study 1, they tested whether there was a difference in effectiveness of team-based empowerment intervention between physician vs. non-physician leaders. They used convenience sampling and recruited all providers located in one of twenty-one geographical divisions. To be included in their sample, a provider had to be working before the beginning of the team-based empowerment intervention. This criterion resulted in the collection of pre- and post-intervention data for a sample of 224 providers.

Qualitative data were collected via participants' interviews, which were conducted as part of a larger study of VHA teams. The interviews were conducted during the initial months of implementing team-based empowerment and follow-up interviews one year later. They used a purposive sampling strategy to recruit team members in the same geographical division as their quantitative sample. In total, they interviewed eight providers, ten care managers, six clinical associates, and six administrative associates.

6.3.1.2. Koh et al. (2004)

They used a partially mixed sequential equal status design. The mixed-methods sampling design was *parallel sampling*—the samples for the qualitative and quantitative components of the study were different, but they were drawn from the same population. Data for both qualitative and quantitative studies were collected in Singapore. In the qualitative strand of the study, they drew samples from the IT Management Association (ITMA) and the Singapore IT Federation (SITF) members. They used *criterion sampling* for the qualitative strand. They contacted four of the largest customer organizations from ITMA and four of the largest supplier organizations from SITF, and requested permission to interview managers with at least three years of experience in managing outsourcing contracts. In total, they interviewed nine customer project managers and six supplier project managers. In the quantitative strand of the study, data collection was conducted in two stages. The sample was drawn from the ITMA and SITF members—the sampling strategy was simple random sampling. They sent invitation letters to all members and then contacted each member by phone a week after the mailing. They excluded managers who participated in study 1 interviews from study 2 to eliminate primacy effects and hypotheses guessing. In total, they received completed responses from 179 customer project managers and 191 supplier project managers, representing a total of 158 organizations.

6.4. Data Collection in Mixed-Methods Research

Having discussed sampling designs in mixed-methods research, we now turn to the specific methods of data collection that are used in qualitative and quantitative research, and how these methods can be combined in mixed-methods research. Researchers need to consider the possible types of data in mixed-methods research and determine what sources of data will best answer the research questions (Creswell et al., 2006). Whereas qualitative research focuses on the use of language data, quantitative research focuses on numerical data.

6.4.1. Qualitative Data Collection Methods

According to Creswell and Poth (2018), there are five different types of qualitative approaches: *biography* (i.e., narrative study of lives) (Creswell & Poth, 2018), *phenomenology* (i.e., study of structures of consciousness as experienced from the first-person perspective) (Smith, 2018), *grounded theory* (i.e., inductive methodology that provides systematic guidelines for gathering, synthesizing, analyzing, and conceptualizing qualitative data for the purpose of theory construction) (Glaser & Strauss, 1967), *ethnography* (i.e., methodology that involves direct and sustained social contact with agents), and *case study* (i.e., empirical inquiry that investigates a contemporary phenomenon within its real-life context) (Creswell, 1998; Yin, 2003). Regardless of the methodological approach involved, the purpose of data gathering in qualitative research is to provide evidence tied to the phenomenon being investigated (Polkinghorne, 2005). Most often, such evidence takes the form of words or texts. Data used in qualitative research are not simply on the surface ready to be gathered. Instead, researchers need to dig below the surface to unearth experiential accounts (Polkinghorne, 2005). Nonetheless, despite qualitative data and induction often seen as approaches in an interprevist paradigm, it should be noted that induction can be positivist. Further, inductive methods can use the literature as a source of the data including in an approach termed top-down induction (Shepherd & Sutcliffe, 2011).

The most common sources of qualitative data are *qualitative surveys*, *open-ended interviews*, *focus groups*, *observation*, and *secondary data* (e.g., personal and official documents, visual data, visual and audio data, other archival data) (Creswell & Poth, 2018; Johnson & Turner, 2003). The strengths and weaknesses of each of these methods are presented in Table 6-4 (adapted from multiple sources including Johnson & Turner, 2003; Kitzinger, 1995; Turner, 2010). As can be seen from this table, one of the major strengths of qualitative methods is their ability to provide a much deeper understanding of the phenomenon under study by allowing researchers to ask participants about their experiences. Because qualitative methods focus on experience data, it can sometimes be challenging to use probability sampling. Thus, purposive sampling is the most common sampling strategy for qualitative research (Miles et al., 2020).

Table 6-4. Strengths and Weaknesses of Qualitative Research Methods

Data Collection Strategy	**Strengths**	**Weaknesses**
Qualitative surveys	• Can be used to gain in-depth information about respondents' underlying reasoning and motivations. • Helps researchers to reach a broader audience similar to a quantitative survey. • Inexpensive, especially if administered online. • Anonymity perceived by respondents is possibly high.	• Open-ended questions in qualitative surveys require more participant time and effort. • Researchers cannot ask follow-up questions. • Responses to open-ended questions possibly result in vague answers. • Responses possibly reflect differences in verbal ability, obscuring issues of interest.
Open-ended interviews	• Can provide in-depth information. • Helps participants to describe what is important to them in their own words. • Researchers can ask for clarification or more detailed information. • Provides high credibility and face validity. • Useful for exploration and confirmation.	• Interviews are time-consuming. • More reactive to personalities, moods, and interpersonal dynamics between interviewer and interviewee. • Difficult to generalize if sample size is small and/or not representative. • Data analysis is usually time-consuming.
Focus groups	• Useful for exploring ideas. • Can obtain in-depth information about exactly how people think about an issue. • Helps interpretive validity. • Helps researchers tap into many different forms of communication that people use in day-to-day interactions. • Allows for participants to respond to each other's comments.	• Can be expensive to administer. • Possibly reactive and subject to investigator effects if participants feel that they are being watched. • May be dominated by one or two participants. • The presence of other research participants may compromise the confidentiality of the research session.

Data Collection Strategy	Strengths	Weaknesses
	• Allows follow-up and probing. • Helps capture most content/ideas. • Allows quick turnaround.	• Difficult to generalize if small unrepresentative samples are used. • Focus group moderators can be biased. • Measurement validity is possibly low.
Qualitative observations	• Helps one to directly see what people do without having to rely on what they say and do. • Allows relatively objective measurement of behavior. • Can be used with participants with weak verbal skills. • Good for description. • Can give access to contextual factors operating in natural settings.	• Reason for behaviors possibly unclear. • Possible reactive and investigator effects when participants know they are being observed. • The possibility of observers being biased is high. • There is a possibility of observers going "native" (i.e., being personally involved within the group being studied). • Interpretative validity is possibly low. • Cannot observe large populations. • Some contexts of interest are not observable. • Can be expensive and time-consuming. • Data analysis can be time-consuming.
Secondary data	• Can provide insight into what people think and what they do. • Can be collected for time periods occurring in the past. • Personal documents often unobtrusive. • Useful for corroboration. • Grounded in local setting. • Useful for exploration. • Archival research data may be available on a wide variety of topics. • Can be used to study trends.	• May be incomplete because of selective reporting or recording. • Access to some types of content possibly difficult. • Interpretive validity can be low. • Might not apply to general populations.

6.4.1.1. Qualitative Surveys

Qualitative surveys are a useful qualitative data collection technique for gaining in-depth information about respondents' underlying reasoning and motivations. A qualitative survey does not count the number of people with the same characteristic (i.e., value of variable), but it establishes meaningful variation (i.e., relevant dimensions and values) within that population (Jansen, 2010). Qualitative surveys are usually administered using the same techniques as quantitative surveys. However, the format of the questions is usually open-ended and participants will need to type or write down their responses on the survey booklet/page.

6.4.1.2. Open-Ended Interviews

Interviews are most appropriate for situations in which you want to ask open-ended questions that elicit depth of information from relatively few people. When using this method for collecting data, interviewers establish rapport and ask the interviewee a series of questions (Johnson & Turner, 2003). There are various forms of interview designs that can be used to obtain rich data using a qualitative investigational perspective (Creswell & Poth, 2018; Turner, 2010). The most common forms of interviews include *informal conversational interviews* (i.e., an interview technique that relies entirely on the spontaneous generation of questions in a natural interaction, typically one that occurs as part of ongoing participant observation fieldwork); *a general interview guide approach* (i.e., this approach is more structured than the information conversational approach but the ways in which questions are worded depend on the researcher who is conducting the interview); and *standardized open-ended interviews* (i.e., participants are asked identical questions but the questions are worded to make sure responses are open-ended) (Patton, 1987, 2014; Turner, 2010).

6.4.1.3. Focus Groups

Focus groups are "a form of group interview that capitalises on communication between research participants in order to generate data" (Kitzinger, 1995, p. 299). Although group interviews are often used simply as a quick and convenient way of collecting data from several people simultaneously, focus groups explicitly use group interaction as a part of the method (Kitzinger, 1995). According to Krueger and Casey (2015, p. 6), focus groups typically have five major characteristics: "(1) a small group of people, who (2) possess certain characteristics, (3) provide qualitative data, (4) in a focused discussion (5) to help understand the topic of interest." The idea behind focus groups is that group processes can help people explore and clarify their views in ways that would be less easily accessible in a one-on-one interview (Kitzinger, 1995).

6.4.1.4. Qualitative Observations

In this method, researchers observe participants in natural or structured settings (Johnson & Turner, 2003). Hence, this method is often described as "naturalistic research" (Mays & Pope, 1995). Observational methods used in social sciences involve a systematic, detailed observation of behavior and talk in a natural environment. The analog in observation is to create an environment where people will act as naturally as possible without considering the researcher's presence (Johnson & Turner, 2003). However, in an attempt to minimize the impact on the environment being studied, investigators sometimes adopt a "participant observer" role, becoming involved in the activities taking place while also observing them (Mays & Pope, 1995). Thus, observers can remain objective and not contaminate the data with their own preconceptions (Mulhall, 2003), though the Hawthorne effect cannot be ruled out.

6.4.1.5. Secondary Data

Secondary data are "data that were originally recorded or 'left behind' or collected at an earlier time by someone other than the current researcher, often for an entirely different purpose from the current research purpose" (Johnson & Turner, 2003, p. 314). Secondary data may be internal to a program or organization (e.g., corporate annual report) or external and personal (e.g., personal notes from daily activities, photographs, anything recorded for private purposes). Archival research files can also be a source of secondary data. These are files originally used for research purposes and then stored for possible later use (Johnson & Turner, 2003). Another source of secondary, qualitative data is social media data. Social media offers a novel opportunity to harvest a massive and diverse range of content without the need for intrusive or intensive data collection procedures (Andreotta et al., 2019). The volume of secondary data continues to grow leaps and bounds, and researchers are using such data extensively.

6.4.2. Quantitative Data Collection Methods

As mentioned previously, quantitative data collection methods focus on numerical data. Thus, quantitative data collection may include any method that will result in numerical data. The most common types of quantitative data collection strategies are quantitative surveys, experiments, quantitative observations, quantitative interviews, and secondary data. The strengths and weaknesses of these methods are summarized in Table 6-5 (adapted from multiple sources, including Johnson & Turner, 2003; McLeod, 2012). As can be seen from Table 6-5, the strength of quantitative methods resides in standardization. All these methods gather numerical data using standardized techniques. However, because these methods involve structured, closed-ended questions, the research outcomes are limited and cannot always represent the actual occurrence of a specific case.

Table 6-5. Strengths and Weaknesses of Quantitative Research Methods

Data Collection Strategy	Strengths	Weaknesses
Quantitative surveys	• Good for measuring attitudes and eliciting other content from participants. • Inexpensive (especially online questionnaires and group-administered questionnaires). • Quick turnaround. • The questions are standardized. All respondents are asked exactly the same questions in the same order. Thus, the study can be replicated easily. • Anonymity perceived by respondents is possibly high. • Moderately high measurement validity for well-constructed and well-tested questionnaires.	• Validation is needed. • Must typically be brief to avoid problems (e.g., quitting, fatigue). • Might have missing data that could have a significant effect on inferences being drawn from the data. • Possible reactive effects (e.g., social desirability bias, common method bias). • Nonresponse to selected items.

Data Collection Strategy	Strengths	Weaknesses
	• Data analysis is relatively easy.	
Laboratory experiments	• Allows for precise control of extraneous and independent variables. Thus, allows a cause-and-effect relationship to be established. • Offers an opportunity to include the independent variables of theoretical interest and exclude irrelevant or confounding variables. • Permits direct comparisons (between conditions in which the factor is present and in which the factor is absent). • Easy to replicate, especially compared to field experiments.	• Low external validity because the artificiality of the laboratory setting may produce unnatural behavior that does not reflect real life. • Certain characteristics of experimenters may bias the results and become confounding variables.
Field and natural experiments	• More likely to reflect real life because of its natural setting (i.e., higher ecological validity). • Less likelihood of experimenter bias because participants may not be aware that they are being studied. • Natural experiments can be used in situations where independent variables cannot be ethically manipulated.	• Less control over extraneous variables that might bias the results. • More expensive and time-consuming than laboratory experiments.
Quantitative observations	• Allows one to directly see what people do without having to rely on what they say and do. • Allows relatively objective measurement of behavior. • Can be used with participants with weak verbal skills. • Good for description/richness in research involving hypothesis testing. • Can give access to contextual factors operating in natural settings. • Less biased than qualitative observations.	• Reason for behaviors possibly unclear. • Can only be used to gather limited types of data. • Possible reactive and investigator effects when participants know they are being observed. • Cannot observe large populations. • Some contexts of interest are unobservable.
Quantitative interviews	• All the strengths of the quantitative surveys, except quantitative interviews can be challenging when	• Typically, must be kept brief. • Possible reactive effects (e.g., social desirability bias, common methods bias).

Data Collection Strategy	Strengths	Weaknesses
	researchers have to deal with a large sample size.	• Anonymity perceived by respondents possibly low.
Secondary data	• Background work needed has already been done. • Can be available/collected for time periods occurring in the past. • Useful for corroboration and exploration. • For archival research data, often available on a wide variety of topics. • Can be used to study trends.	• May be incomplete because of selective reporting or recording. • Access to some types of content possibly difficult. • May be inaccurate to measure specific constructs. • May not contain sufficiently detailed information for the research purpose.

6.4.2.1. Quantitative Surveys

Surveys are one of the most common methods of data collection in quantitative research. When using this method, researchers typically develop a self-report data collection instrument that is filled out by participants (Johnson & Turner, 2003). Quantitative surveys permit the collection of data from large numbers of people in standardized ways, thus enabling a comparison across different settings (e.g., communities, countries, time periods) (Hentschel, 1998). The response categories often take the form of rating scales (e.g., Likert scale), rankings, semantic differentials, and checklists (Johnson & Turner, 2003). Johnson and Christensen (2019) proposed 15 principles of questionnaire construction:

1. Make sure that the questionnaire items match your research objectives.
2. Understand your research participants.
3. Use natural and familiar language.
4. Write items in a clear, simple, and precise way.
5. Do not use “leading” or “loaded” questions.
6. Avoid double-barreled questions.
7. Avoid double negatives.
8. Determine whether an open-ended and a closed-ended question is needed.
9. Use mutually exclusive and exhaustive response categories for closed-ended questions.
10. Consider the different types or response categories available for closed-ended questions.
11. Use multiple items to measure abstract constructs.
12. Consider using multiple methods when measuring abstract constructs.
13. Use caution if you reverse the wording in some of the items to prevent response sets in multi-item scales.
14. Develop a questionnaire that is properly organized and easy for the participants to use.
15. Always pilot-test your questionnaire.

The interested reader can refer to various sources, including DeVellis and Thorpe (2021), Hoehle and Venkatesh (2015), and MacKenzie et al. (2011).

6.4.2.2. Experiments

Experiments refer to a research approach in which variables are manipulated and their effects on other variables are observed (Campbell & Stanley, 1963). The two most common types of experiments in the social sciences are *laboratory experiments* and *field experiments*. A laboratory experiment is commonly used in psychology; it allows tight control of decision environments. The environment created in a laboratory setting is *artificial*. That is, laboratory experiments allow observation in a situation that has been designed and created by investigators rather than one that occurs in nature (Webster & Sell, 2014). From a methodology perspective, the major benefit of laboratory experiments is its potential for high internal validity (demonstration of causality) (McGrath et al., 1982). This is because researchers are able to control the level of an independent variable before measuring the level of a dependent variable (Webster & Sell, 2014).

In contrast, field experiments take place in naturally occurring environments rather than in a laboratory. Experimenters still manipulate the independent variables but in a real-life setting. Field experiments attempt to simulate, as closely as possible, the conditions under which a causal process occurs to enhance the external validity or generalizability of experimental findings (Gerber & Green, 2008, 2012). Field experiments can be differentiated into three types: (1) *an artefactual experiment*; (2) *a framed field experiment*; and (3) *a natural field experiment* (Harrison & List, 2004). In an artefactual experiment, experimenters use nonstandard subject pools (i.e., actual field subjects) instead of using a standard subject pool (i.e., using a student sample). A framed field experiment is the same as an artefactual field experiment, but the research experiment is framed in the field context of the commodity, tasks, or information set of the subjects (List, 2011). Lastly, a natural field experiment is the same as a framed field experiment, but the experiment takes place in the environment where subjects naturally undertake their experimental tasks and where the subjects do not know that they are in an experiment (Harrison & List, 2004). In natural experiments, participants are exposed to experimental and control conditions that are determined by nature or by factors outside the control of researchers (Craig et al., 2017). Natural experiments are often used to study situations in which controlled experimentation is not possible—e.g., when an exposure of interest (intervention/manipulation)cannot be practically or ethically assigned to participants (Messer, 2008). Natural experiments are quasi-experiment in nature—although independent variables are manipulated, participants are not randomly assigned to conditions (Cook & Campbell, 1979). Therefore, the assumptions and analytical techniques applied to experimental designs are not valid for them (Dunning, 2012). Given the absence of random assignment in a natural experiment, researchers need to make sure the pre-conditions of control and treatment groups are comparable by providing convincing empirical evidence for the same (Murnane & Willett, 2011).

The popularity and convenience of online transactions and interactions have created both the need and opportunity for online experiments for all types of experiments discussed above (Dandurand et al., 2008; Reips, 2002). Although the move to online experiments may lead to new threats to validity (e.g., loss of control over subjects and environments, loss of ability to collect verbal protocols), this practice comes with benefits including: (1) reducing the cost and the amount of time spent managing the experiment; (2) increasing the uniformity of the procedure across participants; (3) maintaining ethical standards by making the experiment publicly available for criticism; (4) increasing external validity by recruiting more diverse samples; (5) leveraging online trace data to understand mechanisms for treatment effects; (6) leveraging large sample sizes to uncover heterogenous treatment effects; and (7) being able to capitalize on naturally occurring events because of the availability of trace data (Dandurand et al., 2008; Karahanna et al., 2018; Reips, 2002).

An example of online experiments is Aiken and Boush (2006). They conducted an online experiment to study the effectiveness of Internet marketers' various attempts to develop customer trust through web signals. They manipulated three web site trust signals (i.e., trustmarks, objective-source ratings, and implied investment in advertising) and created eight experimental web sites (i.e., one web site with all three signals, three web sites with combinations of two signals, three web sites with one signal, and one web site with no signal). They sent emails with an invitation letter to participants that pointed them to the study's web site. If participants agreed to participate, they logged on, read through a procedural description and greeting, followed instructions, and then clicked through to the experimental stimuli. They were randomly assigned to view one of the eight possible websites and answered the same survey questions after exposure. Although the authors were not able to control the study environment conditions (e.g., type of devices participants used in the study), they were able to leverage online trace data to rule out alternative causal mechanisms.

6.4.2.3. Quantitative Observations

Quantitative observations involve using standardized observational procedures in order to obtain reliable research data (Johnson & Christensen, 2019). This technique is similar to qualitative observations. However, it usually results in quantitative data (e.g., counts, frequencies, percentages). Different events that may be of interest in quantitative observation include observing nonverbal behaviors (e.g., body movement, eye contacts), observing spatial behavior (e.g., the distance between people and objects), and observing extralinguistic behaviors (e.g., speech rate and volume) (Johnson & Christensen, 2019).

6.4.2.4. Quantitative Interviews

The goal of a quantitative interview is to standardize what is presented to interviewees (Johnson & Christensen, 2019). In a quantitative interview, interviewers simply read a series of closed-ended questions to the respondents and record the answer (Johnson & Turner, 2003). The key idea is to expose each participant to the same stimulus so that the results will be comparable (Johnson & Christensen, 2019). Any probes and/or responses to interview questions are pre-planned. The only questions to which interviewers can respond are clarification questions to closed-ended questions being asked (e.g., what do you mean by 'group dynamic'?) (Johnson & Turner, 2003).

6.4.2.5. Secondary Data

Another source of data in quantitative research is secondary data. These data were originally collected by other researchers or external parties, often for a different purpose. For example, companies might publish their financial report every year to meet legal requirements. Researchers can use these publicly available, quantitative data in their research.

6.4.3. Mixed-Methods Data Collection Procedures

Having discussed the most common qualitative and quantitative data collection methods, we now turn to specific mixed-methods data collection procedures. We propose four key ideas for collecting data using a mixed-methods approach:

1. The research questions and purposes of mixed-methods research should drive the selection of data collection techniques. Like all research, the goal of data collection in mixed-methods research is to develop answers to research questions (Creswell & Plano Clark, 2018; Teddlie & Yu, 2007). Thus, researchers should determine whether the techniques and types of data they are collecting will help answer the research questions. For example, if the research objective is to study properties of some natural setting (e.g., characteristics of team-based empowerment initiative within the Veteran Health Administration), a combination of field experiments, surveys, or interviews is suitable, whereas the use of a laboratory experiment or secondary data is less suitable.
2. Researchers should follow the fundamental principle of mixed-methods research: "methods should be mixed in a way that has complementary strengths and nonoverlapping weaknesses" (Johnson & Turner, 2003, p. 299). Researchers can use Tables 6-4 and 6-5 as references when comparing the strengths and weaknesses of different qualitative and quantitative methods.
3. Researchers should link the sampling strategy with the data collection strategies. As we mentioned earlier, although qualitative data collection techniques are typically associated with non-purposive sampling and quantitative data collection techniques are associated with purposive sampling, both qualitative and quantitative data collection techniques can use either type of sampling strategy. Although researchers can use one type of sampling strategy, we encourage them to use both, especially if the design is a sequential equal status design in which both types of methods are given equal weight (Kemper et al., 2003). Using a combination of purposive and non-purposive sampling procedures will help researchers offset the limitations of any one sampling technique.
4. Given that in a mixed-methods research study, researchers should collect both qualitative and quantitative data, they need to be familiar with the array of qualitative and quantitative data collection methods discussed earlier. A mistake that novice mixed-methods researchers tend to make is using the research paradigm with which they are familiar in all stages of data collection. For example, they use the same principles of questionnaire construction to develop interview protocols. When it comes to collecting data in mixed-methods research, we encourage researchers to learn how to make *Gestalt switches* from a qualitative lens to a quantitative lens to go back-and-forth. If a single researcher is not competent or an expert at this, assembling a heterogeneous team of researchers whose primary paradigms are different is a potential solution (Onwuegbuzie et al., 2011).

These four principles should guide researchers in selecting the most suitable data collection techniques for their mixed-methods study. Next, we propose a data collection matrix consisting of qualitative and quantitative data collection techniques.

6.4.4. Mixed-Methods Data Collection Matrix

Thirty alternative data collection designs for mixed-methods research are listed in Table 6-6. This table is formed by integrating five different approaches to qualitative data collection and six different approaches to quantitative data collection previously discussed. According to Kemper et al. (2003), the mixing can take place in two different forms: *intramethod mixing* and *intermethod mixing*. Intramethod mixing occurs when a concurrent or sequential use of a single method includes both qualitative and quantitative components. For example, a concurrent use of open- and closed-ended items on a single questionnaire or on different questionnaires but in the same research study. Types 1, 19, 22, and 30 are categorized as intramethod mixing. In contrast, intermethod mixing occurs when a mixed-methods research study includes both qualitative and quantitative components from different approaches—for example, a sequential use of quantitative surveys and open-ended interviews in the same research study.

Table 6-6. Mixed-Methods Data Collection Matrix

Qual / Quant	Qualitative Surveys	Open-ended Interviews	Focus Groups	Qualitative Observations	Secondary Data (e.g., Personal and Official Documents, Archival Data)
Quantitative Surveys	(1) Intra	(2)	(3)	(4)	(5)
Field (and Natural) Experiments	(6)	(7)	(8)	(9)	(10)
Laboratory Experiments	(11)	(12)	(13)	(14)	(15)
Quantitative Observations	(16)	(17)	(18)	(19) Intra	(20)
Quantitative Interviews	(21)	(22) Intra	(23)	(24)	(25)
Secondary Data (e.g., Company's Financial Reports)	(26)	(27)	(28)	(29)	(30) Intra

Researchers should also take into account the general properties of mixed-methods research, discussed in Chapter 5, when they make a decision about their data collection procedure. The procedure needs to consider the research questions, the purposes of mixed-methods research, the timing of the study, and the emphasis placed on the quantitative and qualitative data (Creswell & Plano Clark, 2018). As the purpose of mixed-methods research plays a significant role in guiding the design decisions, we approach the data collection strategies from the perspective of the mixed-methods purpose. Tables 6-7 and 6-8 summarize our recommendations for mixed-methods data collection procedures based on the study purpose.

Table 6-7. Mixed-Methods Design, and Data Collection Procedures for Research with Corroboration, [some] Diversity, Complementarity, and [some] Completeness Purposes

Possible Design Options	Recommendations for Mixed-Methods Data Collection
• A partially mixed concurrent equal status design • A partially mixed concurrent dominant status design • A fully mixed concurrent equal status design	• Determine whether the qualitative and quantitative approaches will address the same research questions. • Based on the research questions and purposes, determine whether data will be gathered using intramethod or intermethod data collection strategies (i.e., designs (1), (19), (22), (30)). • If intramethod data collection strategies are used, carefully consider the strengths and tradeoffs for the types of data collection. The most efficient way to collect data using intramethod data collection strategies is to use the same individuals in both the qualitative and quantitative strands of the study (i.e., identical sampling or nested sampling). • If intramethod data collection strategies are used, carefully decide on the format and/or wording of the qualitative and quantitative instruments to avoid overlapping questions being asked. • If intermethod data collection strategies are used, carefully decide on the duration for the qualitative and quantitative data collection. If the goal is to compare and to investigate differences within the same populations, use parallel sampling. • If the quantitative methods involve the use of some types of experiments and the qualitative methods involve asking participants open-ended questions (designs (6), (7), (8), (11), (12), and (13)), researchers should consider using parallel samples because any verbal interactions (unrelated to the study protocols) during an experimental study may impose threats to validity. • It is recommended that researchers adopt parallel samples when they use intermethod data collection strategies (2), (3), (4), (9), (14), (16), (17), (18), (21), (23), and (24) to minimize participant-related biases. However, identical sampling can also be used if researchers have limited resources. In that case, the study should be designed carefully to ensure participants' responses collected using one method does not affect their responses collected using a different method. • If the study uses an equal status design, consider using intermethod data collection strategies (e.g., questionnaires for the quantitative strand and interviews for the qualitative strand) to ensure the strengths of each method are able to shed light on different aspects of the phenomenon under study. • Determine a sampling strategy for each approach and based on the sampling strategy, estimate the necessary sample size. • If more emphasis is given to one approach, determine what type of data will be embedded in the dominant strand of the study.

Table 6-8. Mixed-Methods Design, and Data Collection Procedures for Research with Compensation, [some] Diversity, Developmental, [some] Completeness, and Expansion Purposes

Possible Design Options	Recommendations for Mixed-Methods Data Collection
• A partially mixed sequential equal status design • A partially mixed sequential dominant status design • A fully mixed sequential equal status design	• The qualitative and quantitative strands of the study should address different research questions. • Based on the research questions and purposes of the study, determine the order of the data collection procedures. • To optimize the strengths of each strand of the study, use methods that do not have overlapping weaknesses (e.g., laboratory experiments for the quantitative method and open-ended interviews for the qualitative method). Intramethod data collection strategies (designs (1), (19), (22), (30)) tend to have overlapping weaknesses. • If intermethod data collection strategies are used, consider using parallel sampling or multiple sampling designs as a sampling strategy. Recruiting different individuals for the qualitative and quantitative strands of the study increases external validity and minimizes participant-related biases. • If the study uses an equal status design, consider using intermethod mixing strategies (e.g., questionnaires for the quantitative strand and interviews for the qualitative strand) to ensure no overlapping weaknesses across methods. • If more emphasis is placed on one strand of the study, determine what type of data will be embedded in the dominant strand of the study.

6.4.4.1. Corroboration, [some] Diversity, Complementarity, and [some] Completeness Purposes

As discussed in Chapter 5, mixed-methods studies with corroboration, and [some studies with] diversity, complementarity, and [some studies with] completeness purposes are best achieved using a concurrent design. Several considerations that need to be taken into account when researchers use this design include the selection of participants, the sample size, and the priority of each study strand. Researchers should start with research questions (e.g., whether the qualitative and quantitative approaches address the same research questions, the relationship between the qualitative and quantitative research questions) and the purposes of mixed-methods research. Based on these preliminary decisions, researchers determine the data collection strategies that follow the general design strategies. With regard to the participants, Creswell and Plano Clark (2018) suggested two options for selecting individuals to participate in the study: the samples can include *different* or the *same* individuals. One can use different individuals if the goal is to compare behaviors and characteristics of two cases or subgroups as one does in a study with a diversity purpose. For example, Chang (2006) investigated the differences between IT and general management regarding the perceived importance of business functions and perceived implementation success factors and benefits. In this study, it was necessary to gather data from two different samples. One can also use the same individuals if intramethod mixing strategies are used. For example, Bhattacherjee and Premkumar (2004) used the same questionnaire to gather both qualitative and quantitative data in their study. Qualitative data analysis of respondents' comments that were gathered at the same time as the quantitative data using questionnaires helped validate the findings from the quantitative study. We also suggest researchers use intermethod mixing strategies (e.g., questionnaires for the quantitative strand and interviews for the qualitative strand) in a concurrent, equal status design to ensure the methods used in data collection do not contain overlapping weaknesses. Further, one should determine a sampling strategy for each approach and, based on that strategy, estimate the sample size. We encourage researchers to use both purposive and non-purposive sampling (e.g., using purposive sampling for the qualitative approach and using non-purposive sampling for the quantitative approach or vice versa) in the same study or the same research program. By doing so, researchers may optimize the strengths associated with each sampling technique.

For example, Stewart et al. (2017) used type (7) design (i.e., a combination of field experiment and open-ended interviews). This type of design is illustrated in Figure 6-2. In the quantitative study, they adopted a longitudinal quasi-experimental design. They selected all providers located in one of 21 geographical divisions to participate in the study. They had a sample of 224 providers with data collected during pre- and post-intervention stages of a team-based empowerment intervention. In the qualitative study, they interviewed several team members in the same geographical division as their quantitative sample. Interviews, each averaging 50 minutes, were conducted by the same interviewer to minimize confounding. They also conducted interviews prior to the quantitative analysis. They used a semi-structured interview format focused broadly on identifying facilitators and barriers associated with the implementation of team-based empowerment.

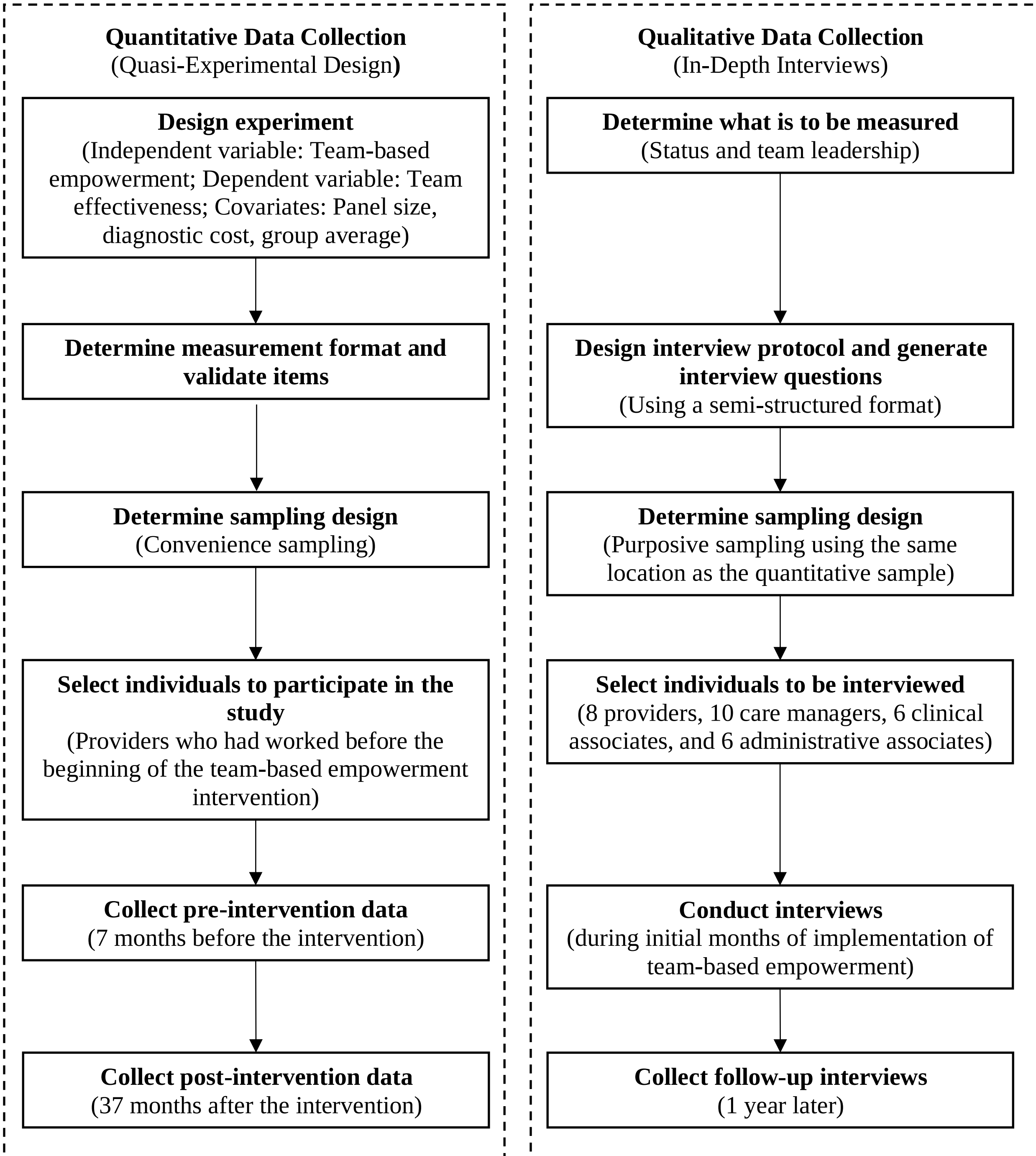

Figure 6-2. Data Collection Procedures for a Concurrent Design with Nested Samples (Quantitative Experiment-Qualitative Interviews)

6.4.4.2. Compensation, [some] Diversity, Developmental, [some] Completeness, and Expansion Purposes

Mixed-methods studies with compensation, and [some studies with] diversity, developmental, [some studies with] completeness, and expansion purposes are best achieved using a sequential design. Studies with these purposes typically address different research questions in each strand of the study. One should determine the order of data collection based on the research questions. For example, if the goal is to use the first strand of the study to identify the important constructs and develop testable hypotheses, then a qualitative data collection, followed by a quantitative data collection will be suitable for the study. We encourage researchers to use methods that do not have overlapping weaknesses to offset weaknesses across methods. For example, the use of both qualitative and quantitative surveys might prevent researchers from asking follow-up questions. Thus, researchers may not want to use both methods in both strands. We also suggest researchers use different sampling strategies in both strands of the study to ensure a mixed-methods research approach can generate different types of generalizability. Lastly, if each strand of the study is given equal weight, we suggest researchers use intermethod mixing strategies to avoid overlapping weaknesses that are likely to exist in intramethod mixing strategies, as previously explained.

In Koh et al. (2004), qualitative data were gathered using in-depth interviews, and quantitative data were gathered using a field study survey (i.e., intermethod mixing strategies). We show their data collection procedure in Figure 6-3. The qualitative and quantitative strands had different participants. They sought to identify both customer and supplier obligations that were critical to success in the first strand of the study. To achieve this goal, they used qualitative interviews. During the interviews, they employed a critical incident technique and asked interviewees to identify an outsourcing project that was currently underway or had been recently completed. They probed interviewees to describe critical incidents illustrating situations where meeting these obligations was particularly challenging and to discuss their obligations to the other contractual party in relation to the project. To assess the impact of fulling these obligations on success, they collected data using a survey. They surveyed 370 managers (i.e., 179 customer project managers and 191 supplier project managers). Whereas some of the instruments they used in the survey were adapted from prior research, they also developed a scale for their key construct (i.e., psychological contract obligations). They crafted a set of items for each obligation, and these items were based on the content analysis of their qualitative data. These items were then pilot-tested with three senior project managers. The actual data collection was conducted in two rounds. In the first round, invitation letters were sent to members of the IT Management Association (ITMA) and the Singapore IT Federation (SITF). In the second round, the authors sent out surveys to 262 customer project managers from the 90 customer organizations, and 341 suppliers project managers from 68 supplier organizations. The authors examined all returned questionnaires for completeness and contacted respondents by phone to obtain any missing information.

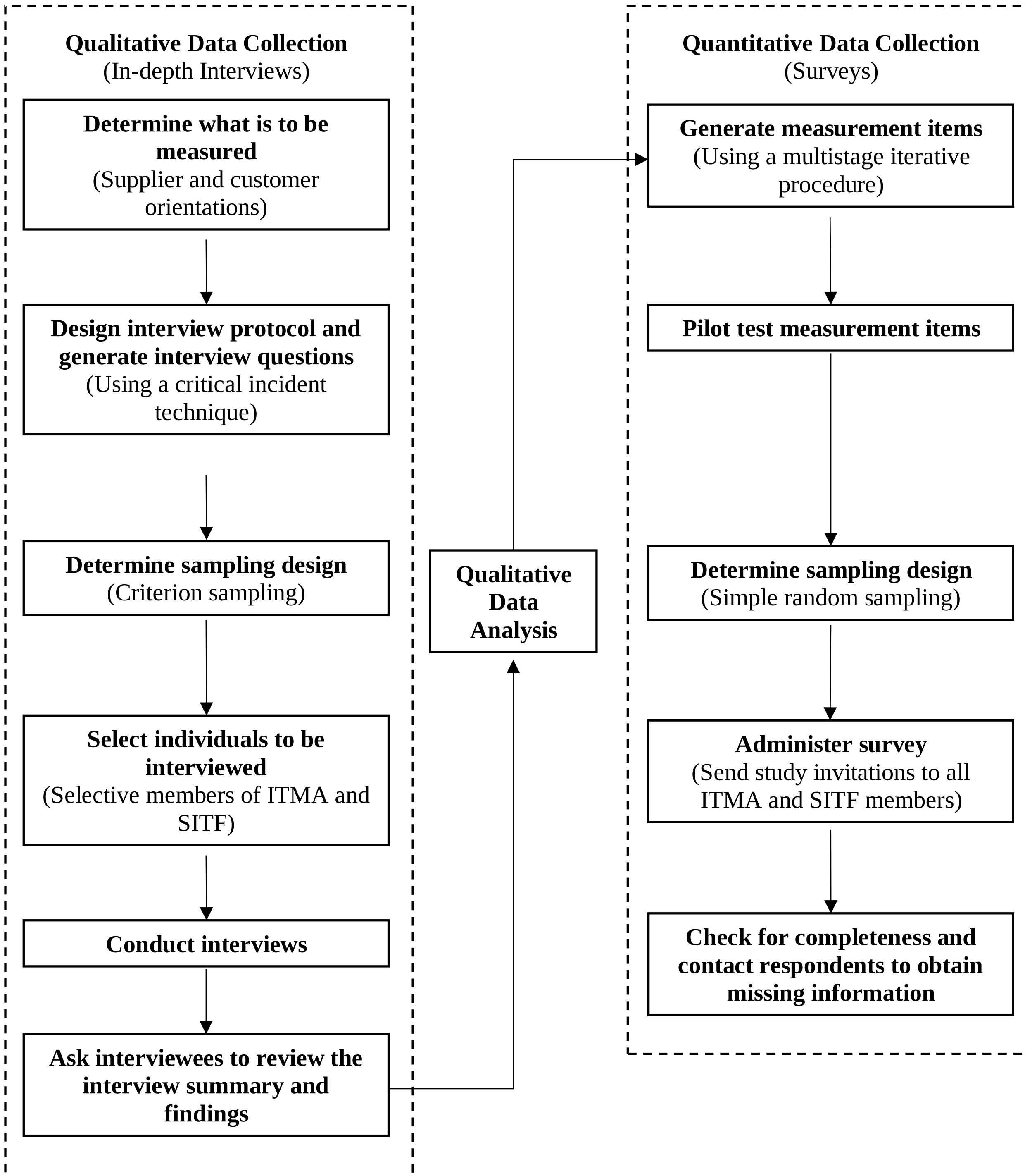

Figure 6-3. Data Collection Procedures for a Sequential Design with Parallel Samples (Qualitative Interviews-Quantitative Surveys)

Summary

- Sampling issues in qualitative research focus on discovering the scope and the nature of the system to be sampled, whereas quantitative research focuses on determining how many cases or observations are needed to reliably represent the whole system and to minimize falsely identifying or missing existing relationships among factors.

- Two important aspects of sampling decisions are sample size and sampling schema.
- In mixed-methods research, researchers must make sampling schema and sample size decisions for both the qualitative and quantitative strands of the study.
- Five major probability sampling schemes are simple random sampling, systematic random sampling, stratified random sampling, cluster random sampling, and multistage random sampling.
- Ten major non-probability sampling schemes are modal instance sampling, expert sampling, heterogeneity sampling, homogeneous sampling, snowball sampling, random purposeful sampling, stratified purposeful sampling, criterion sampling, critical case sampling, and quota sampling.
- Four types of sampling strategies for mixed-methods research are basic sampling, sequential sampling, concurrent sampling, and multilevel sampling.
- The selection of sampling designs determines the types of inferences and generalizations that can be generated from a study.
- The most common sources of qualitative data are qualitative surveys, open-ended interviews, focus groups, observation, and secondary data (e.g., personal and official documents, visual data, visual and audio data, and archival data).
- The most common types of quantitative data collection strategies are quantitative surveys, experiments, quantitative observations, quantitative interviews, and secondary data.
- In making decisions on data collection strategies, researchers should follow the fundamental principle of mixed-methods research: "methods should be mixed in a way that has complementary strengths and nonoverlapping weaknesses" (Johnson & Turner, 2003, p. 299).

Exercises

1. Find a mixed-methods study with a concurrent design published in a journal in your field or a related field. Review the data collection procedure for the qualitative and quantitative strands in that paper and answer the following questions:
   a. What qualitative, quantitative, and mixed-methods sampling strategies were used?
   b. What data collection strategies were used? Use Table 6-6 as your guide.
   c. List all the steps the authors used to develop the data collection procedure. Use a diagram to illustrate this process.
2. Find a mixed-methods study with a sequential design published in a journal in your field or a related field. Review the data collection procedure for the qualitative and quantitative studies in that paper and answer the following questions:
   a. What qualitative, quantitative, and mixed-methods sampling strategies were used?
   b. What data collection strategies were used? Use Table 6-6 as your guide.
   c. List all the steps the authors used to develop the data collection procedure. Use a diagram to illustrate this process.
3. Select a topic of interest to you and develop a research question that can be studied using a mixed-methods research approach. Determine the purpose of your mixed-methods research and develop a plan to collect data as a part of your mixed-methods study. Discuss possible data collection approaches (including a discussion of the sampling approaches) that you can use and to what extent they are appropriate to help answer your research questions.

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CHAPTER 7

QUALITATIVE AND QUANTITATIVE DATA ANALYSIS STRATEGIES

After researchers complete data collection (Chapter 6), the next step is to analyze the data. Given that the research questions and purpose(s) are the foundations of mixed-methods research, mixed-methods data analysis strategies should be used to address the research questions and achieve the purpose(s) set forth in conducting mixed-methods research, although, as noted in Chapter 4, there may be emergent purposes. Ideally, data analysis in mixed-methods research involves separately analyzing the qualitative and quantitative data using qualitative and quantitative data analysis techniques, respectively, and/or combining both types of data using approaches that mix or integrate the qualitative and quantitative data to yield integrated results (Creswell & Plano Clark, 2018). In this chapter, we discuss the most common techniques used to analyze qualitative and quantitative data. Because it is not our goal to cover all possible data analysis strategies, we focus primarily on the general discussion and procedures for how to analyze data in qualitative and quantitative research.

We underscore that this chapter is not meant to substitute for a strong education in qualitative and quantitative data analyses. The interested reader is referred to a variety of sources on these topics—some of these are discussed throughout this chapter. In the next chapter (Chapter 8), we will discuss the procedures for selecting the most appropriate data analysis techniques for mixed-methods research.

7.1. Data Analysis in Qualitative Research

Qualitative data analysis is "the classification and interpretation of linguistic (or visual) material to make statements about implicit and explicit dimensions and structures of meaning-making in the material and what is represented in it" (Flick, 2014, p. 5). Qualitative data analysis can support either a confirmatory or exploratory goal. It can be directed by a conceptual framework, suggesting, in part, *a deductive process*, or driven more by the data, suggesting *an inductive process* (Mihas, 2019). Thus, the analysis of qualitative data can have several objectives, including to describe a phenomenon in some, or greater, detail; to compare several cases based on what they have in common or on the differences between them; and/or to develop a theory of the phenomenon under study from the analysis of empirical material (Flick, 2014).

There are a number of approaches to collecting and analyzing qualitative data. Some of the best-known approaches are: case study (Yin, 2003, 2006), grounded theory (Corbin & Strauss, 1990; Glaser & Strauss, 1967), direct and pragmatic (Miles et al., 2020), narrative analysis (Bamberg, 2012), content analysis (Krippendorff, 1980; Mayring, 2004; Weber, 1990), classification (Bailey, 1994; Doty & Glick, 1994; Nickerson et al., 2012), event analysis (Earl et al., 2004; Happ et al., 2004; Olzak, 1989), metaphorical analysis (Schmitt, 2005), hermeneutic analysis (Bergman, 2010; Lee, 1994), discourse analysis (Brown & Yule, 1983; Gee, 2010), and phenomenology/heuristic analysis (Sadala & Adorno, 2002; Sanders, 1982; Starks & Trinidad, 2007). A summary of these approaches is shown in Table 7-1. Although each of these techniques are different from one another, they have the same orientation—focusing on how data should be organized and coded so that the key issues emerging from the dataset can be easily interpreted.

Table 7-1. Common Qualitative Data Analysis Approaches

Approach	Reference(s)	Summary of Data Analysis
Case study	Yin (2003, 2006)	Three strategies to analyze case studies are relying on theoretical propositions, setting up a framework based on rival explanations, and developing case descriptions. Any of these strategies can be used when practicing five specific techniques for analyzing case studies: (1) *pattern matching* (i.e., to compare an empirical pattern to a predicted one); (2) *explanation building* (i.e., to stipulate a presumed set of causal relationships about the phenomenon under study); (3) *time-series analysis* (i.e., to use an essential feature to identify the specific indicator(s) to be traced over time); (4) *logic model* (i.e., to match empirically observed events to theoretically predicted events); and (5) *cross-case synthesis* (i.e., to compare two or more cases to identify patterns, similarities, and differences).
Grounded theory	Corbin and Strauss (1990); Glaser and Strauss (1967)	In the grounded theory approach, data collection and analysis are interrelated processes. Like many other qualitative techniques, coding is a crucial process in grounded theory. Here, there are three basic types of coding, per Corbin and Strauss (1990): (1) *open coding*—"the interpretive process by which data are broken down analytically" (p. 12); (2) *axial coding*—"categories are related to their subcategories, and the relationships are tested against data" (p. 13); and (3) *selective coding*—"the process by which all categories are unified around a 'core' category, and categories that need further explication are filled-in with descriptive detail" (p. 14).
Direct and pragmatic	Miles et al. (2020)	In the direct and pragmatic approach, the analysis consists of three activities: (1) data reduction; (2) data display; and (3) conclusion drawing/verification. In this approach, analysis can take place at three different phases/points: • analysis during data collection to allow researchers to cycle back and forth between thinking about the existing data and generating strategies for collecting new data; • within-site analysis by optimizing the use of different displays (e.g., narrative text, matrix); and • cross-site analysis to increase explanatory power and generalizability.

Approach	Reference(s)	Summary of Data Analysis
Narrative analysis	Bamberg (2012)	There are three different approaches in analyzing narrative data: (1) *analytical or linguistic orientation* (i.e., the focus of analysis is on the linear sequence of clauses—the way narratives form a cohesive sequence of events); (2) *conceptual orientation* (i.e., focuses on the way events are conceived as parts of episodes that in turn are parts of larger thematic structures, such as plots); and (3) *interactive-performance orientation* (i.e., focuses not only on the linguistic means, but also on expression and communication used in the narrative context).
Content analysis	Krippendorff (1980); Mayring (2004); Weber (1990)	Content analysis commonly consists of six steps: (1) *design*—researchers define the context of their study; (2) *unitizing*—defining and identifying the unit of analysis; (3) *sampling*—determining sampling strategies; (4) *coding*—classifying units in terms of categories of the analytical constructs chosen; (5) *drawing inferences*; and (6) *validation*. The coding step can be conducted either manually (by trained human coders) or using software.
Classification: Typology and taxonomy	Bailey, (1994); Nickerson et al. (2012)	In developing typologies, researchers start with a conceptual or theoretical foundation and then derive the typological structure through deduction (Bailey, 1994). In developing taxonomies, researchers first identify the meta-characteristics. Next, the conditions (i.e., subjective and objective) that end the process need to be determined. After these steps, researchers can begin with either an empirical approach or a conceptual approach (Nickerson et al., 2012).
Event analysis	Earl et al. (2004); Happ et al. (2004); Olzak (1989)	Event analysis is conducted using four different designs: (1) *cross-sectional*—record occurrences of events in one period for multiple units; (2) *time series*—record occurrences of events by period for a single unit; (3) *panel*—record occurrences for multiple units in two or more periods; and (4) *event history*—record the exact timing and sequence of events (Olzak, 1989, p. 130).
Metaphorical analysis	Schmitt (2005)	A metaphor is used to describe the findings and the research process. A metaphor is determined when: (a) a word or phrase can be understood beyond the literal meaning in context of what is being said; and (b) the literal meaning stems from an area of physical or cultural experience (i.e., source area); and (c) it can be transferred to a second, often abstract, area (i.e., target area) (Schmitt, 2005).

Approach	Reference(s)	Summary of Data Analysis
Hermeneutic analysis	Bergman (2010); Lee (1994)	Hermeneutic analysis is carried out in three steps. First, researchers conduct an initial content analysis, in alignment with the hermeneutic limits, to identify themes, concepts, components, identities, agents, interactions, and structures relevant to the research question. In the second step, researchers conduct dimensional analysis of themes, narrative components, and concepts derived from the previous step. After researchers complete this step, they conduct a second recontextualizing qualitative analysis (Bergman, 2010).
Discourse analysis	Brown and Yule (1983); Gee (2010)	In doing discourse analysis, researchers view the data as the record of a dynamic process in which language is used as an instrument of communication in the context of a speaker/writer to express meanings and achieve intentions (discourse) (Brown & Yule, 1983).
Phenomenology/ heuristic analysis	Sadala and Adorno (2002); Sanders (1982); Starks and Trinidad (2007)	An analysis of the structure of a phenomenon is carried out in three steps: (1) *phenomenological description*—this step is intended to mirror and express a participant's conscious experience; (2) *phenomenological reduction*—a step to critically reflect the descriptive content; and (3) *phenomenological interpretation*—in this step, researchers construct meanings from the text using hermeneutic procedures (Sadala & Adorno, 2002).

7.1.1. Case Study

According to Yin (2003), in analyzing case study evidence, researchers should (1) rely on theoretical propositions; (2) setting up a framework based on rival explanations; and (3) developing case descriptions. The propositions shape a researcher's data collection plan and, therefore, will give priority to the relevant analysis strategies. When a case study includes specific propositions, it increases the likelihood that researchers will be able to place limits on the scope of the study and increase the feasibility of completing the project (Baxter & Jack, 2008). By defining and testing rival explanations, researchers can eliminate other possible explanations and be more confident in their findings. Lastly, developing case descriptions can serve as an alternative strategy when researchers have difficulty in making either of the other two approaches work (Yin, 2003).

Yin (2003) described five specific analysis techniques that can be used in analyzing data from case studies. These are: (1) *pattern matching*—researchers compare an empirical pattern with a predicted one, and if the patterns coincide, the results can help a case study to strengthen its internal validity; (2) *explanation building*—a process of refining a set of ideas to eliminate other plausible or rival explanations; (3) *time-series analysis*—to show the occurrence of events in a chronological order; (4) *logic model*—a similar technique to pattern matching though the events are staged in repeated cause-effect-cause-effect patterns, whereby a dependent variable at an earlier stage becomes the independent variable for the next stage; and (5) *cross-case analysis*—a technique used to compare multiple case studies. Whereas the first four techniques can be used both in single or multiple study designs, the last technique, due to its nature, can only be used in a multiple case study design. In a multiple case study design, it is helpful to analyze data relating to the individual component cases first and then make comparisons across cases (Crowe et al., 2011). In analyzing case study data, researchers must ensure the data converge in an attempt to understand the overall case, not the various components of the case, or the contributing factors that influence the case (Baxter & Jack, 2008).

7.1.2. Grounded Theory

Data for a grounded theory study can come from various sources (e.g., books, government documents, interviews, letters, newspapers, video tapes) (Corbin & Strauss, 1990). Each of these sources can be coded in the same way as interviews and observations are (Glaser & Strauss, 1967). Researchers will use the typical ideas/approaches suggested for the interviews and fieldwork to assure credibility of respondents and to avoid biasing their responses and observations (Corbin & Strauss, 1990; Guba, 1981). According to Corbin and Strauss (1990), in grounded theory, the analysis begins as soon as the first bit of data is collected. The analysis is necessary from the start because it is used to direct the next interview and observations. Every concept brought into the study or discovered in the research process needs to be tested to earn its way to the theory by repeatedly being present in the dataset in one form or another (Corbin & Strauss, 1990).

Corbin and Strauss (1990) also note that "concepts that pertain to the same phenomenon may be grouped to form categories. . . Categories are the 'cornerstones' of a developing theory. They provide the means by which a theory can be integrated" (p. 7). Further, data must be examined for regularities and for an understanding of where the regularity is not apparent. As the data are analyzed and coded, ideas and potential insights will begin to develop that are then recorded in theoretical memos; "it is the data that develops theoretical sensitivity" (Heath & Cowley, 2004, p. 144). According to this technique, ideas generated must be verified by all data and categories must be constantly refitted (Heath & Cowley, 2004).

There are three types of basic coding processes in grounded theory research: (1) open coding; (2) axial coding; and (3) selective coding (Corbin & Strauss, 1990). Open coding is "the interpretive process by which data are broken down analytically" (p. 12). The purpose of this coding is to give researchers insights by breaking through standard ways of thinking about or interpreting phenomena reflected in the data. In axial coding, categories are related to their subcategories, and the relationships are tested against data. Lastly, in the selective coding process, all categories are unified around a "core" category, and categories that need further explication are filled-in with more detailed descriptions.

7.1.3. Direct and Pragmatic Approach

Data analysis in qualitative research consists of three steps: (1) data consolidation; (2) data display; and (3) conclusion drawing/verification (see also Miles et al., 2020). The first step is data consolidation—i.e., "the process of selecting, focusing, simplifying, abstracting, and transforming the 'raw' data that appear in the full corpus (body) of written-up field notes, interview transcripts, documents, and other empirical materials " (Miles et al., 2020, p. 8). Data consolidation takes place throughout the research process of conducting qualitative research. As Glaser and Strauss (1965) noted, "in qualitative work, just as there is no clear-cut line between data collection and analysis . . . there is no sharp division between implicit coding and either data collection and data analysis. There tends to be a continual blurring and intertwining of all three operations from the beginning of the investigation until its near end" (p. 6). Anticipatory data consolidation takes place when researchers decide which conceptual framework, which sites, which research questions, and which data collection approaches to choose. As data collection proceeds, there are further episodes of data consolidation (e.g., doing summaries, coding, making clusters, writing memos), and this process continues after fieldwork, until a final report is complete (Miles et al., 2020; Miles & Huberman, 1984).

Miles et al. (2020) suggested the following strategies to analyze data from multiple cases (the interested reader is referred to the cited references for more information):

- *Replication strategy*—i.e., a theoretical framework is used to study one case in depth and then successive cases are examined to see whether the pattern found matches that in previous cases.
- *Multiple exemplar*—i.e., after deconstructing prior conceptions of a particular phenomenon, researchers collect multiple instances (cases) and then "bracket" them, inspecting them carefully for essential elements or components.
- *Forming types or families*—e.g., typology, taxonomy.

The second step is data display. Data display is a process of organizing information that enables researchers to draw conclusions and take actions (Miles et al., 2020). There are two ways of displaying qualitative data analysis results: *textual* and *diagrammatic displays*. Text and diagrams (pictures) together communicate more than either could alone (Miles et al., 2020). Although text is a useful vehicle for presenting and explaining information, a picture, as the old adage goes, is worth a thousand words and can thus portray information more concisely to illustrate details provided in longer blocks of text (Verdinelli & Scagnoli, 2013). When researchers deal with complex and voluminous data, diagrams can help them disentangle the threads of data analysis and present results in an interactive form (Dey, 1993). By trying to construct diagrams, researchers can force themselves to clarify the main points in their analysis and how they are related (Dey, 1993).

The third step is conclusion drawing or verification. Researchers note regularities, explain patterns, test causal flows, and draw propositions or conclusions (Miles et al., 2020). These conclusions are also verified, tested for their plausibility, robustness, sturdiness, and validity (Miles et al., 2020).

7.1.4. Narrative Analysis

Narrative analysis attempts to explain or normalize what has occurred; it lays out the reasons why things are the way they are or have become the way they are (Bamberg, 2012). This approach is typically used to analyze autobiographical data (i.e., about non-shared, personal experience, single past events) (Georgakopoulou, 2007). There are three common approaches used to analyze narrative data.

The first approach views *text as a linguistic structure* (Bamberg, 2012). According to this view, a narrative consists of at least two narrative event clauses. This approach assumes that events do not happen in the world. The flow of continuously changing time needs to be stopped and packaged into bounded units—events and event sequences. This is accomplished by the use of particular verb-type predicates in conjunction with the kinds of temporal marking that particular languages have at their disposal (Bamberg, 2012).

The second approach views *text as a cognitive structure* (i.e., plots, themes, and coherence). According to this view, to describe the units that emerge in the course of narrative cohesion building, the emerging units are not just the linguistic elements per se. They typically consist of "an (optional) *abstract*, followed by an *orientation* (or *setting* or *exposition*), followed by the *complication* (also called *problem* or *crisis*), maybe an action or action orientation toward a resolution, resulting in the *resolution* (or occasionally *failure*), which then is ultimately followed by a *coda* (or *closure*)" (Bamberg, 2012, p. 90). Like the linguistic approach, the cognitive approach focuses on monologic text. The purpose of the story is to encode information, and the way the information is structured is relevant for the effect of the story on the audience, as eloquently noted by Bamberg (2012): "linguistic and conceptual structures of the story are functions in the service of the theme, the overall plot, and the content" (p. 91).

The third approach is called *an interactive-performance approach*. It goes beyond the text and is intended to address such questions as why this story takes place now (Bamberg, 2012). Unlike the linguistic and cognitive approaches, this approach focuses on situating the narratives within a dialog (Bamberg, 2012). According to this third performance type approach, linguistic and cognitive structuring is a part of what speakers accomplish with their narratives. This approach views a participant as an actor in cultural performances within their daily lives (Schechner, 2002). Thus, through an interactive-performance approach, researchers are afforded a more intimate understanding of culture through an ethnographic performance and "'travels' into the life-world of the subject" (Madison, 2005, p. 478).

7.1.5. Content Analysis

Content analysis is "a research method that uses a set of procedures to make valid inferences from text" (Weber, 1990, p. 9). It seeks to analyze data within a specific context in view of the meaning someone attributes to them (Krippendorff, 1989). The sources for content analysis can be any kind of communication (e.g., discourses, documents, protocols of observations, transcripts of interviews, video tapes) (Krippendorff, 1989; Mayring, 2004). Compared to other qualitative data analysis techniques, content analysis has several advantages including that it operates directly on text or transcripts of human communications; it uses both qualitative and quantitative operations on text; it documents various kinds of events that exist over a long period of time; and it usually yields unobtrusive measures in which neither the sender nor the receiver of the message is aware that it is being analyzed (Weber, 1990).

Content analysis commonly consists of six steps: (1) defining the context of the study; (2) defining and identifying the unit of analysis; (3) determining sampling strategies; (4) classifying units in terms of categories of the analytical constructs chosen; (5) drawing inferences; and (6) validating the results (Krippendorff, 1989). The two most common approaches to coding in content analysis are *inductive category development* and *deductive category application* (Mayring, 2000). In inductive category development, researchers inductively formulate new categories from the material. These categories are tentative and revised throughout the coding process until the key categories emerge. In deductive category development, researchers begin by defining the key categories or criteria derived from the theoretical background and following these criteria; the material is coded, and categories are revised.

7.1.6. Classification: Typology and Taxonomy

Classification is a fundamental mechanism for organizing knowledge (Wand et al., 1995). Classification involves the ordering of cases in terms of their similarity and can be broken down into two essential approaches: *typology* and *taxonomy* (Bailey, 1994). A typology is defined as "systematic classifications of types of social phenomenon as they fall within a particular category" (Layder, 1998, p. 73). In contrast, a taxonomy refers to the "classification systems that categorize phenomena into mutually exclusive and exhaustive sets with a series of discrete decision rules" (Doty & Glick, 1994, p. 232). Unlike typologies, taxonomies provide decision rules for classifying objects. Although Bailey (1994) argued that the basic difference between a typology and taxonomy is that a typology is primarily conceptual, whereas a taxonomy is generally empirical, researchers typically use taxonomy for systems of grouping that are derived conceptually and empirically, making it an appropriate qualitative data analysis method in certain research situations (Nickerson et al., 2012). Next, we discuss each of the classification methods in detail.

The classification of data in the typology approach is based on the theoretically derived, and more or less intuitively categorized, qualities of observed phenomena (Rich, 1992). Typologies generally define conceptually "ideal types," each one presenting a unique combination of individual attributes or dimensions that constitute a categorical type (Martín-Peña & Díaz-Garrido, 2008). The ideal type is used to examine empirical cases in terms of how much they deviate from the ideal (Nickerson et al., 2012). In developing typologies, researchers start with a conceptual or theoretical foundation and then derive the typological structure through deduction. Researchers may conceive of a single type and then add dimensions until a satisfactorily complete typology is reached (Bailey, 1994). Alternatively, researchers could conceptualize an extensive typology and then eliminate certain dimensions in a process called reduction until a sufficiently parsimonious typology is reached (Bailey, 1994).

Taxonomies provide a structure and an organization to the knowledge of a field, thus enabling researchers to study the relationships among concepts (Glass & Vessey, 1995). Taxonomies also help us understand divergence in previous findings (Sabherwal & King, 1995). According to Nickerson et al. (2012), the development of taxonomies involves "determining the characteristics of the objects of interest" (p. 343). The choice of such meta-characteristics should be based on the purpose of the taxonomy. The development of taxonomies also needs to meet ending conditions, which could be objective and/or subjective. An objective ending condition is that the taxonomy must satisfy a researcher's definition of a taxonomy, specifically that it consists of a set of dimensions with mutually exclusive and collectively exhaustive characteristics (Nickerson et al., 2012). In contrast, to meet a subjective ending condition, a researcher must ensure the taxonomy is concise, robust, comprehensive, extensible, and explanatory. Nickerson et al. noted that the development of taxonomies involves a combination of both conceptual and empirical strategies in a single method (see Figure 7-1).

The first step is to identify the meta-characteristics. Next, the conditions (i.e., subjective and objective) that end the process need to be determined. After these steps, researchers can begin with either a conceptual approach or an empirical approach. If little data are available but researchers have significant understanding of the domain, they can then start with the conceptual-to-empirical approach. However, if researchers have little understanding of the domain but significant data about the object are available, they should start with the empirical-to-conceptual approach. At the end of these processes, researchers should check whether the ending conditions are met.

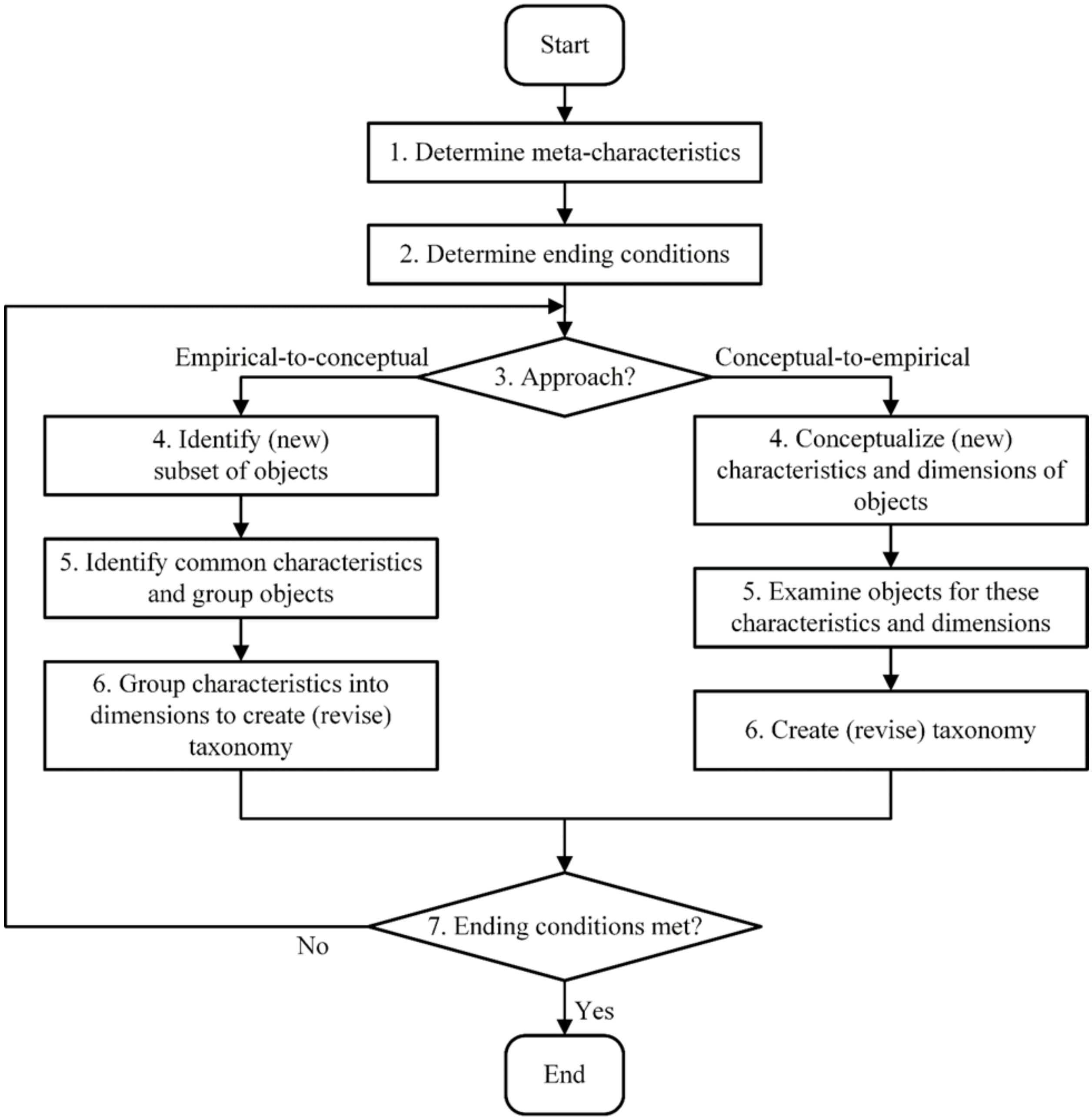

Figure 7-1. Taxonomy Development Method

7.1.7. Event Analysis

Event analysis is popular among sociologists who study social movements. Event analysis is a form of qualitative data collection method that focuses on data collection around a particular event, activity, or issue occurring with a research participant (Happ et al., 2004). Events are defined as "nonroutine, collective, and public acts that involve claims on behalf of a larger collective" (Olzak, 1989, p. 124). Qualitative event analysis consists of a detailed description and assessment of events using a variety of data sources: secondary document review, published listings of events originally compiled from various newspaper sources, and official archival records (Happ et al., 2004; Olzak, 1989). Event analysis allows diverse forms of collective action to be measured and compared because observations are collected in commensurate dimensions (Olzak, 1989). This data analysis technique is useful in limiting the focus of data collection in complex settings and in obtaining and managing multiple perspectives about an event while situating the event within appropriate social and environmental contexts (Happ et al., 2004). Event data also allow for the examination of multiple types of collective action and facilitate longitudinal research (Earl et al., 2004; Olzak, 1989).

There are four variations of event analysis designs that have been dominant: (1) *cross-sectional*—record occurrences of events in one period for multiple units; (2) *time series*—record occurrences of events by period for a single unit; (3) *panel*—record occurrences for multiple units in two or more periods; and (4) *event-history*—record the exact timing and sequence of events (Olzak, 1989, p. 130). A major challenge associated with event analysis is the media bias if the major data source is newspapers. To correct for this bias, researchers should complement media data with additional non-media sources, such as records of organizations, public records, or other administrative archives (Barranco & Wisler, 1999).

7.1.8. Metaphorical Analysis

Metaphorical analysis is a qualitative data analysis technique that focuses on describing everyday cognitive structures using linguistic models (Schmitt, 2005). This analysis technique was originally based on Lakoff and Johnson's theory of metaphor (Lakoff & Johnson, 1980). Metaphors enable the reconstruction of cognitive strategies in action (Schmitt, 2005). In qualitative research, metaphors can be used to describe the findings and the research process. Because qualitative research often yields a multitude of heterogeneous pieces of information, metaphors can be used to reduce this complexity by clearly illustrating the meaning using linguistic models. In term of the research process, metaphors can be used to give some orientation for the researchers in their endeavor and its presentation (Schmitt, 2005). According to Schmitt (2005), a metaphor can be determined when:

- a word or phrase can be understood beyond the literal meaning in context of what is being said;
- the literal meaning stems from an area of physical or cultural experience (i.e., source area); and
- it can be transferred to a second, often abstract, area (i.e., target area).

For example, when an interviewee says, "today things are already going *much* better for me," the abstract "better" is the target area, which extends the meaning of the word "much" that stems from substance quantification (source area). Here, to be "better" means having "more," cf. the metaphors of giving and providing (Schmitt, 2005, p. 385).

Metaphorical analysis requires that different people are able to conceptualize the subject being analyzed differently and the question being researched is targeted at least in part at the various subjective, group-specific or cultural conceptualizations of the phenomenon being investigated (Schmitt, 2005). Steinke (2004) proposed four different types of quality criteria to evaluate the trustworthiness of a metaphor: (1) the reflection on or testing of the limits and range of the results of a study; (2) the coherence of the theory developed; (3) its relevance for research and practice; and (4) documentation of a reflective subjectivity.

7.1.9. Hermeneutic Analysis

Hermeneutic analysis is "the study of interpretation, especially the process of coming to understand a text" (Lee, 1994, p. 147). The guiding assumption of hermeneutic analysis is that the content and associated meanings of the text may never be identified unequivocally. This is due to the fact that the text material as a whole can only be understood by studying some of its parts, while the parts under study can only be understood in relation to the whole. However, the meaning of the parts does not unequivocally represent the meaning of the whole (Bergman, 2010). Researchers become part of the hermeneutic circle, moving repeatedly between interpretations of parts of the text and interpretations of the whole text, representing an emerging understanding of the phenomenon (Paterson & Higgs, 2005). In addition, all research activities, from conceptualization to interpretation of the findings, are always linked and must be understood in relation to their cultural, historical, political, and social contexts (Bergman, 2010).

Five concepts central to hermeneutic analysis are: (1) *distanciation*—"the separation, in time and distance, that occurs between a text and its authors, its originally intended audience, and/or its originating culture and society"; (2) *autonomization*—"the text's taking on a life of its own, despite the distanciation"; (3) *social construction*—the text is a manifestation of a socially constructed reality; (4) *appropriation*—"'to make one's own what was initially alien' as it 'actualises' the meaning of the text for the present reader"; and (5) *enactment*—a meaning which is constituted by the actions independent of human actors (Lee, 1994, pp. 149-151).

Hermeneutic analysis can be carried out in three simple steps (Bergman, 2010). First, researchers conduct an initial content analysis, in alignment with the hermeneutic limits, to identify themes, concepts, components, identities, agents, interactions, and structures relevant to the research question. In the second step, researchers conduct dimensional analysis of themes, narrative components, concepts, etc. derived from the previous step. The goal of this step is to decontextualize the elements identified in the previous step to examine the latent structure and patterns among them. After researchers complete this step, they conduct a second recontextualization. This step is intended to assist in the interpretation of the results from the dimensional analysis by associating the findings with the context.

7.1.10. Discourse Analysis

Discourse analysis is a technique that focuses on the use of language within a social context (Salkind, 2010). Discourse analysis encompasses a broad range of theories, topics, and analytic approaches for explaining language in use, whether in a conversation or in text (Shaw & Bailey, 2009). There are many different approaches to discourse analysis. Some of them look only at the "content" of the language being used, the themes being discussed in the conversation or an article, or the structure of language and how this structure functions to make meanings in specific contexts (Gee, 2010). In doing discourse analysis, researchers view the data as the record of a dynamic process in which language is used as an instrument of communication in the context of a speaker/writer to express meanings and achieve intentions (discourse) (Brown & Yule, 1983).

In discourse analysis, researchers can build or construct things through language. There are seven things or seven areas of reality that can be built using discourse analysis: (1) significance; (2) practices (activities); (3) identities; (4) relationships; (5) politics; (6) connections; and (7) sign systems and knowledge (Gee, 2010). Some tools that researchers can use to analyze the working of these building tasks in specific instances of language-in-use include (Gee, 2010):

- *Social languages*—using different styles or varieties of languages for different purposes.
- *Discourses*—combining and integrating language, actions, interactions, ways of thinking, and using various tools and objects to enact a particular sort of socially recognizable identity.
- *Conversations*—using conversations as a tool to identify themes, debates, or motifs to interpret language within a social group.
- *Intertextuality*—relying on multiple sources (e.g., spoken words, written text) to identify meanings.

An example of discourse analysis is a study by Munir and Phillips (2005). This study examined how the meanings and uses of new technologies were discursively constructed. Specifically, they examined how Kodak managed to transform photography from a highly specialized activity to one that became an integrated part of everyday life. Discourse analysis provided them with a useful theoretical framework to explore how the socially constructed ideas and objects that constitute a social world are created and maintained. It enabled them to "observe how institutional entrepreneurs engage in discursive strategies to transform the 'meaning' embodied by particular technologies, by producing new *concepts*, *objects*, and *subject positions*" (p. 1666). Using this technique, they were able to develop a typology of the strategies available for entrepreneurs who wish to affect the processes of social construction that lead to change in institutional fields.

7.1.11. Phenomenology/Heuristic Analysis

Phenomenology or heuristic analysis is "a study of conscious phenomena" (Sanders, 1982, p. 354) and is concerned with understanding a phenomenon rather than explaining it (Starks & Trinidad, 2007). It involves the use of thick description and close analysis of lived experience to understand how meaning is created through embodied perception (Sokolowski, 2000; Starks & Trinidad, 2007). Phenomenology seeks to make explicit the implicit structure and meaning of human experiences (Sanders, 1982). Starks and Trinidad (2007) explain, "In phenomenology reality is comprehended through embodied experience. Through close examination of individual experiences, phenomenological analysts seek to capture the meaning and common features, or essences, of an experience or event. The truth of the event, as an abstract entity, is subjective and knowable only through embodied perception; we create meaning through the experience of moving through space and across time" (p. 1374).

The core of phenomenology is the *intentionality of consciousness*, understood as the direction of consciousness toward understanding the world (Sadala & Adorno, 2002). Thus, in doing phenomenology analysis, the researcher's task is to analyze the intentional experiences of consciousness in order to perceive how a phenomenon is given meaning (Sadala & Adorno, 2002). The researcher's thoughts, responses, and decision-making processes should be acknowledged and explicated throughout the research process (Donalek, 2004).

An analysis of the structure of a phenomenon can be carried out using the steps suggested by Sadala and Adorno (2002). The first step is called *phenomenological description*. This step is intended to mirror and express a participant's conscious experience. The second step is *phenomenological reduction*, a step to critically reflect the descriptive content. This can be conducted in three different moments: (1) at the first moment, researchers keep the description in its original format, aiming to analyze the experience as it is without allowing personal or theoretical concepts to influence the analysis; (2) at the second moment, a radical gestalt perspective is created where observers and subjects are the focus of the description; and (3) at the third moment, researchers try to focus on the pre-reflexive sources (i.e., what subjects said about their daily lives) and state the meaning of the experience by taking into account their understanding of the experience. The third step is called *phenomenological interpretation*, when the four stages of hermeneutic procedures are identified: (1) locating the invisible elements that can be found in the text; (2) producing the reflective phenomena present in the consciousness (i.e., radical cogito); (3) the manifestation of preconscious phenomena; and (4) the specification of the existential meaning (Sadala & Adorno, 2002).

7.2. Data Analysis in Quantitative Research

Quantitative research yields data that provide quantifiable results. Similar to approaches for qualitative research, the choice of method for data analysis is determined by the research questions as well as the processes by which selection is made from the sources of data (Blaikie, 2003). In analyzing quantitative data, researchers first need to recognize the scales of measurement (i.e., nominal, ordinal, interval, or ratio). A *nominal scale* separates objects, events, or people into groups (e.g., categorizing people according to their gender, marital status, education level). When a nominal scale can be ordered according to their magnitude, the measurement scale is an *ordinal scale* (e.g., ranking) (Tashakkori & Teddlie, 1998). Both nominal and ordinal scales are also known as categorical data. An *interval scale* is a set of ordered and equal interval categories on a contrived measurement scale (Blaikie, 2003). Unlike on a nominal scale, the distances between categories in the interval scale can be assumed to be equal. For example, the difference between 90 and 100 degrees is the same as the difference between 10 and 20 degrees. The interval scale has a zero point, but not an absolute zero. A measurement scale with an absolute zero is called a *ratio scale* (e.g., age, number of medical treatments). The ratio scale has all the attributes of the interval scale but with an absolute zero.

Understanding these approaches to measurement helps researchers determine the best way of organizing their data. For most nominal variables, *nonparametric statistics* (e.g., chi-square test, Wilcoxon rank sum test, logistic regression) are appropriate, whereas for interval/ratio-level variables, *parametric statistics* (e.g., Pearson correlation, multiple regression) are appropriate (Tashakkori & Teddlie, 1998). In nonparametric statistical procedures, it is not necessary to assume that the random variable of the population has a normal distribution, whereas in parametric procedures, it is assumed the random variable is normally distributed. Interval, ratio, and some ordinal scales have a greater possibility to meet this requirement, although whether they do will depend on the characteristics of the population (Blaikie, 2003).

The choice of quantitative data analysis methods is also determined by the research questions. Various data analysis methods are used to describe the characteristics of a social phenomenon, and to understand, explain, and predict patterns that exist in the social environment. The data can also be analyzed to estimate whether characteristics and relationships found in a sample could be expected to exist in the population (Blaikie, 2003). Thus, quantitative data analysis techniques can be divided into three types: *descriptive, explanatory,* and *inferential analysis*, and each can be further divided into *univariate*, *bivariate,* and/or *multivariate statistics*.

7.2.1. Descriptive Analysis

Descriptive analysis provides simple summaries of the sample and the measures (Trochim, 2006). The main objective of these analyses is to provide images and/or summaries that can help readers understand the nature of the variables and their relationships (Tashakkori & Teddlie, 1998). With descriptive methods, researchers simply discuss what is or what the data show. Descriptive statistics can be divided into two categories: *univariate* and *bivariate*. Univariate descriptive analysis is used to represent the characteristics of a single variable at a time (e.g., the average score of students' GPAs for a particular semester) (Blaikie, 2003; Trochim, 2006). The three most commonly used methods of univariate descriptive analysis are: (1) *measures of data distribution*; (2) *measures of central tendency*; and (3) *dispersion* (Trochim, 2006). Measures of data distribution represent a summary of the frequency of individual values or range of values for a variable (Trochim, 2006). One of the most common methods to observe the distribution is a *frequency distribution* that can be presented in a pictorial or graphical form. Measures of central tendency summarize a group of observations/scores into a single score. The three major types of estimates of central tendency are *mean*, *median*, and *mode*. Mean is the average score (by summing all the values and dividing the sum by the number of value); median is the score found at the exact middle of the set of values; and mode is the most frequently occurring value in the set of scores. Researchers can also calculate the spread of frequencies around this central tendency. This type of measure is called dispersion. There are two common measures of dispersion: range (i.e., highest value and lowest value) and standard deviation (i.e., dispersion of a dataset relative to the mean).

Bivariate descriptive analysis involves two variables. The goal of bivariate descriptive statistics is to either establish similarities or differences between the characteristics of categories of objects, events, or people, or to describe patterns or connections between such characteristics (Blaikie, 2003). The most common methods that have been used to establish an association between two variables include contingency coefficient (x^2 measures of association), phi and Cramer's V (nominal level), gamma (ordinal-level data and categorized interval-level and ratio-level data), and Pearson's correlation coefficient (interval-level and ratio-level data) (Blaikie, 2003). The Pearson correlation, ranging from -1 (perfect negative relationship) to +1 (perfect positive relationship), is a widely used bivariate statistic (Tashakkori & Teddlie, 1998). A summary of descriptive analysis techniques is presented in Table 7-2 (adapted from Blaikie, 2003).

Table 7-2. Descriptive Analysis Techniques

Type	**Variation**
Univariate	1. Frequency distribution. 2. Measures of central tendency (e.g., mean, median, mode). 3. Dispersion (e.g., range, standard deviation, variance).
Bivariate	1. Nominal variables: Contingency coefficient (C), standardized contingency coefficient (C_s), phi, and Cramer's V (nominal level). 2. Nominal and ordinal variables: Contingency coefficient (C), standardized contingency coefficient (C_s), phi, and Cramer's V (nominal). 3. Ordinal variables: Goodman and Kruskal's gamma (G), Kendall's tau-b, Spearman's rank correlation coefficient (r_s). 4. Categorical (nominal or ordinal) and metric variables (interval or ratio): (a) transform metric variables into categorical form and then use G or C_s or V; and (b) if the categorical variable is a dichotomy or can be dichotomized, use Pearson's *r*. 5. Interval and ratio variables: Covariance, Pearson's *r*.

7.2.2. Explanatory Analysis

In explanatory analysis, the goal is to test for the existence of causality or influence. Table 7-3 (adapted from Blaikie, 2003) summarizes the methods used for explanatory analysis based on the types of measurement used. Although explanatory analysis is built on bivariate descriptive (association) analysis, the existence of association is a necessary, but insufficient, condition for explanatory analysis (Blaikie, 2003). Causality is to *explain* the occurrence of events and to understand *why* particular events occur (Marini & Singer, 1988). Although in-depth discussions on causality are beyond the scope of this book, they are necessary to differentiate independent variables (predictors) from dependent variables (outcomes) in explanatory analysis. Explanatory analysis can be conducted on both bivariate and multivariate relationships. The most common methods used in bivariate explanatory analysis are lambda (nominal variables), Somer's *d* (ordinal variables), and bivariate regression (metric variables) (Blaikie, 2003).

Multivariate explanatory analysis aims to establish networks of relationships among variables (Blaikie, 2003). In multivariate analysis in which the effect of a predictor variable on an outcome variable is controlled by a third variable, and all variables are categorical, researchers can use methods of association or influence previously discussed (i.e., lambda, Somer's *d*, Cramer's V). In this case, the methods of analysis are dependent on the levels of measurement of the predictor and outcome variables (Blaikie, 2003). Some more popular techniques for multivariate explanatory analysis that are used to establish the relative influence of two or more predictor variables on one or more outcome variables include multiple regression, logistic regression, ANOVA, MANOVA, discriminant analysis, and structural equation modeling (see Table 7-3).

There are also some other multivariate analysis techniques that allow users to group parts of the data into clusters or factors. These techniques focus on grouping the data based on what they have in common and reducing them to a number of factors or dimensions. The four most common methods used in social sciences for this data reduction purpose are exploratory factor analysis, cluster analysis, perceptual mapping or multidimensional scaling, and profile analysis. Whereas factor analysis is used to discover underlying patterns or relationships in a large number of variables and reduce them to a smaller set of factors (Pituch & Stevens, 2015), cluster analysis is concerned with grouping individuals or objects based on similarities among them (Blaikie, 2003). Multidimensional scaling is a method to uncover the "hidden structure" of data—it uses proximities among any kind of object as input (Kruskal & Wish, 1978). Lastly, profile analysis is a multivariate technique equivalent to repeated measures or mixed ANOVA. This technique uses data plots to visually compare different groups.

Table 7-3. Explanatory Analysis Techniques

Levels of Measurement	Statistical Techniques
For (bivariate) explanatory analysis:	
1. Nominal predictor and nominal outcome	Lambda
2. Ordinal predictor and ordinal outcome	Somer's *d*
3. Interval predictor and interval outcome	Bivariate regression
4. Nominal predictor and ordinal outcome	Lambda
5. Nominal predictor and metric outcome	(a) Transform metric outcome to ordinal and then use lambda

Levels of Measurement	Statistical Techniques
	(b) Conduct means analysis and then use η (η^2 is just as like R^2—it indicates the proportion of variance explained by the predictor variables) (c) Use regression with dummy variables
6. Ordinal predictor and metric outcome	(a) Transform metric outcome to ordinal and then use Somer's *d* (b) Conduct means analysis and then use eta (c) Use regression with dummy variables
7. Metric predictor and nominal outcome	Code predictor to ordinal and then use lambda
8. Metric predictor and ordinal outcome	Code predictor to ordinal and then use Somer's *d*
For explanatory analysis with a predictor, an outcome, and control variables:	
9. Nominal predictor and nominal outcome	Lambda, Cramer's V, C_s (loglinear analysis)
10. Ordinal predictor and ordinal outcome	Somer's *d*, gamma (loglinear analysis)
11. A combination of nominal and ordinal variables	Lambda, Cramer's V, C_s (loglinear analysis)
12. A combination of metric and categorical predictor and outcome	Transform the metric variable into ordinal categories and use (10) or (11)
13. Metric predictor and outcome variable	Partial correlation
For (multivariate) explanatory analysis used to establish the influence of two or more independent variables on one or more outcomes:	
14. Two or more groups compared on a metric outcome	ANOVA, if covariates are included, use ANCOVA
15. Two or more groups compared on two or more metric outcomes	MANOVA, if covariates are included, use MANCOVA
16. Metric predictors and outcomes	Multiple regression
17. Metric and/or categorical predictors and metric outcome(s)	Multiple regression with categorical predictors as dummy variables
18. Metric and/or categorical predictors and dichotomous outcome	Logistic regression
19. Metric and/or categorical predictors and multichotomous outcome	Logistic regression
20. Metric predictors and categorical outcome	Discriminant analysis
21. A collection of interrelated categorical and metric predictors and metric outcomes	Structural equation modeling, hierarchical linear modeling
Interdependence technique:	
1. Ordinal variables	Factor analysis, multidimensional scaling
2. Metric variables	Factor analysis, cluster analysis, multidimensional scaling, profile analysis

7.2.3. Inferential Analysis

In inferential analysis, researchers use a random sample of data from a population to describe and make inferences about the population (Tashakkori & Teddlie, 1998; Trochim, 2006). Whereas we use descriptive statistics to describe the basic features of the data in a study, we use inferential statistics to draw inferences that generalize to broader settings (Trochim et al., 2015). Inferential statistics is only appropriate when the sample is drawn using probability or random selection procedures (see Chapter 5). Some examples of inferential statistics are the *t*-test for testing significant differences between two group means and the F-test for the significance of a multiple correlation.

Inferential analysis is a collection of methods for estimating what the population characteristics (i.e., parameters) might be, based on the sample characteristics (i.e., statistics) (Blaikie, 2003). When data from a single variable are obtained from a probability sample and the population value is required, inferential analysis must be used (Blaikie, 2003). This is called univariate inferential statistics. The goal of this analysis is to estimate whether the sample and population means are the same. Some examples of univariate inferential analysis are one-way chi-square and one-sample t-test (Trochim et al., 2015). When the analysis is concerned with relationships between two variables, different inferential procedures are required. These procedures are commonly referred to as "tests of significance"—a statistical test to estimate whether the relationship that we have found in the sample could also be expected to exist in the population from which the population is drawn (Blaikie, 2003, p. 177). The process of testing statistical hypotheses generally follows five basic steps (see Figure 7-2). A researcher first starts with stating the null and alternative hypotheses. These hypotheses specify the possible relationships that exist between two variables in a population. After that, the researcher selects the level of significance with Type I and Type II errors in mind. A Type I error occurs when the null hypothesis is rejected when it is true and a Type II error occurs when the null hypothesis is not rejected when it is false (Warner, 2013). The researcher then identifies the appropriate test statistic based on the level of measurement and the type of analysis. Some of the most common test statistics are the chi-square, *z*-score, *t*-statistic, and *F*-statistic. The researcher then computes the value of the test statistic using the appropriate procedure and decides whether to reject or not to reject the null hypothesis (Blaikie, 2003).

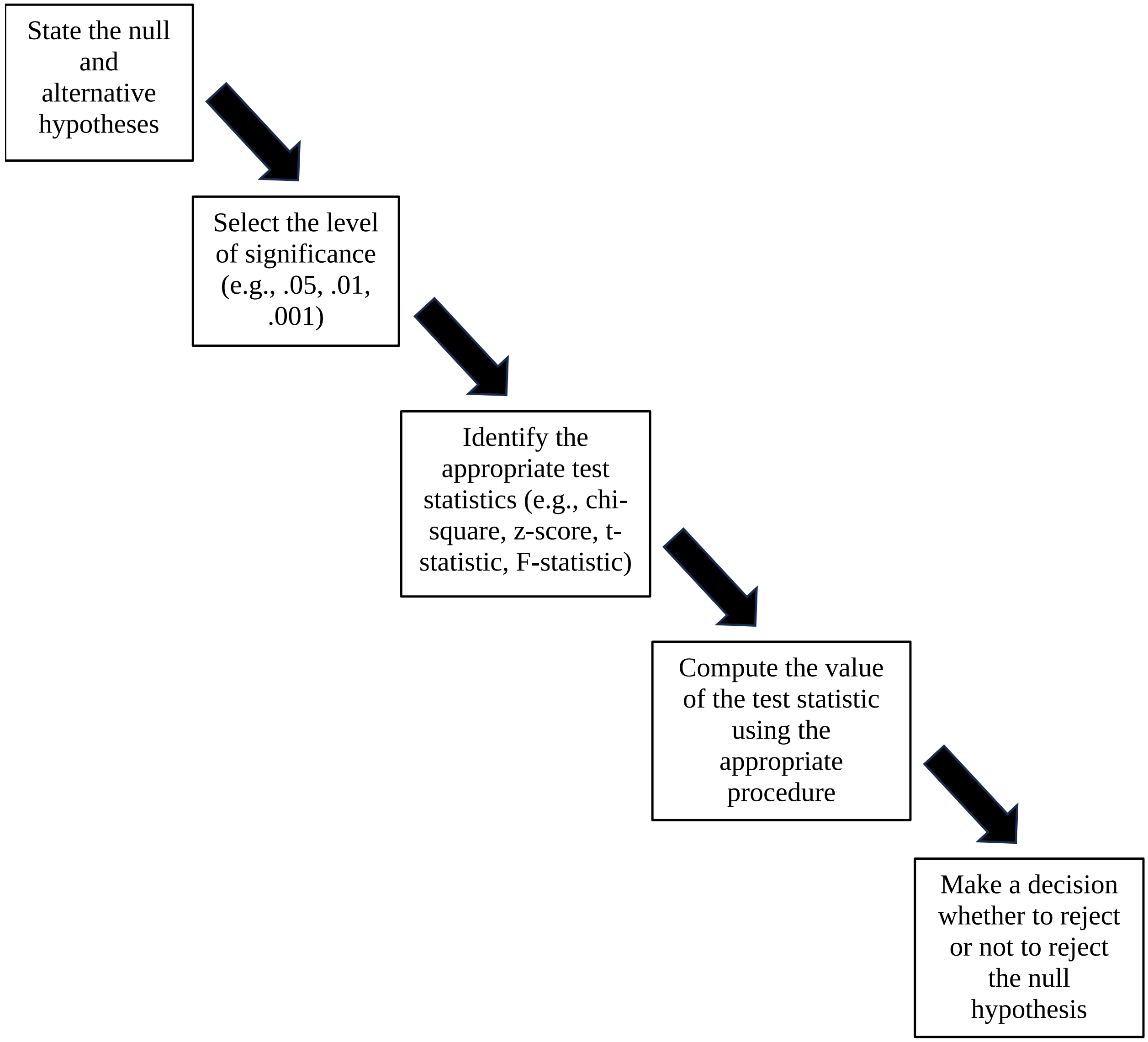

Figure 7-2. Hypothesis Testing Procedure

Inferential statistics can be used for *associational analysis* (bivariate descriptive) and *explanatory analysis*. In associational analysis, the goal is to test for the existence of associations between two variables (i.e., hypothesized relationships are non-directional). What researchers want to know is whether the association found in the sample also exists in the population. As we mentioned previously, the type of analysis method is dependent on the levels of measurement. For example, to test the significance of association between two nominal variables, the chi-square test is appropriate. We summarize the most common test statistics used for explanatory analysis, dependent on the scales of measurement, in Table 7-4 (adapted from Blaikie, 2003).

Table 7-4. Inferential Analysis

Levels of Measurement	Test Statistic
For associational analysis (bivariate):	
1. Nominal variable with nominal variable	Chi-square (x^2) test for C_s, V
2. Nominal variable with ordinal variable	Chi-square (x^2) test for C_s, V
3. Ordinal variable with ordinal variable	z-test for *Gamma coefficient* (i.e., Goodman and Kruskal's Gamma)
4. Metric variable with metric variable	*t*-test for Pearson's correlation (*r*)
5. Nominal variable with metric variable	(a) Recode metric variable into ordinal categories and use chi-square test (b) If nominal variable is a dichotomy or can be dichotomized, use *t*-test for *r* (c) Conduct means analysis: • Paired t-test, if parametric requirements are met; Mann-Whiney U-test or Wilcoxon test, if not • Comparison of more than two means, use *F*-test with one-way ANOVA
6. Ordinal variable with metric variable	(a) Recode metric variable into ordinal categories and use z-test for Gamma coefficient (b) Conduct means analysis as for (5)
For explanatory analysis (a single dependent variable):	
7. Nominal predictor and nominal outcome	z-test for Goodman and Kruskal's *lambda* (λ)
8. Nominal predictor and ordinal outcome	z-test for lambda
9. Ordinal predictor and ordinal outcome	z-test for Somer's *d*
10. Interval predictor and interval outcome	(a) Bivariate regression, *t*-test for R (b) Multiple regression, *F*-test for R
11. Nominal or ordinal predictors and interval outcome	(a) Use dummy variables with multiple regression *F*-test for R
12. Nominal, ordinal, and metric predictors and interval outcome	(a) Combine 10(b) and 11

As shown in Table 7-4, some of the most common test statistics used are z-test, t-test, and F-test. The test statistic for inferential analysis also depends on the type of measurement as well as the objective of the analysis—e.g., whether it's an associative analysis or explanatory analysis.

Summary

- Qualitative data analysis is associated with the classification and interpretation of linguistic (or visual) materials. Some of the best-known techniques are case study, grounded theory, direct and pragmatic, narrative analysis, content analysis, classification, event analysis, metaphorical analysis, hermeneutic analysis, discourse analysis, and phenomenology/heuristic analysis.
- Quantitative research yields data that provide quantifiable results. In analyzing quantitative data, researchers first need to recognize the types of measurement scales (i.e., nominal, ordinal, interval, or ratio). Quantitative data analysis techniques can be divided into three types:

descriptive, explanatory, and inferential, and each of them can be further divided into univariate, bivariate, and/or multivariate.

- Descriptive analysis provides simple summaries about the sample and the measures. The three most commonly used methods of univariate descriptive analysis are: (1) measures of data distribution; (2) measures of central tendency; and (3) dispersion.
- The goal of explanatory analysis is to test the existence of causality or influence. Some most popular techniques of multivariate explanatory analysis that are used to establish the relative influence of two or more predictor variables on one or more outcome variables include multiple regression, logistic regression, ANOVA, MANOVA, discriminant analysis, and structural equation modeling.
- Inferential analysis is a collection of methods for estimating what the population characteristics (i.e., parameters) might be based on the sample characteristics (i.e., statistics).

Exercises

1. Building on exercises in previous chapters where you designed a mixed-methods study, develop the qualitative and quantitative data analysis section of your study. Describe (a) what types of data you will gather; (b) how you will prepare your qualitative and quantitative data for analysis; and (c) what types of qualitative and quantitative analyses you will perform.
2. Select one or two articles in your field or a related field that used mixed-methods research and answer the following questions:
    a. How were the qualitative and quantitative data analyzed?
    b. How did the approaches selected contribute to the findings and inferences?

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CHAPTER 8

MIXED-METHODS DATA ANALYSIS STRATEGIES

We discussed different strategies to analyze qualitative and quantitative data in Chapter 7. In this chapter, we discuss data analysis strategies for mixed-methods research. Specifically, we identify factors that should inform researchers' decisions in selecting the most appropriate data analysis strategies for mixed-methods research. The most common approach of analyzing data in mixed-methods research is to compare the separate results of the two data analyses using techniques discussed in Chapter 7. In conducting mixed-methods data analyses, researchers must not only be competent in conducting an array of quantitative and qualitative analyses, but also know how to mix and embed these analyses so that the findings enable researchers to generate high-quality meta-inferences (Onwuegbuzie et al., 2009). Moreover, mixed-methods data analyses should be conducted in a way that is consistent with the purpose(s) of the study (e.g., completeness). The analyses should also address the research questions (e.g., explain, predict, describe) (Onwuegbuzie et al., 2009). Next, we discuss the criteria that need to be met in conducting mixed-methods data analyses. We also briefly discuss potential threats to quality in mixed-methods research, including potential threats to internal and external validity in qualitative and quantitative research.

8.1. Criteria for Mixed-Methods Data Analysis

Onwuegbuzie and Combs (2011) argue that mixed-methods data analysis involves "the use of both quantitative and qualitative analytical techniques within the same framework, which is guided either a priori, a posteriori, or iteratively (representing analytical decisions that occur both prior to the study and during the study)" (p. 3). The critical criteria that researchers need to consider during the data analysis phases include: (1) number of data types that will be analyzed; (2) number of data analysis types that will be used; (3) time sequence of the analysis; (4) priority of analytical components; (5) number of analytical phases; and (6) analysis orientation (Onwuegbuzie & Combs, 2011).

8.1.1. Number of Data Types That Will Be Analyzed

Traditionally, data analysis in mixed-methods research involves analyzing qualitative data using qualitative methods and analyzing quantitative data using quantitative methods (Creswell & Plano Clark, 2018; Onwuegbuzie & Combs, 2011). However, mixed-methods data analysis can also involve a sequential analysis of one type of data, i.e., data that are generated from the initial analysis (either qualitative or quantitative) are then converted into the other data type (Venkatesh et al., 2016). A type of mixed-methods design involving only one type of data but using both qualitative and quantitative data analyses is known as conversion mixed designs (Teddlie & Tashakkori, 2006). Conversion mixed designs only consist of one strand of a research study (see Chapter 5 for a review on mixed-methods monostrand designs). These designs are considered mixed-methods research because they switch approaches in the experiential phase of the study, when the data that are originally collected (e.g., narrative, numerical) are converted into the other form (e.g., numeric, narrative) (Teddlie & Tashakkori, 2006). For example, a researcher could conduct a content analysis of interview transcripts and then perform an exploratory factor analysis of the qualitative codes that emerge from the qualitative analysis and that are transformed to quantitative data. A technique for transforming qualitative data to quantitative data is known as *quantitizing* (Venkatesh et al., 2016). Alternatively, a researcher could conduct a quantitative analysis of quantitative data (e.g., using linear regression) and then qualitatively analyze the quantitative data that emerge from the quantitative analysis that are transformed to qualitative data (e.g., narrative profiling formation of a set of test scores) (Onwuegbuzie & Combs, 2011). This method is known as *qualitizing*. For example, Ferguson and Hull (2018) applied latent profile analysis (LPA) to model personality. They first gathered quantitative data from a sample of high school students. They conducted descriptive analysis and then confirmatory factor analysis (CFA) to examine the overall factor structure. They then performed LPA to identify latent profiles of individuals based on the five-factor personality scores. After several analytical phases, they found three profiles of personality types: reserved, well-adjusted, and excitable. The authors discussed this categorization from both quantitative and qualitative perspectives. Specifically, whereas the CFA they performed did not meet the cut-offs for fit indexes, LPA provided an alternative method to address the challenge of adequately modeling the personality inventory data. LPA uses a person-centric approach and focuses on sub-scales and individual patterns of responses.

While the proliferation of big data brings new opportunities to the mixed-methods research community, it has yet to make major inroads into mixed-methods research. Big data hold great promise for discovering subtle population patterns and heterogeneities that are not possible with small-scale data (Fan et al., 2014). Unlike traditional datasets where the sample size is typically larger than the number of dimensions, big data are characterized by a massive sample size and high dimensionality (Fan et al., 2014). These data are less structured and often contain both text (e.g., customer opinion) and numbers (e.g., number of clicks, number of visits). By carefully analyzing the application and data characteristics, researchers and practitioners can then use appropriate mixed-methods data analysis techniques to develop high-quality meta-inferences. Although we specifically discuss more about big data and mixed-methods research in Chapter 9, it is important to mention here that qualitizing and quantitizing are the two of the most common practices in analyzing big data. For example, D. Yin et al. (2014) collected and analyzed actual review data from the Yahoo! shopping website. These data contained both user ratings (i.e., quantitative data) and text reviews for online merchants (i.e., qualitative data). They used review helpfulness, measured as the proportion of helpful votes out of the total votes a review received, as the dependent variable. To measure the independent variables (i.e., anxiety and anger), they quantitized the qualitative data (i.e., text reviews). Specifically, they used Linguistic Inquiry and Word Count (LIWC), a text analysis software, to evaluate psychological and structural components of text samples. Using quantitizing, they were able to statistically analyze the relationship between emotions and overall helpfulness ratings.

Although it is practically sufficient to gather one type of data and transform it to another type of data in mixed-methods research, we encourage researchers to gather both types of data and perform a data transformation within the same strand of a research study only if such a transformation can bring additional insights. Gathering both types of data will allow researchers to perform a more complete analysis and benefit from the inherent strength of the types of data and associated analyses. When both types of data are available in a mixed-methods research study, researchers can rely on multiple techniques that yield high quality of meta-inferences as different types of data complement each other (Creswell et al., 2004). In addition, researchers can avoid methodological issues associated with conversion designs (e.g., loss of depth and flexibility of qualitative data, overgeneralization of the observed numeric data).

8.1.2. Number of Data Analysis Types That Will Be Used

We discussed different types of data analyses in qualitative and quantitative research in the previous chapter—several examples are shown in Table 8-1. In mixed-methods research, researchers need to use at least one qualitative analysis and one quantitative analysis. A key question in mixed-methods research is how many different qualitative and quantitative analysis techniques will be used in the study (Onwuegbuzie & Combs, 2010). The decision on data analysis techniques is influenced by the types of data collected by the researchers as well as the purposes of the study (e.g., completeness). For example, if the purpose is to explain *why* the phenomenon under study occurs, descriptive statistics will be insufficient. Researchers may want to use interviews and/or a grounded theory approach (if the goal is to develop a theory or to address the why question) and statistical analysis techniques that will allow them to test for causality (e.g., regression analysis, structural equation modeling).

Table 8-1. Summary of Illustrative Qualitative and Quantitative Data Analysis Methods

Qualitative Data Analysis Methods	Quantitative Data Analysis Methods
1. Case study	1. Descriptive statistics
2. Grounded theory	2. Lambda
3. Direct and pragmatic approach	3. Somer's *d*
4. Narrative analysis	4. Crosstabulations/contingency table
5. Content analysis	5. Bivariate regression
6. Classification: Typology and taxonomy	6. Regression with dummy variables
7. Event analysis	7. Multiple regression
8. Metaphorical analysis	8. Means analysis
9. Hermeneutic analysis	9. ANOVA, ANCOVA
10. Discourse analysis	10. MANOVA, MANCOVA
11. Phenomenology/heuristic analysis	11. Factor analysis
	12. Cluster analysis
	13. Profile analysis
	14. Logistic regression
	15. Discriminant analysis
	16. Structural equation modeling
	17. Hierarchical linear model
	18. Multidimensional scaling
	19. Time series analysis

8.1.3. Time Sequence of Mixed-Methods Data Analysis

Time sequence refers to whether or not the analysis phases occur in a chronological order (Creswell & Plano Clark, 2018; Onwuegbuzie & Combs, 2010). Based on the order of data analysis, there are three strategies for analyzing data in mixed-methods research: (1) c*oncurrent mixed-analyses* (i.e., simultaneously analyze qualitative and quantitative data); (2) *sequential qualitative-quantitative data analyses* (i.e., qualitative data analysis followed by quantitative data analysis); and (3) *sequential quantitative-qualitative data analyses* (i.e., quantitative data analysis followed by qualitative data analysis) (Tashakkori & Teddlie, 1998; Venkatesh et al., 2016).

Tashakkori and Teddlie (1998) proposed three different types of *sequential qualitative-quantitative data analyses*. These are the following:

1. Researchers form groups of people or settings on the basis of qualitative data or observations. Researchers then compare the groups on quantitative data (e.g., using cluster analysis, discriminant analysis, MANCOVA). This technique is also called typology development (Tashakkori & Teddlie, 1998).
2. Researchers form groups of attributes or themes through qualitative analysis (e.g., content analysis), followed by confirmatory quantitative analysis (e.g., factor analysis, structural equation modeling). For example, Sarker et al. (2018) used qualitative data to identify key variables (or relevant categories and factors) that play a role in determining the level of work-life conflict in the context of globally distributed software development personnel. They then used the quantitative data and analysis to test the effect of these key variables on work-life conflict.
3. Researchers establish a theoretical order of a relationship or causality through exploratory qualitative analysis and then confirm the proposed theoretical order using quantitative data and analysis. For example, Stefano et al. (2015) examined sanctioning behaviors in the gourmet cuisine industry. They used qualitative data to develop their hypotheses and then tested their predictions using a field experiment.

Some of the variations of *sequential quantitative-qualitative data analyses* are:

1. Forming groups of people or setting on the basis of quantitative data (e.g., cluster analysis) and then comparing the groups on qualitative data.
2. Forming groups of attributes or themes through exploratory quantitative analysis and then confirming with available or new qualitative data and analysis.
3. Establishing a theoretical model using exploratory quantitative analysis and then confirming the obtained sequence through qualitative data analysis.

8.1.4. Priority of Analytical Components

Another aspect of mixed-methods research that influences data analysis decisions is the priority of the study, whether it's an equal-status design or a dominant-less dominant status design. For example, a study in which the quantitative phase(s) has (have) less priority than does the qualitative phase(s) is (are) less likely to involve a complex quantitative-based research question that requires sophisticated quantitative data analysis techniques than a study where the quantitative phase(s) has (have) greater priority (Onwuegbuzie & Combs, 2010). If the qualitative analysis component is given significantly higher priority, then the analysis essentially is a qualitative-dominant mixed analysis. In contrast, if the quantitative analysis component is given significantly higher priority, then the analysis is essentially a quantitative-dominant mixed analysis.

8.1.5. Number of Analytical Phases

Mixed-methods data analysis can be conducted in several phases. Onwuegbuzie and Teddlie (2003) conceptualized seven phases of mixed-methods data analysis. These phases are:

1. *Data reduction*: Reducing dimensionality of the qualitative and quantitative data. To reduce dimensionality of the qualitative data, researchers can use different coding strategies to create themes and categories that describe the characteristics of the data. In quantitative research, researchers can use factor analysis.
2. *Data display*: Visually describing the quantitative and qualitative data. Whereas quantitative data can be easily presented using a variety of different tables and diagrams, the visual

presentation of qualitative data, which is typically characterized by unstructured content, is different and more difficult. Miles et al. (2020) proposed different types of displays that we believe can be used to display not only qualitative findings, but also mixed-methods findings, and several examples of these formats are shown in Table 8-2. If the qualitative study's objective is to explore and describe, and the study only consists of one case (e.g., one organization, one event), then partially ordered displays, time-ordered displays, role-ordered displays, and conceptually ordered displays are recommended. If the qualitative study's objective is to explain and predict and the study only consists of one case, then explanatory effect matrix, case dynamic matrix, and causal network can be used. Cross-case displays for exploring and describing purposes include partially ordered meta-matrix, content-analytic summary table, substructing a variable, construct table, case-ordered descriptive meta-matrix, scatterplot, time-ordered meta matrix, and composite sequence analysis. Cross-case displays for ordering and explaining purposes include case-ordered effects matrix, case-ordered predictor-outcome matrix, variable-by-variable matrix, causal model, and causal networks (Miles et al., 2020).

Visual displays provide a pragmatic way to share mixed-methods findings. With increased access to technology and use of advanced graphic software, the capacity to produce more efficient and easily understood graphical information displays can be a powerful visual tool for mixed-methods data analysis (Dickinson, 2010).

Table 8-2. Data Display Formats for Qualitative Data

Type of Analysis	Display	Variation
Within-case displays: Exploring and describing	*Partially ordered displays*—i.e., aimed at uncovering and describing what is happening in a local setting.	• *Context chart*—i.e., "network or mapping in graphic form the interrelationships among the roles and groups . . . that make up the contexts of individual actions" (Miles et al., 2020, p. 161). • *Checklist matrix*—i.e., "format for analyzing field data on a major variable or general domain of interest" (Miles et al., 2020, p. 137).
	Time-ordered displays—i.e., aimed at understanding the flow and sequence of events and processes.	• *Event listing*—i.e., "matrix that arranges a series of concrete events by chronological time periods, sorting them into several categories" (Miles et al., 2020, p. 192). • *Time-ordered matrix*—i.e., more general form of the event listing, but it has its own columns arranged by time period in sequence.
	Role-ordered displays—aimed at sorting people according to	• *Role-ordered matrix*—i.e., used to sort "data in its rows and columns that have been gathered from or about a

Type of Analysis	Display	Variation
	their position-related experiences.	certain set of ‘role occupants’—data reflecting their views” (Miles et al., 2020, p. 157).
	Conceptually ordered displays— aimed at presenting well-defined variables and their interactions.	• *Conceptually clustered matrix*—i.e., “matrix has its rows and columns arranged to bring together major roles, research subtopics, variables, concepts, and/or themes for at-a-glance summative documentation and analysis” (Miles et al., 2020, p. 168). • *Process maps*—i.e., “drawing, usually freehand, by a participant or researcher that depicts social action in relationship to or as it progresses through time and geographic or conceptual space” (Miles et al., 2020, p. 204). • *Effects matrix*—i.e., “displays data on one or more outcomes as the study requires” (Miles et al., 2014, p. 228).
Within-case displays: Explaining and predicting	*Explanatory effect matrix*—i.e., a matrix aimed to help researchers clarify a domain in conceptual terms and understand things temporally.	
	Case dynamic matrix—i.e., displays a set of forces for change and traces the consequential processes and outcomes.	
	Causal network—i.e., “a display of the most important variables (represented in boxes) in a field study and the relationships among them (represented by arrows)” (Miles et al., 2020, p. 238).	
Cross-case displays: Exploring and describing	*Partially ordered displays.*	• *Partially ordered meta-matrix*—i.e., “master charts assembling descriptive data from each of several cases into a standard format” (Miles et al., 2020, p. 131).
	Conceptually ordered displays.	• *Content-analytic summary table*—i.e., similar to meta-matrix, but with the dimensions in which researchers are interested and the pertinent data are arranged in readily analyzable form. • *Substructing a variable*—i.e., way of locating underlying dimensions systematically. • *Construct table*—i.e., table consisting of the focal constructs generated from the data.

<table>
<tr><th>Type of Analysis</th><th>Display</th><th>Variation</th></tr>
<tr><td rowspan="2"></td><td>Case-ordered displays—i.e., used to array data case by case, but the cases are ordered according to some variable of interest so that researchers can easily see the differences among high, medium, and low cases.</td><td>Case-ordered descriptive meta-matrix—i.e., matrix that “contains first-level descriptive data from all cases, but the cases are ordered (e.g., high, medium, low) according to the main variable being examined” (Miles et al., 2020, p. 215).
Scatterplot—i.e., “figures that display data from all cases on two or more dimensions of interest that you think are related to each other” (Miles & Huberman, 1994, p. 198).</td></tr>
<tr><td>Time-ordered displays.</td><td>Time-ordered meta-matrix—i.e., table with columns organized sequentially by time period; the rows need not be ordered but can have cases in arbitrary order.
Scatterplot—see definition above.
Composite sequence analysis—i.e., shows stories, plots, or scenarios that a number of cases share without destroying the narratives.</td></tr>
<tr><td rowspan="5">Cross-case displays: Ordering and explaining</td><td colspan="2">Case-ordered effects matrix—i.e., used to sort the cases by degrees of the major cause being studied and to show the diverse effects for each case.</td></tr>
<tr><td colspan="2">Case-ordered predictor-outcome matrix—i.e., used to arrange information sources with respect to a main outcome or criterion variable, and provide data for each case on the main antecedent variables that are thought to be the most important contributions to the outcome.</td></tr>
<tr><td colspan="2">Variable-by-variable matrix—i.e., table display with two main variables in its rows and columns, and specific indicators of each variable are ordered by intensity.</td></tr>
<tr><td colspan="2">Causal-prediction model—i.e., “network of variables with causal connections among them, drawn from multiple-case analyses” (Miles et al., 2020, p. 265).</td></tr>
<tr><td colspan="2">Causal network—i.e., “both a display and a thematic narrative derived from systematic comparison of within-case causal network displays” (Miles et al., 2020, p. 248).</td></tr>
</table>

3. *Data transformation*: Using quantitized or qualitized methods described previously.
4. *Data correlation and comparison*: Correlating and comparing quantitative data with qualitative data.
5. *Data consolidation*: Combining both quantitative and qualitative data to create new or consolidated variables or data sets. The joint review of both data types can produce new or

consolidated variables that can be expressed in either qualitative or quantitative forms (Caracelli & Greene, 1993).
6. *Data comparison*: Comparing data from quantitative and qualitative data sources. Comparing qualitative and quantitative data sources can be done using one of the display formats presented in Table 8-2.
7. *Data integration*: Integrating both qualitative and quantitative data into a coherent whole.

8.1.6. Analysis Orientation

Onwuegbuzie et al. (2009) proposed a classification of mixed analysis techniques into three orientations: (1) *case-oriented approach*; (2) *variable-oriented approach*; and (3) *process-oriented approach*. Case-oriented analysis focuses mainly on the selected case(s) in order to "analyze and to interpret the meanings, experiences, perceptions, beliefs, or the like of one or more people—with a goal of particularizing and making analytical generalizations" (Onwuegbuzie & Combs, 2010, p. 418). Conversely, variable-oriented analysis involves "identifying relationships—typically probabilistic in nature—among constructs that are treated as variables in a way that facilitates research that often is conceptual or theory-centered from the onset and has a tendency toward external generalizations" (Onwuegbuzie & Combs, 2010, p. 418). The building blocks of a variable-oriented approach are variables and their relationships, rather than cases. Whereas qualitative methods generally focus on cases (i.e., case-oriented approach), quantitative methods usually focus on variables (i.e., variable-oriented approach).

Although variable-oriented analysis is good for finding probabilistic relationships among variables in a large population, it is poor at handling the real complexities of causation or dealing with multiple subsamples, and its findings are often very general (Miles et al., 2020). In contrast, case-oriented analysis focuses on a small sample size and usually points at similarities and differences through dense narratives. Thus, its findings are often very specific (Porta, 2008).

Mixed-methods research allows researchers to combine variable-oriented and case-oriented strategies in the same study or research program (i.e., process-oriented analysis). Process-oriented analysis involves evaluating processes or experiences relating to one or more cases within a specific context over time, with processes tending to be linked to variables and experiences to cases (Onwuegbuzie & Combs, 2010). For example, researchers who use case-oriented methods to study several companies that have implemented artificial intelligence tools might benefit from conducting surveys of their members and performing a conventional quantitative analysis of these data. Building on Tables 8-1 and 8-2, in Table 8-3, we present the listed techniques and additional techniques and how both qualitative and quantitative data analysis methods can be used for case-oriented and variable-oriented approaches. We complement and modify this table from Onwuegbuzie et al. (2009) by adding some additional data analysis techniques from multiple sources, including Miles et al. (2020). Process-oriented analyses usually use a combination of both case-oriented and variable-oriented analysis methods.

The list is by no means exhaustive but covers a range of techniques. Researchers can use a combination of these techniques as long as such a combination helps them obtain consistency between meta-inferences and the elements that characterize the study (i.e., research objectives, mixing purposes, research questions, mixed-methods sampling designs, and other research design decisions).

Table 8-3. Mapping Qualitative and Quantitative Data Analysis Methods to Case-Oriented and Variable-Oriented Approaches

Phase	**Case-Oriented**	**Variable-Oriented**
Qualitative	Within-case only: • Grounded theory • Narrative analysis • Content analysis • Metaphorical analysis • Hermeneutic analysis • Discourse analysis • Phenomenology/heuristic analysis • Pattern matching • Explanation building • Time-series analysis • Logic model Cross-case (all of the above and the following): • Classification: Typology and taxonomy • Event analysis • Cross-case synthesis • Replication strategy • Multiple exemplar	• Grounded theory • Classification: Typology and taxonomy • Pattern identification • Text mining (e.g., sentiment analysis) • Mixed strategies (e.g., stacking comparable cases—write up each of a series of cases using a more or less standard set of variables)
Quantitative	• Descriptive statistics • Cluster analysis • Profile analysis • Multidimensional scaling • Time-series analysis • Single-subject analysis	• Descriptive statistics • Lambda • Somer's *d* • Correlation analysis • Regression analysis • Loglinear analysis • Cramer's V • ANOVA, ANCOVA • MANOVA, MANCOVA • Factor analysis • Cluster analysis • Profile analysis • Logistic regression • Discriminant analysis • Structural equation modeling • Hierarchical linear modeling • Multidimensional scaling • Time-series analysis

8.2. Validation in Mixed-Methods Research

Validation is a cornerstone in social sciences research and is a symbol of research quality and rigor (Venkatesh et al., 2013). Prior to considering the quality of mixed-methods research, researchers need to describe and report the accepted criteria for the qualitative and quantitative strands of the study. This is an important step because researchers collect, analyze, and interpret both types of data. Thus, traditional approaches to validation should not be ignored regardless of the types of mixed-methods designs employed. For instance, if researchers leverage a dominant/less-dominant status design, validity should be established for both the dominant and less-dominant strands of the study.

The most widely used validation concepts from qualitative and quantitative research are summarized in Table 8-4 (Venkatesh et al., 2013).

Table 8-4. Examples of Validity in Qualitative and Quantitative Research

Method	Criteria	Strategies
	Qualitative Methods	
Design Validity	*Descriptive validity*: Accuracy of what is reported (e.g., events, objects, behaviors, settings).	Provide actual descriptions of what is reported (e.g., events, objects, behaviors).
	Credibility: Involves the confidence that can be placed in the truth of the research findings (Anney, 2014; Macnee & McCabe, 2008).	Prolonged engagement in the field or research site, use of peer debriefing, triangulation, member checks, negative case analysis, and persistent observation (Anney, 2014; Lincoln & Guba, 1985).
	Transferability: Degree to which the results of qualitative research can be generalized or transferred to other contexts or settings.	Provide thick descriptions and do theoretical/purposeful sampling (Anney, 2014).
Analytical Validity	*Theoretical validity*: Extent to which the theoretical explanation developed fits the data and, therefore, is credible and defensible.	Collecting data over an extended period of time, theory triangulation, and pattern matching (R. K. Yin, 2003).
	Dependability: Emphasizes the need to describe the changes that occur in the setting and how these changes affect the way the researcher approaches the study.	An audit trial, stepwise replication, code-recode strategy, and peer examination (Anney, 2014).
	Consistency: Emphasizes the process of verifying the steps of qualitative research through examination of such items as raw data, data reduction products, and process notes.	Use well-established protocols and develop qualitative data database (R. K. Yin, 2003).
	Plausibility: Concerned with determining whether the findings of the study in the	Do explanation-building, pattern-matching, address rival

Method	Criteria	Strategies
	form of description, explanation, or theory fit the data from which they are derived.	explanation, and use logic models (R. K. Yin, 2003).
Inferential Validity	*Interpretive validity*: Accuracy of interpreting what is going on in the minds of the participants and the degree to which the participants' views, thoughts, feelings, intentions, and experiences are accurately understood.	Use participant feedback and confirmability audit (Tashakkori & Teddlie, 1998).
	Confirmability: Degree to which the results could be confirmed or corroborated by others.	Reflective journal or practice (Tashakkori & Teddlie, 1998), use theory in single-case studies or replication logic in multiple case studies (R. K. Yin, 2003).
Quantitative Methods		
Design Validity	*Internal validity*: Validity of the inference about whether the observed covariation between independent and dependent variables reflects a causal relationship (e.g., ability to rule out alternative explanations).	Demonstrate temporal precedence, covariation of the cause and effect, use randomization, control groups, and rapid experiments (Shadish et al., 2002).
	External validity: Validity of the inference about whether the cause-effect relationship holds over variation in persons, settings, treatment variables, and measurement variables.	Using random selection or probability sampling (Campbell & Stanley, 1966); include a statement describing the authors' assessment of the population to which the results can be generalized (Slack & Draugalis, 2001).
Measurement Validity	*Reliability*: Reliability means repeatability or consistency. A measure is considered to be reliable if it produces the same result over and over again. There are various types of reliability, such as inter-rater or interobserver reliability, test-retest reliability, parallel-forms reliability, and internal consistency reliability.	Use the split-half method (i.e., extent to which a measure is consistent with itself); compute reliability scores (e.g., inter-rater, test-retest reliability, internal consistency reliability).
	Construct validity: Degree to which inferences can legitimately be made from the operationalizations in a study to the theoretical constructs on which those operationalizations are based. There are many different types of construct validity, such as face, content, criterion-related, predictive, concurrent, convergent, discriminant, and factorial.	Use multitrait-multimethod matrix; demonstrate measures that are theoretically supposed to be highly interrelated are, in practice, highly interrelated; demonstrate measures that should not be related to each other are, in fact, not (Trochim, 2006).

Method	Criteria	Strategies
Inferential Validity	*Statistical conclusion validity*: Validity of inferences about the correlation (covariation) between independent and dependent variables.	Assess statistical significance (e.g., using t-statistics); assess the possibility of Type I and Type II errors (Cook & Campbell, 1979).

8.2.1. Validation in Qualitative Research

Qualitative research does not have general guidelines or evaluation criteria for validation that are widely accepted (Venkatesh et al., 2013). Perhaps the best-known quality criteria have been developed specifically for qualitative research are the four proposed by Lincoln and Guba (1985) (see Table 8-4): (1) *credibility*—i.e., involves the confidence that can be placed in the truth of the research findings; (2) *confirmability*—i.e., degree to which the results could be confirmed or corroborated by others; (3) *transferability*—i.e., degree to which the results of qualitative research can be generalized or transferred to other contexts or settings; and (4) *dependability*—i.e., emphasizes the need for the researcher to describe the changes that occur in the setting and how these changes affected the way the researcher approached the study (Venkatesh et al., 2013). According to Lincoln and Guba, concern for credibility should replace truth value; transferability should replace external validity; dependability should replace reliability; and confirmability should replace the conventional criterion of neutrality and objectivity.

Using the classification of validity types presented in Table 8-4, Venkatesh et al. (2013) organized different types of quality for qualitative research into three broad categories: (1) *design validity*—e.g., descriptive validity, credibility, transferability; (2) *analytical validity*—e.g., theoretical validity, dependability, consistency, plausibility; and (3) *inference quality*—e.g., interpretive validity, confirmability.

8.2.2. Validation in Quantitative Research

Quantitative research that has widely accepted guidelines for validation (e.g., Cook & Campbell, 1979; Nunnally & Bernstein, 1994). Typically, in quantitative research, two primary validation issues are addressed (i.e., reliability and validity of measures) (Venkatesh et al., 2013). In its everyday sense, reliability is the "consistency" or "repeatability" of your measures (Trochim, 2006). A measure is considered reliable if it yields the same result over and over again (Straub et al., 2004). Without reliable measures, a quantitative study is considered invalid. Thus, reliability is a necessary condition for validity in quantitative research (Venkatesh et al., 2013).

Validity refers to "the legitimacy of the findings (i.e., how accurately the findings represent the truth in the objective world)" (Venkatesh et al., 2013, p. 32). According to Cook and Campbell (1979) and Shadish et al. (2002), validity in quantitative research can be categorized into three groups: (1) *measurement validity* (e.g., content and construct validity); (2) *design validity* (i.e., internal and external validity); and (3) *inferential validity* (e.g., statistical conclusion validity) (Venkatesh et al., 2013). The definition of each type of validity as well as its variations and strategies to establish the validity were summarized earlier in Table 8-4.

8.2.3. Quality Criteria in Mixed-Methods Research

Just like qualitative and quantitative research, mixed-methods research needs its own quality criteria. Here, we use the term "domains of quality" to refer to the areas of mixed-methods where the quality of data on which they are based must be assessed (Caracelli & Riggin, 1994; O'Cathain, 2010). There are two quality domains that have been widely discussed in mixed-methods research: (1) *design quality*—i.e., degree to which a researcher has selected the most appropriate procedures for answering the research questions; and (2) *interpretive rigor*—i.e., degree to which one has made credible interpretations based on the obtained results (Tashakkori & Teddlie, 2010a; Venkatesh et al., 2013, 2016). The different types of quality in each domain along with the questions researchers need to ask about when they assess the quality of their research design and its implementation are presented in Table 8-5 (Teddlie & Tashakkori, 2009).

Table 8-5. Quality Criteria in Mixed-Methods Research

Quality Domain	Definition	Indicator(s)
Design Quality		
1. Design suitability (appropriateness)	The degree to which methods selected and research design employed are appropriate for answering the research question.	a. Are the methods of study appropriate for answering the research questions? Does the design match the research questions? b. Does the mixed-methods design match the stated purpose of conducting mixed-methods research? c. Do the strands of the mixed-methods study address the same research questions?
2. Design fidelity (adequacy)	The degree to which the methods are implemented in a way that remains true to the design.	a. Are the qualitative, quantitative, and mixed-methods procedures or design components implemented with the quality and rigor necessary for capturing the meanings, effects, or relationships?
3. Within-design consistency	The degree to which the design components fit together in a seamless and cohesive manner.	a. Do the components of the design fit together in a seamless manner? Is there within-design consistency across all aspects of the study? b. Do the strands of the mixed-methods study follow each other (or are they linked) in a logical or seamless manner?
4. Analytical adequacy	The degree to which the methods are appropriate and adequate to provide plausible answers to the research questions.	a. Are the data analysis procedures/strategies appropriate and adequate to provide possible answer to research questions? b. Are the mixed-methods analytic strategies implemented effectively?
Interpretive Rigor		
5. Interpretive consistency	The degree to which the results from one strand of the study are consistent with the results from another strand of the study.	a. Do the inferences closely follow the relevant findings in terms of type, scope, and intensity? b. Are multiple inferences made on the basis of the same findings consistent with each other?

Quality Domain	Definition	Indicator(s)
6. Theoretical consistency	The degree to which meta-inferences are consistent with theory.	a. Are the inferences consistent with theory and state of knowledge in the field?
7. Interpretive agreement	The degree to which meta-inferences from mixed-methods research are generalizable or transferable to other contexts or settings.	a. Are other scholars likely to reach the same conclusions on the basis of the same results? b. Do the inferences match participants' constructions?
8. Interpretive distinctiveness	The degree to which each conclusion is different from other plausible explanations based on the same results.	a. Is each inference distinctively more credible/plausible than other possible conclusions that might be made on the basis of the same results?
9. Integrative efficacy (mixed and multiple methods)	The degree to which one effectively integrates inferences made in each strand of a mixed-methods research inquiry into a theoretically consistent meta-inference.	a. Do the meta-inferences adequately incorporate the inferences that are made in each strand of the study? b. If there are credible inconsistencies between the inferences made within/across strands, are the theoretical explanations for these inconsistencies explored and possible explanations offered?
10. Interpretive correspondence	The degree to which meta-inferences from mixed-methods research satisfy the initial purpose for using a mixed-methods approach.	a. Do the inferences correspond to the stated purposes/questions of the study? Do the inferences made in each strand address the purposes of the study in that strand? b. Do the meta-inferences meet the stated need for using a mixed-methods research design?

As can be seen from Table 8-5, the domain of design quality focuses on how well the design elements are consistent with the research questions and purposes for conducting mixed-methods research. These quality criteria include design suitability, design fidelity, within-case consistency, and analytical adequacy. The domain of interpretive rigor concerns the credibility and trustworthiness of the findings (i.e., meta-inferences). These include interpretive consistency, theoretical consistency, interpretive agreement, interpretive distinctiveness, integrative efficacy, and interpretive correspondence. We will discuss meta-inferences and how to establish high quality meta-inferences in Chapter 10.

Other key quality criteria are those recommended by Onwuegbuzie and Johnson (2006):

1. *Sample integration*: Applies to situations in which researchers aim to make statistical generalizations from a sample population to a larger population.
2. *Inside-outside*: "The extent to which the researcher accurately presents and appropriately utilizes the insider's views and the observer's views for purposes, such as description and explanation" (p. 57).

3. *Weakness minimization*: "The extent to which the weakness from one approach is compensated by the strengths from the other approach" (p. 57).
4. *Sequential legitimation*: "The extent to which one has minimized the potential problem wherein the meta-inferences could be affected by revising the sequence of the quantitative and qualitative phases" (p. 57).
5. *Conversion legitimation*: The extent to which quantitizing and qualitizing lead to interpretable data and high inference quality.
6. *Paradigmatic mixing*: The extent to which researchers successfully combine and blend their paradigmatic assumptions underlying the qualitative and quantitative approaches "into a usable package" (p. 57).
7. *Commensurability*: "Mixed-methods researchers need to be able to make Gestalt switches (i.e., to switch back and forth from a qualitative lens to a quantitative lens)" (Venkatesh et al., 2016, p. 450).
8. *Multiple validities*: The extent to which one uses all relevant research strategies and the study meets multiple relevant validity criteria.
9. *Political legitimation*: "The extent to which consumers of mixed methods research value the meta-inferences stemming from both the qualitative and quantitative components of a study" (p. 57).

8.3. Threats to Quality in Mixed-Methods Research

There are various potential threats in mixed-methods research that need to be addressed throughout the research process (i.e., the design, data collection, data analysis and interpretation stages). As with all research, plausible threats should be identified in the qualitative and quantitative strands of the study (Dellinger & Leech, 2007) and careful attention should be paid to alleviating or managing these threats.

8.3.1. Threats to Internal Validity

In qualitative research, internal validity is also known as internal credibility (Onwuegbuzie, 2002). Table 8-6 provides examples of threats to internal credibility in qualitative research (Ihantola & Kihn, 2011; Onwuegbuzie & Leech, 2007b). These include insufficient or biased knowledge of earlier studies and theories during the research design stage; selection bias and researcher bias during the data collection stage; and lack of descriptive legitimation and lack of interpretive legitimation during the data analysis and interpretations stage (Ihantola & Kihn, 2011).

Table 8-6. Examples of Threats to Internal Credibility in Qualitative Research

Stage of Research	Examples of Threats to Internal Validity
Research design	• Insufficient or biased knowledge of earlier studies and theories. • Contradictions in the logic among research questions, theory, hypotheses, statistical tests and analyses.
Data collection	• Observer-caused effect (i.e., subjects in the field may seek to behave differently from their usual selves in front of researchers). • Observer bias (i.e., insufficient data is collected and interpretation gaps closed with the researcher's own values, projections and expectations). • Researcher bias (i.e., occurs when researchers have personal biases or a priori assumption that they are not able to rule out).

Stage of Research	Examples of Threats to Internal Validity
	• Data access limitations—i.e., researchers are on site for a limited period of time and their access to certain documents, events, or people may be restricted. • Complexities and limitations of the human mind—i.e., subjects may consciously seek to mislead or deceive the researcher, or their statements or reports are affected by natural human tendencies and fallibilities. • Serious reactivity—i.e., changes in informants' responses that result from being excessively conscious of participating in a study.
Data analysis and interpretation	• Lack of descriptive legitimation of settings and events. • Lack of interpretive legitimation of statements about the meanings or perspectives held by participants. • Lack of explanatory or theoretical legitimation about causal processes and relationships. • Lack of generalizability—e.g., lack of inability to generalize to theory. • Issues in ironic legitimation—i.e., ability to reveal co-existing opposites of the same phenomenon. • Issues in paralogical legitimation—i.e., ability to reveal paradoxes. • Issues in rhizomatic legitimation—i.e., ability to map and not merely describe data. • Voluptuous legitimation—i.e., the extent to which the researchers' level of interpretation exceeds their knowledge base stemming from the data. • Confidential information—i.e., problems in treating confidential information in writing case reports. • Difficulty in interpreting the typicality of instances and findings. • All data are not analyzed and treated equally regardless of whether it fits the theory. • Lack of structural corroboration—i.e., utilization of multiple types of data to support or to contradict the interpretation. • Confirmation bias—i.e., interpretations and conclusions based on new data are overly congruent with a priori hypotheses. • Illusory correlation—i.e., a tendency to identify a relationship when no relationship actually prevails. • Causal error—i.e., providing causal explanations and attributions for observed behaviors and attitudes without attempting to verify such interpretations.

In quantitative research, internal validity asserts that variations in the dependent variable result from variations in the independent variables—not from other confounding factors (Trochim, 2006). During the research design stage, possible threats to internal validity include contradictions in the logic used to develop research questions, theories, hypotheses, statistical tests and analyses. During the data collection stage, possible threats include instrumentation issues (Tashakkori &

Teddlie, 1998), selection bias, and researcher bias (Ihantola & Kihn, 2011; Onwuegbuzie & McLean, 2003). During data analysis and interpretation, possible threats include statistical regression bias and confirmation bias (Ihantola & Kihn, 2011). The interested reader is referred to Bhattacherjee (2012), Tashakkori and Teddlie (1998), and Trochim (2006).

8.3.2. Threats to External Validity

In qualitative research, threats to external validity or external credibility include *catalytic legitimation* (i.e., degree to which a given study empowers and liberates a research community), *communicative legitimation* (i.e., occurs when researchers disagree on knowledge claims in a discourse), *interpretive legitimation* (i.e., "extent to which a researcher's interpretation of an account represents an understanding of the perspective of the group under study and the meaning attached to their words and actions"), and *population generalizability* (i.e., tendency to generalize findings rather than to utilize the data to obtain insights into particular underlying processes and practices that prevail within a specific location) (Onwuegbuzie & Leech, 2007a, pp. 237–238).

In quantitative research, external validity determines whether one can draw more general conclusions on the basis of data collected and whether the results may be generalized to other samples, time periods, and settings (Ryan et al., 2002). Threats to external validity in quantitative research include *selection bias* (i.e., if the sample size is inadequate and/or the sample is not random) and *interaction of history and treatment effect* (i.e., as time passes, the conditions under which treatments work change) (Bracht & Glass, 1968; Ryan et al., 2002).

8.3.3. Threats to Quality in Mixed-Methods Research

As we discussed earlier, there are two types of quality criteria in mixed-methods research: *design quality* and *interpretive rigor* (Tashakkori & Teddlie, 2010b). Teddlie and Tashakkori (2003) suggested that "within-design consistency" (i.e., the consistency of the procedures/study design from which meta-inferences emerge) is threatened if any of the following conditions are present: (1) the design is not consistent with the research questions/purpose; (2) the observations/measures do not demonstrate validity; (3) the data analysis techniques are not sufficient and appropriate for providing answers to research questions; (4) the results do not have the necessary strength to warrant high-quality meta-inferences; (5) the inferences are not consistent with the results of data analysis; and (6) the inferences are not consistent with research questions/purposes (Ihantola & Kihn, 2011).

Threats to interpretive rigor include the inconsistency of inferences and the findings from each strand of the study, the inconsistency of inferences with empirical findings of other studies, the inconsistency of interpretations across scholars and participants' construction of reality (e.g., other scholars do not agree that the inferences are the most plausible interpretations of the findings; participations' construction of events is important to researchers, but the interpretations do not make sense to participants), failure to distinguish inferences from other possible interpretations of the findings, and failure to adequately integrate the findings (Ihantola & Kihn, 2011; Teddlie & Tashakkori, 2003). All these threats should be properly addressed in a mixed-methods inquiry. Although not all the threats are likely to appear in a single research inquiry, one should, nevertheless, take them into consideration and address them when necessary to ensure high-quality meta-inferences.

8.4. Data Collection and Analysis in Mixed-Methods Research in Practice

We provide two exemplars that have been discussed in previous chapters—i.e., Sonenshein et al. (2014) and Stewart et al. (2017)—to illustrate how data are analyzed in mixed-methods research.

8.4.1. Sonenshein et al. (2014)

As discussed in Chapter 4, Sonenshein et al. (2014) conducted a sequential qualitative-quantitative mixed-methods study of self-evaluations in explaining support of environmental issues. The purpose of mixed-methods research in this study was *complementarity* (with an element of developmental). They used type (2) data collection—qualitative interviews and quantitative survey (see Table 6-6, Chapter 6).

8.4.1.1. Qualitative Data Collection

In their study 1, they used a sample of identified issue supporters of a variety of environmental issues, including climate change. They located a program at a North American university called the Environment and Business Program (EBP). They provided a justification why they selected this sample: "Although obviously different from the general population, our sample was important for theory development, as it allowed us to learn from a highly deviant set of individuals…. While many individuals in the general population may want to address climate change at some point, our sample represented individuals who had taken distinctive steps to learn about how to do so and to be in the position to do so" (p. 12). They also explained how they recruited the participants in their study, providing descriptive validity. They interviewed twenty-nine participants (i.e., fourteen current students and fifteen working alumni of EBP). They provided a detailed description of their interview protocol, establishing analytical validity (i.e., consistency). They also supplemented the interview data with field observations and secondary documents.

8.4.1.2. Analysis of Qualitative Data

They adopted a grounded theory approach (Strauss & Corbin, 1998) to analyze their qualitative data. They followed a three-step approach: (1) *initial data coding*; (2) *theoretical categorization*; and (3) *theory induction*. During the initial data coding, they used open codes to classify informants' statements. To establish credibility, they were mindful of the different settings in which informants attempted to address climate change, inside and outside their formal organizational settings. They developed a list of open codes that attempted to stay close to informants' interpretations. During this stage, they began to shift their focus to self-interpretations, as their first-order codes highlighted significant attention informants gave to the self. In the second step, they moved to create abstract, theoretical codes that grouped informants' self-meaning and other constructs into more generalizable categories. "This step involved abstracting informants' categories to match theoretical concepts, with the goal of grouping informants' conceptual schemes into theoretical categories" (p. 13). This practice also established theoretical validity. After settling on a set of theoretical categories, the authors identified three key aggregate theoretical dimensions that they grouped into their theoretical categories. These aggregate dimensions—*issue support challenges*, *self-assets*, and *self-doubts*—served as the basis for their induced theory. They used several different display formats to illustrate their qualitative data and findings. For example, they used a causal network (Figure 8-1, reproduced from Sonenshein et al., 2014, p. 14) to illustrate the data structure (i.e., how the first-order categories were related to the second-order themes and how these second-order themes led to aggregate dimensions). They also used a construct table to show the representative quotes underlying the second-order themes.

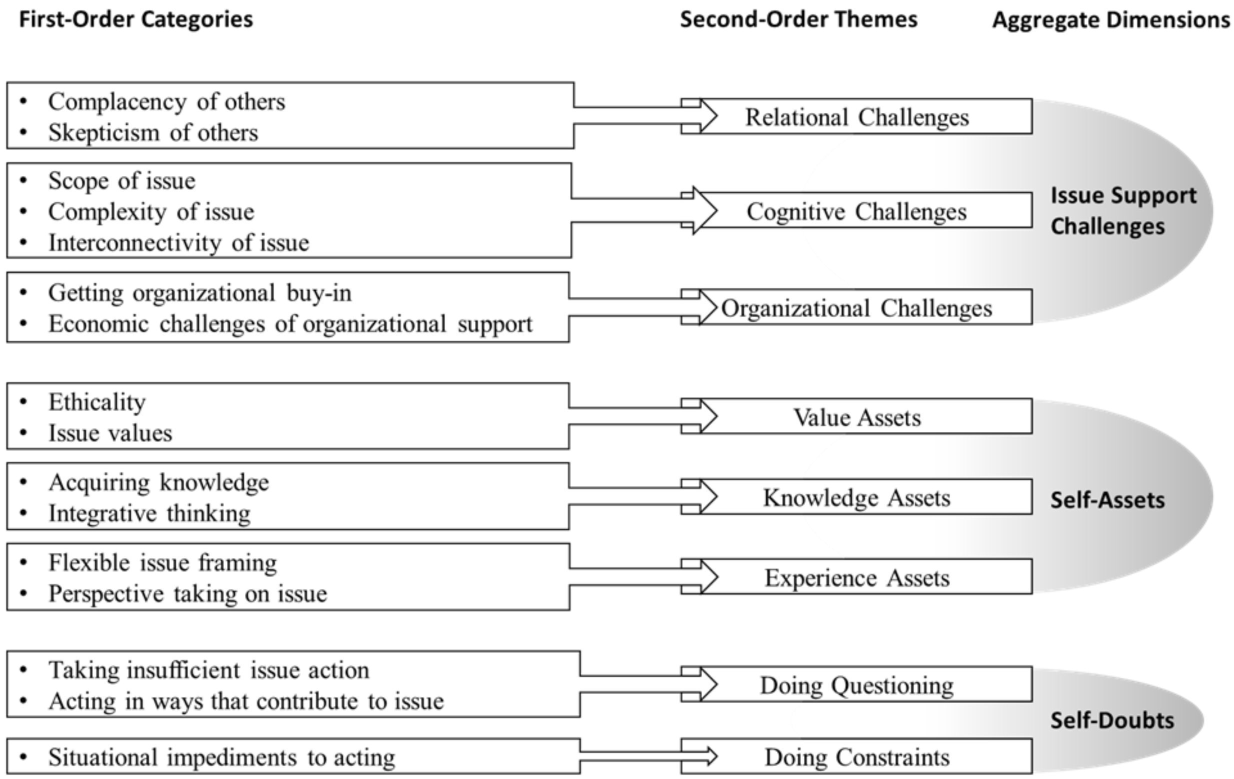

Figure 8-1. Example of a Causal Network in Qualitative Data Analysis

8.4.1.3. Quantitative Data Collection

In their study 2, they conducted an observational study to empirically and theoretically test their theoretical premise that social issue supporters experience a mixed self. They inductively examined the different ways this mixed self is manifested and how these differences relate to issue-supportive behaviors. They first collected pre-test data to demonstrate construct validity for measures of self-assets and self-doubts. They then recruited a second sample of issue supporters and used surveys with concealed observations to inductively examine patterns of self-assets and self-doubts and investigated how these patterns related to issue-supportive behaviors. They collected data from 91 environmental issue supporters who were active members of environmental groups in a North American city.

Participants were invited to come to a lab to complete the survey. Following the completion of surveys, participants received a beverage, three slices of pizza, vegetables, and strawberries (with the greens still attached), with the expectation that participants would be less likely to eat everything on their plate, even if they were hungry. The participants were told to stay as long as they wished and to finish all food and beverages in the lab. A research assistant took notes of each participant's composting behavior. When participants left the building, two research assistants, posing as environmental activists on the street, approached participants, told them about Earth Hour—a real upcoming event sponsored by WWF—and asked them whether they would like to sign the pledge and include their email address for a reminder to turn their lights off for Earth Hour. They also videotaped the street activists' interactions with participants to identify them after the study. They provided actual descriptions of the events and study settings, establishing descriptive validity. They did checks to ensure the credibility of their observations.

8.4.1.4. Quantitative Data Analysis

To analyze the survey data, they first conducted a *confirmatory factor analysis* on all independent measures. Because of their small sample size, they ran a bootstrapped model. They reported the goodness of fit indices of their results. Specifically, they mentioned, "although we had limited power to reject a model, our results demonstrated a sufficient fit to the data ($X^2[44] = 68.96$, $p < .01$; CFI = .96, RMSEA = .08). Each item loaded significantly with its intended construct and with no significant cross-loadings ($p < .001$)" (p. 27). They also used *cluster analysis* to inductively examine how participants grouped into three self-evaluation profiles based on degree of self-assets and self-doubts. After examining the scores associated with the individuals in each cluster, they proposed three clusters of participants: (1) *self-affirmers* (i.e., those with low self-doubts and high self-assets); (2) *self-equivocators* (i.e., those with high self-doubts and high self-assets); and (3) *self-critics* (i.e., those with high self-doubts and low self-assets).

To analyze issue-supportive behaviors, they coded participant behaviors that they observed during study 2. First, they coded participants who composted their leftover food and/or dishware as having composted (i.e., consumption-offset opportunity). Second, participants had the opportunity to offer feedback in their handwritten survey (i.e., qualitative survey). They binary coded each participant who exhibited either a written or verbal complaint about environmental issues with their studies as having engaged in an interpersonal influence attempt or not (i.e., interpersonal influence opportunity). Finally, they examined whether participants signed the pledge to turn their lights off for Earth Hour (i.e., collective advocacy opportunity). These opportunities data were used as the dependent variables. To examine how different profiles of environmental issue supporters' three self-evaluation profiles (i.e., self-affirmers, self-critics, self-equivocators) engaged in different levels of issue-supportive action, they assigned categorical codes to each profile membership and ran a one-way ANOVA with post-hoc comparisons. They found that self-critics engaged in the lowest number of actions, followed by self-equivocators, and finally self-affirmers.

8.4.1.5. Mixed-Methods Data Analysis (Summary)

They used mixed-methods research to develop a theory of situated self-work and then examined how two core constructs in this theory (i.e., self-assets and self-doubts) related to real issue-supportive behaviors. Although they did not explicitly discuss the quality criteria of their mixed-methods research study, their methods were appropriate for answering the research questions. They not only did a mixed-methods study, but also embedded a multi-method element in their study 2 (i.e., survey and quantitative/qualitative observation). They reported the study setting, along with events that took place during the study in detail. The components of the design fit together—the findings of study 1 were used to develop a theory that was later used to develop another theory in study 2. In study 2, they examined self-assets and self-doubts and their relationship with real behaviors. They transformed the qualitative observation data into quantitative data by assigning a binary number (0 or 1). These research elements were linked together seamlessly. They also used different data analysis methods to ensure high-quality meta-inferences.

8.4.2. Stewart et al. (2017)

As we discussed in the previous chapter, Stewart et al. (2017) used type (7) design—i.e., a combination of field experiment and open-ended interviews in their mixed-methods research study. The purpose of mixed-methods research was *completeness*.

8.4.2.1. Quantitative Study

In their study 1, they adopted a longitudinal quasi-experiment design to test the effect of team-based empowerment on team effectiveness. They collected pre- and post-intervention data for a sample of 224 providers. They also analyzed monthly time series measures for 142 physician providers and 82 nonphysician providers obtained seven months before and thirty-seven months after the adoption of team-based empowerment. An important objective of the Veteran Health Administration (VHA) transformation to team-based empowerment was improving patients' timely access to care. Thus, to measure team effectiveness, they used the "VHA metric same-day appointment access, operationalized as the percentage of same-day appointment requests granted within a monthly reporting period" (p. 2272). They coded the status of each team, provided as a dichotomous variable (i.e., 1 represented higher-status physician providers and 0 represented lower-status nonphysician providers). To code the time variable, they used an absolute coding scheme for discontinuous growth modeling time variables.

They reported the descriptive data and intercorrelations and intraclass correlation coefficient to establish reliability. To analyze the quantitative data, they conducted *discontinuous growth modeling analyses* using the *nlme* package included in the R software. They began the discontinuous growth modeling process by first adding covariates to the model. They then tested different forms of time (e.g., linear, quadratic) to properly model fixed effects for change trajectories. Next, they tested variations of the basic linear model to account for random effects in the change terms. They then added status as a predictor to model its main effect. They also added interaction terms between status and the pre- and post-intervention time indicators to examine whether trajectories of access significantly differ based on the status of a team's provider. To estimate the percentage of variance accounted for by time and status, they also calculated pseudo-R^2 values. From the quantitative study, they concluded that teams led by lower-status providers improved access at a faster rate than did teams led by higher-status providers.

8.4.2.2. Qualitative Study

In the second stage of the study, they inductively developed theory about status and team leadership. Qualitative data were drawn from participant interviews (during the initial months of implementing team-based empowerment and follow-up interviews one year later) conducted as part of a larger study of VHA teams. They used a purposive sampling strategy to recruit participants. Interviews were conducted using a semi-structured format, focusing broadly on identifying facilitators and barriers associated with the implementation of team-based empowerment.

They followed the procedures described by Miles and Huberman (1994). Specifically, they followed a three-step analysis: (1) *identifying themes*; (2) *creating categories within themes*; and (3) *connecting patterns between categories*. In order to guard against confirmatory bias, a research assistant blind to both the findings and developing theory was involved in the coding process. In the first step (i.e., identifying themes), they identified two themes: leader identity work and leader delegation. In the second step (i.e., creating categories within themes), they identified two categories under "identity work": (1) embracing empowering identity; and (2) protecting hierarchical identity; and three categories under leader delegation: (1) insufficient delegation; (2) overabundant delegation; and (3) balanced delegation. In the third step, they associated nonphysician providers with embracing the new team-based empowerment identity. They illustrated the qualitative findings using an explanatory effect matrix.

8.4.2.3. Mixed-Methods Data Analysis (Summary)

Although the qualitative and quantitative data were collected concurrently, the data were analyzed sequentially. Stewart et al. (2017) did not explicitly provide the quality criteria for their mixed-methods study. Based on our reading, we argue that the methods were appropriate to answer the research questions. The quantitative and qualitative strands of the study addressed different research questions and together they provided a complete picture of the phenomenon. In study 1, their findings confirmed the hypothesis that teams with high-status leaders were less effective in implementing team-based empowerment. To examine leader behaviors in-depth, they conducted qualitative data analyses, and found identity and delegation were two behaviors that facilitated team effectiveness. Due to the richness of the qualitative data, they should have used different visual formats to display their findings. For example, they can use a time-ordered matrix to show the flow and sequence of the impact of team-based empowerment. However, the integration of findings was well reported. They integrated the qualitative and quantitative findings and illustrated them using a causal model (Figure 8-2).

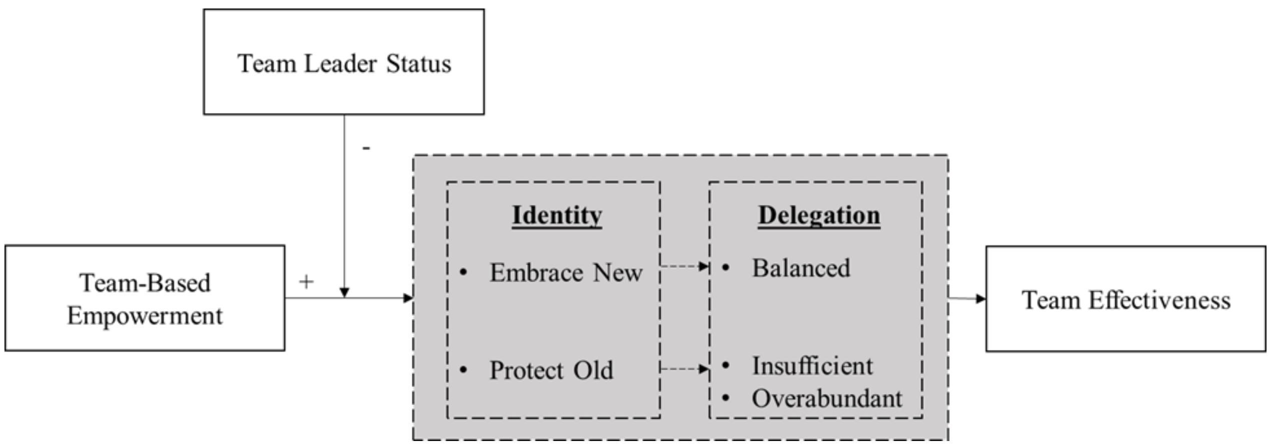

Figure 8-2. Example of Joint Display Quantitative and Qualitative Findings

Summary

- The main objective of data analysis in mixed-methods research is to enable researchers to use both of the qualitative and quantitative types of analyses simultaneously or sequentially in the same study or research program.
- The critical criteria that researchers need to consider during the data analysis phases include: (1) number of data types that will be analyzed; (2) number of data analysis types that will be used; (3) time sequence of the analysis; (4) priority of analytical components; (5) number of analytical phases; and (6) analysis orientation.
- Prior to considering the quality of mixed-methods research, researchers need to describe and report the accepted criteria for the qualitative and quantitative strands of the study. Validity in quantitative research can be categorized into three groups: (1) measurement validity—e.g., content and construct validity; (2) design validity—i.e., internal and external validity; and (3) inferential validity—e.g., statistical conclusion validity. Validity in qualitative research can be categorized into three groups: (1) *design validity*—e.g., descriptive validity, credibility, transferability; (2) *analytical validity*—e.g., theoretical validity, dependability, consistency, plausibility; and (3) *inference quality*—e.g., interpretive validity, confirmability.

- There are two quality domains that have been widely discussed in mixed-methods research: (1) design quality—i.e., degree to which a researcher has selected the most appropriate procedures for answering the research questions; and (2) interpretive rigor—i.e., degree to which one has made credible interpretations based on the obtained results.

Exercises

1. Revisit the research proposal you developed in Chapter 7. Describe how the selection of your data analysis methods are informed by six criteria of mixed-methods data analysis discussed in this chapter.
2. Select one or two articles in your field that has used a mixed-methods research approach and answer the following questions:
    a. How did the authors present their data and findings? What types of displays did the authors use?
    b. How did the authors validate their data?
    c. If the quality of mixed-methods research was not reported, explain whether or not the authors met the quality criteria of mixed-methods research.

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SECTION 3.

MAKING CONTRIBUTIONS AND PUBLISHING PAPERS USING MIXED-METHODS RESEARCH

In the third and final section of the book, we discuss the unique aspects of mixed-methods research in terms of crafting contributions and publishing papers. We begin in *Chapter 9. Mixed-Methods Research and Big Data Analytics* with a discussion of how trends of massive amounts of numerical, text, and other forms of non-numerical data today can be leveraged to generate rich insights and consequent contributions. In *Chapter 10. Generating Meta-Inferences in Mixed-Methods Research*, we discuss three theoretical reasoning techniques for generating meta-inferences. We also discuss convergence and divergence in meta-inferences and various strategies to address divergence meta-inferences. We recommend readers review Chapter 8 on quality criteria in mixed-methods research to assess the credibility and trustworthiness of meta-inferences.

We then focus on various practical issues in publishing a mixed-methods research paper. In *Chapter 11. Mixed-Methods Research Paper Templates*, we provide a number of templates that researchers can use to develop and structure their mixed-methods paper. We specifically offer templates to organize a mixed-methods research paper based specifically on the mixed-methods purpose. In *Chapter 12. Guidelines for Editors and Reviewers*, we provide guidance that editors and reviewers can use to review and judge the quality of mixed-methods papers. In *Chapter 13. Challenges and Strategies in Conducting, Writing, and Publishing Mixed-Methods Research*, we especially focus on unique challenges associated with mixed-methods research, ranging from paradigmatic issues to preparation of findings. We also provide recommendations to address these challenges.

CHAPTER 9

MIXED-METHODS RESEARCH AND BIG DATA ANALYTICS

The rapid development of technology and the associated collection of data over the past few years has led to the availability of a massive amount of diverse data, commonly referred to as "big data" (Tay et al., 2018; Wamba et al., 2015). Big data can be thought as "data whose scale and complexity go beyond typical database software tools, requiring new technical architectures and analytics to enable insights that unlock new sources of business value" (Tay et al., 2018, p. 661). The opportunities associated with this type of data have generated significant interest in various ways of analyzing the data including techniques, technologies, practices, methodologies, and applications that facilitate the analysis of unstructured data and generation of richer insights (H. Chen et al., 2012).

In this chapter, we discuss how mixed-methods research and different ways of mixing qualitative and quantitative strategies dovetail with analytics research, especially given the widespread availability of different types of data, ranging from numerical data to text data to audio and video data that could be codified as both quantitative and qualitative data. Whereas quantitative research provides numerical and thematic analysis, qualitative research offers insights that enhance meaning and understanding (Frizzo-Barker et al., 2016). Both types of methodologies are valuable to unravel relationships or insights that may exist in large-scale datasets. Together, both quantitative and qualitative research can provide a basis for the investigation of a variety of problems in big data analytics endeavors. We first discuss the properties of big data and analytics and then propose several mixed-methods design strategies that can be used in analytics research.

9.1. Big Data and Analytics

Big data describes "data that are 'generated from an increasing plurality of sources, including Internet clicks, mobile transactions, user-generated content, and social media as well as purposefully generated content through sensor networks or business transactions such as sales queries and purchase transactions'" (Lehrer et al., 2018, p. 428). The big data era is interconnected with the development and extensive use of social media platforms (e.g., blogs, Facebook, Twitter, YouTube), as well as the rise of wearable (e.g., smartwatches) and mobile technologies (e.g., smartphones) that generate quantitative and qualitative data (Hesse et al., 2019). Big data are characterized by *volume* (i.e., "large volume of data that either consume huge storage or consist of large number of records"), *variety* (i.e., "data generated from greater variety of sources and formats, and contain multidimensional data fields," *velocity* (i.e., "frequency of data generated and/or frequency of data delivery"), *veracity* (i.e., "inherent unpredictability of some data requires analysis of big data to gain reliable prediction"), and *value* (i.e., "the extent to which big data generates economically worthy insights and or benefits through extraction and transformation") (Wamba et al., 2015, p. 236). If a dataset can be characterized by at least two of these properties, it can be considered big data (Gorodov & Gubarev, 2013; Tay et al., 2018). For example, online customer review data can be considered as big data because of its high volume, velocity, and variety (Zhou et al., 2018).

Analytics techniques refer to scalable techniques, such as text analytics and web analytics, that enable researchers to process and analyze big data (e.g., digital records and activities from websites and social media including users' online activities and online conversations) (Lehrer et al., 2018). Many tools and techniques for data mining and analysis are available. Table 9-1 provides an overview of key analytics techniques. First, general analytics techniques involve processing of data from different sources in different formats (Choi et al., 2018). Data sources can be from Internet clicks, social media networks, sensors, web service data, and Internet of Things devices (e.g., power meters) (Mohamed et al., 2020). The various formats of data in analytics research include: (1) *structured data* (i.e., data with a specific format and a relational structure); (2) *unstructured data* (i.e., data that do not follow any specific format, such as videos, text, time information, and geographic location); and (3) *semi-structured* (i.e., data with a mix of structured and unstructured elements) (Mohamed et al., 2020). General analytics techniques rely on mature commercial technologies of relational DBMS, data warehousing, ETL, and OLAP. Various data mining algorithms (e.g., C4.5 algorithm to generate a decision tree, *k*-means, support vector machine) that cover classification, clustering, regression, association analysis, and network analysis have been used to incorporate commercial and open source data mining systems (H. Chen et al., 2012). The most commonly used data analytics approaches include multivariate statistical analysis, optimizing techniques and heuristic search, statistical machine learning techniques, spatial data mining approach, and data mining for high-speed data streams and sensor data.

Table 9-1. Different Types of Analytics Techniques

Analytics Type	Description	Possible Analysis Techniques	Example
General Analytics Techniques	Processing of data from different sources (e.g., Internet, social media, sensors) in different formats (e.g., structured, unstructured, semi-structured) (Choi et al., 2018).	• Multivariate statistical analysis (e.g., regression, factor analysis, clustering, discriminant analysis) • Optimization techniques and heuristic search • Statistical machine learning techniques (e.g., Bayesian networks, Hidden Markov models, support vector machine, reinforcement learning, ensemble models, fast learning algorithms, parallel processing) • Sequential/temporal mining and spatial mining • Data mining for high-speed data streams and sensor data • Semantic analysis	Researchers use an API technology to access sensor data and clickstream data to understand usage behaviors.
Text analytics	Analytics techniques that process and analyze unstructured content in text format from email communication and	• Information retrieval and query processing techniques (e.g., vector space model, Boolean retrieval model, probabilistic retrieval model)	Researchers analyze social media data (e.g., user posts) to gain insights on customers' activities,

Analytics Type	Description	Possible Analysis Techniques	Example
	corporate documents to webpages and social media content (H. Chen et al., 2012).	• Text representation techniques, such as statistical natural language processing (NLP) techniques for lexical acquisition, word sensing disambiguation, part-of-speech-tagging (POST), and probabilistic context-free grammars • Information extraction techniques, such as NER (named entity recognition) • Unsupervised learning methods (e.g., clustering and topic modeling) • Supervised learning methods • Probabilistic methods for text mining (e.g., probabilistic latent semantic analysis)	sentiment, opinions, and preferences (Lehrer et al., 2018).
Web analytics	Techniques used to analyze clickstream data logs to provide insights on customers' online activities and reveal their browsing and purchasing patterns (Lehrer et al., 2018).	• Data mining and statistical analysis techniques can be used for web analytics • Web site crawling/spidering, web page updating, web site ranking, web site traffic, and search log analysis	Researchers analyze data about bid history and other features of auctions on eBay and Amazon to understand how rules of an action influence bidding behaviors (Roth & Ockenfels, 2002).
Network analytics	The process of analyzing networked data with entities being modeled as nodes and their connections as edges, comprising large networks (Pržulj & Malod-Dognin, 2016).	• Bibliometric analysis, citation networks, and co-authorship networks • Social network analysis (e.g., centrality, betweenness, structural holes) • Exponential random graph models to analyze social data and other network data • Visualization	Researchers use h-index to measure the productivity and impact of the published work of a scholar; and use social network analysis to understand the relationships among scientists (e.g., mathematicians, computer scientists)

Analytics Type	Description	Possible Analysis Techniques	Example
			(H. Chen et al., 2012).
Mobile analytics	Techniques used to analyze clickstream data logs and sensor data (e.g., location data) generated by mobile devices to provide insights on customers' mobile activities and movement patterns (Lehrer et al., 2018).	• Mobile sensing apps that are location-aware and activity-sensitive • Mobile social innovation for m-health and m-learning • Mobile social network and crowd-sourcing • Mobile visualization • Personalization and behavior modeling for mobile apps	Researchers gather mobile app use data (e.g., amount of time users spent on the app) through sensor-equipped mobile phones to understand which features customers used most at a particular time.

Second, text analytics refers to the process of automatically extracting quantitative data from text (e.g., email communication, corporate documents, webpages, social media content, online reviews) (Allahyari et al., 2017; H. Chen et al., 2012). Some techniques used to process such data include information retrieval and query processing techniques (e.g., vector space model, Boolean retrieval model, probabilistic retrieval model), text representation techniques (e.g., statistical natural language processing (NLP) techniques for lexical acquisition, word sensing disambiguation, part-of-speech-tagging (POST), probabilistic context-free grammars), information extraction techniques (e.g., NER: Named Entity Recognition) (H. Chen et al., 2012), supervised and supervised learning methods, and probabilistic methods for text mining (e.g., probabilistic latent semantic analysis) (Allahyari et al., 2017). Text analytics techniques can help researchers analyze a massive amount of text data and discover knowledge that may be hidden in the text (Hu & Liu, 2012). In Chapter 5, we discussed the concept of quantitizing in the context of mixed-methods research—text analytics is thus *quantitizing* (i.e., transforming qualitative data into numerical, quantitative data for further analysis). For example, Raman et al. (2022) converted sentiments conveyed in news articles into quantitative data that were then analyzed using various quantitative techniques.

Third, web analytics aims to measure and understand the relationship between customers and a website (Phippen et al., 2004). Web analytics techniques are built on data mining and statistical analysis foundations of data analytics and on information retrieval and NLP models in text analytics (H. Chen et al., 2012). Website crawling/spidering, webpage updating, website ranking, and search log analysis are some of the techniques that researchers can use to gather and analyze large-scale datasets generated from the web.

Fourth, network analytics refers to the process of analyzing network data with entities being modeled as nodes and their connections as edges, comprising large networks (Pržulj & Malod-Dognin, 2016). Network analytics is built on the earlier citation-based bibliometric analytics to include new computational models for online community and social network analysis (H. Chen et al., 2012). Network analytics investigates the relations among various relationships in the network (e.g., the formation of clusters) and the influence of structural properties of networks and social relations on social integration (Hollstein, 2014). Various social network theories, network metrics, topology, and mathematical models have been developed to understand network properties and relationships. For example, Benson et al. (2016) proposed a scalable heuristic framework for grouping entities based on their wiring patterns and using the discovered patterns for revealing the higher-order organizational principles of several real-world networked systems. Another network analytics technique that has gained popularity in recent years is the use of visualization tools to present and understand information drawn from a large-scale dataset.

Fifth, mobile analytics refers to techniques used to analyze clickstream data logs and sensor data (e.g., location data) generated by mobile devices to provide insights on customers' mobile activities and movement patterns (Lehrer et al., 2018). The number of downloads and the direct, quantitative measurement of use, habit, and engagement are some of the types of data that can be analyzed using mobile analytics techniques (Han et al., 2016). The most common mobile analytics techniques include mobile sensing apps that are location-aware and activity-sensitive, mobile social innovation for m-health and m-learning, mobile social network and crowdsourcing, mobile visualization, and personalization and behavior modeling for mobile apps (H. Chen et al., 2012).

The various analytics techniques, discussed in this chapter, can be used in either qualitative or quantitative research. An example of quantitative research in the analytics context is a study by Wang et al. (2020). Wang et al. used an analytics approach to address the following research question: "how does environmental crowdedness moderate the impact of non-customized information-only posts on (1) unfollowing and (2) long-term sales?" (p. 1522). They leveraged a longitudinal dataset from a large Chinese fashion retailer who regularly posted on WeChat, which is the leading Chinese mobile social media platform. Their quantitative data captured the retailer's social media posts during a five-month period, as well as the hourly purchases and unfollowing of the focal retailer's approximately 80,000 followers. They ran a pooled regression and a discontinuous regression to analyze the data. They found that changes in unfollowing and long-term sales were larger when firms post in densely populated areas or when they post at times of peak travel stress, thus suggesting that "the stress formed by personal crowding and the follower's environment may play a key role in followers' reactions to social media postings" (p. 1521).

An example of qualitative research in the analytics context is Karamshuk et al. (2017). They conducted a case study of Twitter responses to high-profile deaths by suicide. To analyze public discourses on social media relating to high-profile suicides, they selected five highly publicized cases. They collected five datasets of related Twitter posts for twenty days following each death. They proposed a semi-automated coding approach to analyze the large-scale data: an approach that starts with manually bootstrapping a coding scheme from a micro-scale sample of data, followed by a crowdsourcing platform to achieve a meso-scale model and machine learning to build a macro-scale model. Using this approach, they showed that it is possible to code text-based data automatically in a large dataset to a high degree of accuracy.

A wide variety of data (e.g., text-based data, numerical data) with high volumes (large-scale data), high velocity (high-speed data), and with a high level of veracity offers opportunities for mixed-methods research. Integrating semantically rich data (i.e., text-based data) and numerical data (e.g., transactional data, activity logs) provides researchers with new opportunities for discovering new values, helps us to gain an in-depth understanding of the hidden values, and poses new challenges (M. Chen et al., 2014). As noted earlier, conducting analytics research using a mixed-methods approach should involve at least one qualitative data strand and one quantitative data strand (i.e., multistrand designs) or a sequential analysis of one type of data (i.e., monostrand design with *quantitizing*—qualitative data are transformed into quantitative data (e.g, Raman et al., 2022)—and *qualitizing*—quantitative data are transformed into qualitative data). Regardless of the number of data types being analyzed, analytics research using a mixed-methods approach can benefit from the use of visualization tools.

9.1.1. Analytics Research Using Mixed-Methods Multistrand Designs

As discussed in earlier chapters, mixed-methods research with a multistrand design contains at least two research strands. Each strand consists of a complete quantitative cycle (including quantitative data collection and analysis) and a complete qualitative cycle (including qualitative data collection and analysis). The integration can take place during the conceptualization, data collection, data analysis, or inferential stage. When researchers adopt a multistrand design in analytics research, they generally mine the patterns from large-scale data in various formats (e.g., the aggregation of email, Twitter feeds, Facebook posts, and other forms of social media that convert and store human interaction as numerical, text, geographic, or visual data). They then uncover insights from such data not only by applying traditional inferential statistics (e.g., ANOVA, regression analysis) and qualitative analysis (e.g., coding of interviews), discussed in Chapter 7, but also by making use of data mining and machine-learning algorithms to analyze both quantitative and qualitative data (Müller et al., 2016).

When adopting a mixed-methods multistrand design, researchers need to decide the sampling methods employed in their mixed-methods research, whether the sample for quantitative and qualitative strands of the study are identical or whether they overlap (see Chapter 5). After data are collected, researchers may choose among different types of analytics techniques (see Table 9-1) to process their quantitative and qualitative data independently. Going back to the purposes of mixed-methods research, if the purposes are corroboration or complementarity, it is more desirable to analyze quantitative and qualitative data simultaneously, rather than sequentially. This is because simultaneous data analysis allows researchers to validate and corroborate results at the same time, and increase explanatory power as well as the generalizability of the results by generating a broad and comprehensive understanding of the phenomenon under study (Hollstein, 2014). However, if the purposes are compensation, developmental, or expansion, researchers are encouraged to adopt a sequential mixed-methods analysis design because one method is meant to deepen and further elucidate the results of another method.

An example of analytics research that adopts multistrand designs is Wu et al. (2017). They developed an assessment that helps firms identify decisive attributes and enhance their understanding of supply chain risks and uncertainties (SCRU) by aggregating various types of data, including quantitative data from business operations and qualitative data from management and social media data. Although they did not explicitly report that they conducted mixed-methods research, our assessment revealed that they adopted a concurrent mixed-methods design with a completeness purpose. They gathered social media data and performed content analysis to capture fragmented terms and frequencies from several LED firms' websites in Taiwan. The analysis established the existence and frequency of SCRU attributes. They converted qualitative social media data into quantitative data (i.e., quantitizing). They used a fuzzy Delphi method (FDM) and a grey Delphi method (GDM) to convert the qualitative data into quantitative data. They also obtained quantitative data from financial statements as well as daily operational information, which includes input and output of raw materials, production time, and number of defective units over the past decade (total 1,951,749 sets of data). They quantitatively transformed the data to a manageable scale. They used several different techniques (e.g., decision-making matrix, causal diagram) to aggregate the qualitative and quantitative findings. The process of data analysis is illustrated in Figure 9-1 (adapted from Wu et al., 2017). The results revealed that capacity and operations had greater influence than other supply-chain attributes did and that risks stemming from triggering events were difficult to diagnose and control.

In this example, although the researchers performed a quantitizing technique, qualitative and quantitative data remain as distinct datasets. The aggregated entropy weights (i.e., the results of the quantitized) and quantitative transformations were then incorporated into the decision-making matrix. Subsequently, a causal diagram was generated and compared with the initial expert judgments gathered in the early stage of the study.

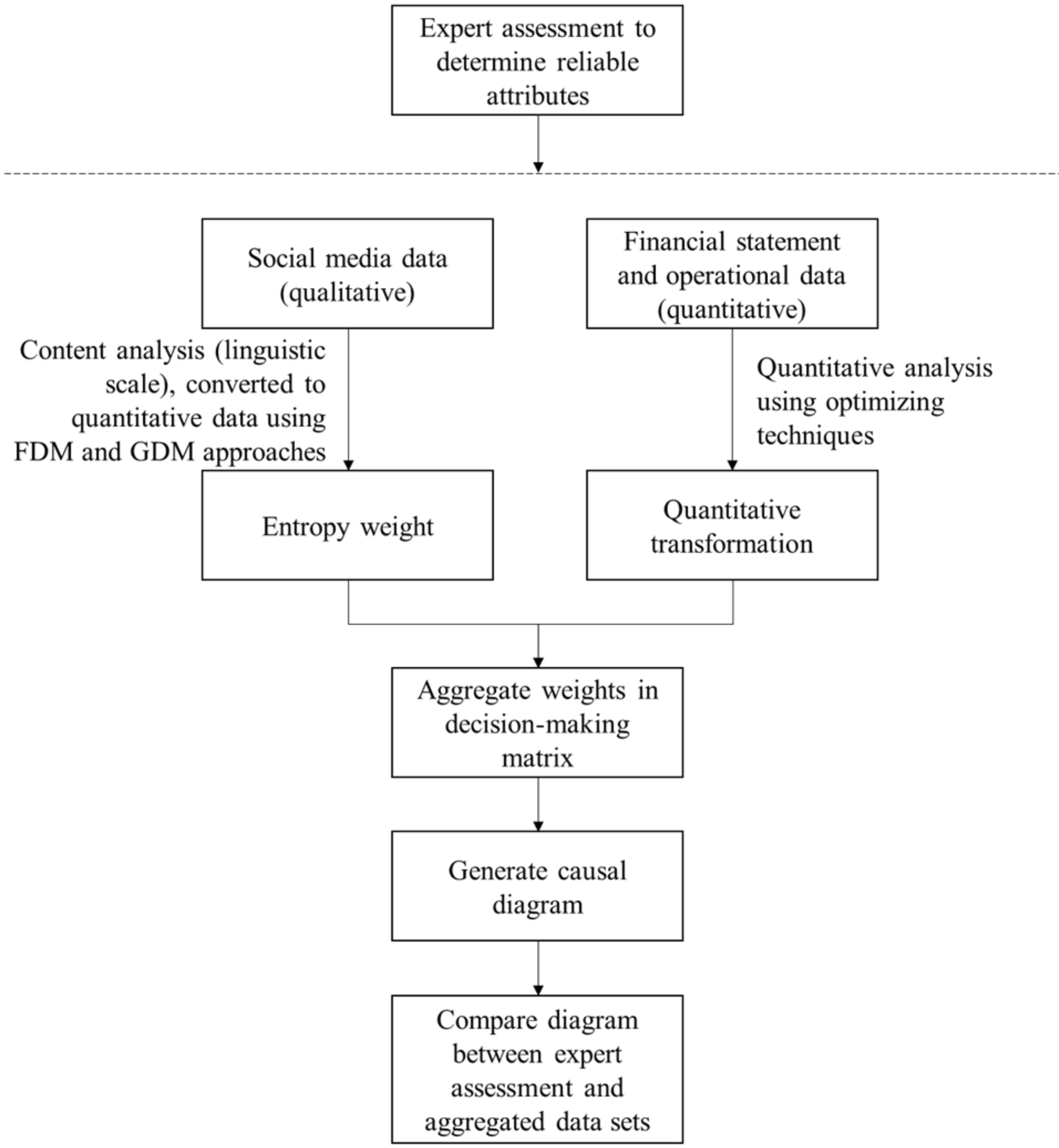

Figure 9-1. Big Data Acquisitions and Transformations

9.1.2. Analytics Research Using Monostrand Conversion Designs

Another popular mixed-methods design in analytics research is a *monostrand conversion design* (i.e., a single strand study in which research questions are answered through an analysis of transformed data, see Chapter 5 for details). In this design, qualitative and quantitative datasets are merged using computational techniques (e.g., qualitative coding is transformed into numerical values for various statistical analyses, such as frequency counts and measures of association) (O'Halloran et al., 2018). One popular quantitizing technique is text mining or text analytics. The schema of preprocessing text before performing text mining is illustrated in Figure 9-2 (adapted from Jo, 2019). Researchers first index a text into a list of words. This step is needed for encoding text into a structured form. The list of nouns, verbs, and adjectives is usually the output of text indexing. The output of text indexing is used in the second step—text encoding (i.e., "the process of mapping texts into numerical vectors" (Jo, 2019, p. 57). A list of words that is generated from the previous step is given a collection of feature candidates or dimensions, values are assigned to selected features, and a numerical vector is constructed as the representation of text. This step occurs when text is converted into numbers using different techniques, such as the wrapper approach (i.e., schema where dimensions are added or deleted) and principal component analysis (i.e., dimension reduction scheme where the covariance matrix is made from the input vectors where all feature candidates are used, and Eigen values are computed to reduce the number of dimensions). Next, researchers can use text association techniques. Text association refers to "the process of extracting association rules as the if-then template from word sets or text sets" (p. 59). Association rules are extracted from word sets or text sets using an association algorithm, such as A priori algorithm. The results from executing the text association are used for displaying the directional relationships among blocks of text (e.g., A → B → C).

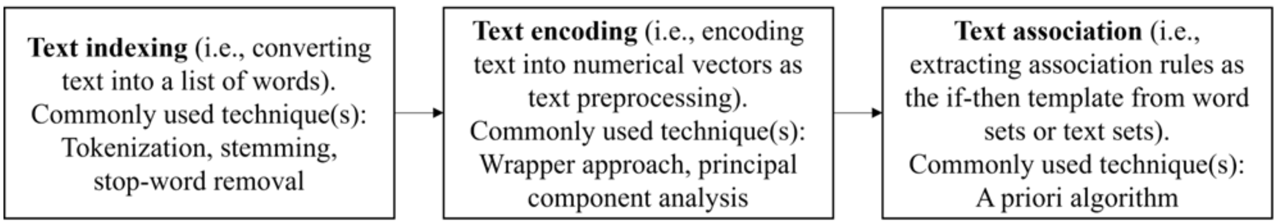

Figure 9-2. Text Indexing and Encoding Process for Text Analytics

Text categorization is one way to perform text mining (Jo, 2019). Text categorization also involves transforming text data into numerical data (i.e., quantitizing). It is the process of assigning one or some of the pre-defined categories to each text through three steps: (1) preliminary task; (2) learning; and (3) classification (see Figure 9-3). First, researchers should pre-define a list or a tree of categories as the frame for classifying data items. In most cases, prior theories are needed as a foundation for creating a pre-defined list or categories. Once the predefined list is established and the decision of which classification or machine learning algorithm is selected, sample text is allocated to each category. All sample text is indexed into a list of words that are called feature candidates. During the learning process, the classification capacity that is given as one of various forms, such as equations, symbolic rules, or optimized parameters, is constructed. After the learning process, text data, separated from the sample text, are classified. Depending on the classification performance, researchers then decide whether the classification algorithm is appropriate.

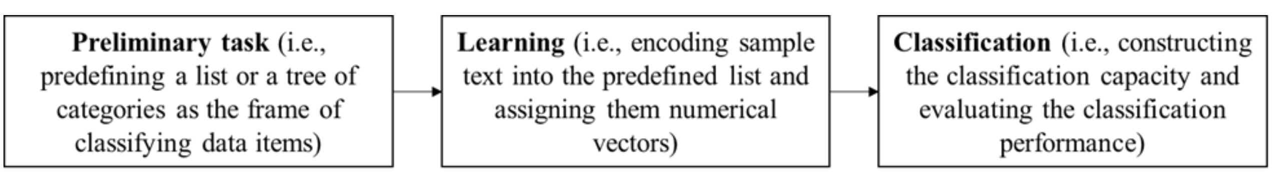

Figure 9-3. Text Categorizing Process for Text Analytics

An example of an analytics study that adopts a monostrand conversion design is Zhou et al. (2018). They investigated the impact of online customer reviews on customer agility and product performance. The purposes of their mixed-methods research were completeness and complementarity. They collected data on the mobile game apps segment from the U.S. Apple app store. They measured product performance based on app sales ranking and review volume as the total number of online customer reviews available. To measure customer agility, they obtained online review data from 2.4 million unique customers that contain rich data including product details and review details. They developed a singular value decomposition-based semantic keyword similarity method to quantify customer agility using large-scale customer review text and product release notes (i.e., quantitized). They first performed standard text data preprocessing on customer reviews and product release notes. They then represented each text document with a bag of words (i.e., nouns, verbs, and adjectives), extracted a keyword list using the standard TF-IDF scheme (i.e., a statistical measure that evaluates how relevant a word is to a document in a collection of documents), and used the list to construct a keyword-by-keyword matrix with each cell containing the Salton Cosine Similarity between the two corresponding keywords. They used the SDV technique to reduce the keyword dimensionality. The process of calculating customer agility, drawing from Zhou et al. (2018), is presented in Figure 9-4. Finally, they regressed review volume and product performance on customer agility. They found that review volume had a curvilinear relationship with customer agility and customer agility had a curvilinear relationship with product performance.

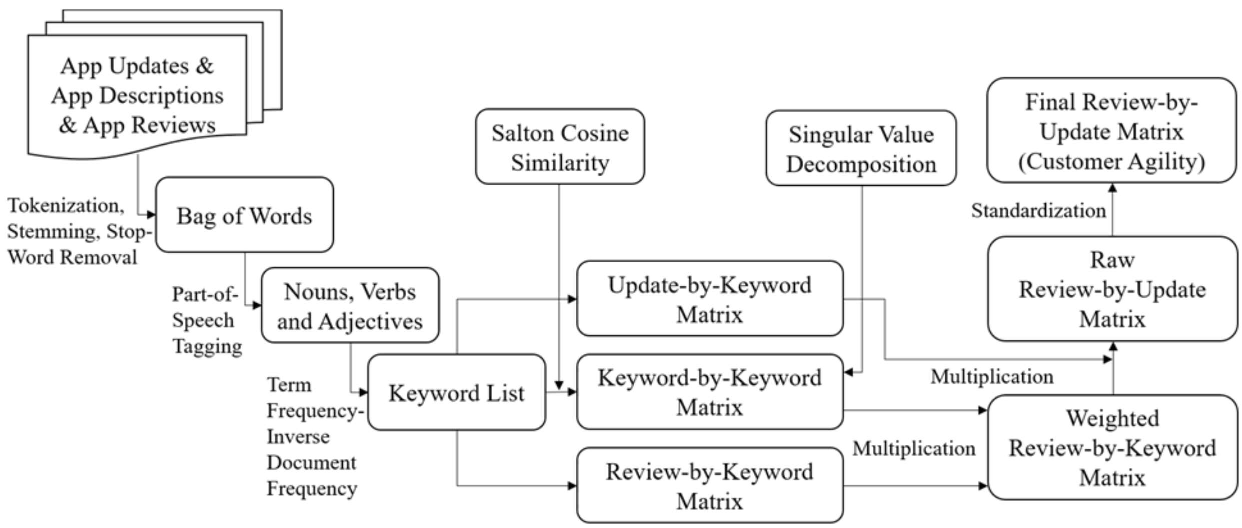

Figure 9-4. Process of Calculating Customer Agility

In this example, customer agility was computed by transforming the qualitative data into numerical values. Mixing the qualitative and quantitative strands took place at all stages, with the qualitative data being quantitized. The quantitized data were then analyzed using only one type of method—in this case, quantitative analysis).

9.1.3. Using Visualization in Analytics Research with Mixed-Methods Designs

Visualization is a popular technique to bring qualitative and quantitative data together visually to discuss the integrated analysis and garner insights (O'Halloran et al., 2018). It is effective not only to present essential information in vast amounts of data, but also to aid complex analyses (Keim et al., 2013). Although big data visualization may not be substantially different from traditional small data visualization, big data visualization in mixed-methods research focus on visual analytics—"a combination of 'automated analysis techniques with interactive visualization for an effective understanding, reasoning and decision making on the basis of very large and complex datasets'" (Tay et al., 2018, p. 664). For example, visual analytics can show statistics-by-themes and side-by-side comparisons, and connect research findings to theoretical frameworks and recommendations (Guetterman et al., 2015; O'Halloran et al., 2018).

To visualize the findings of quantitative and qualitative research strands in analytics research, researchers need to visually deal with a massive number of data points. There are methods for reducing data points, dimensions, and clutter in order to produce better visual information. These methods include the *aggregation* or *simplification* of data, *data subset* (i.e., selecting only a portion of relevant data rather than the entire dataset), *jittering* (i.e., "a method to add random noise to the data samples so that points are not plotted at a specific location"), and *data binning* (i.e., "a technique for data visualization of grouping a dataset of *N* values into fewer than *N* discrete groups") (Tay et al., 2018, p. 666).

Researchers also need to recognize various attributes in their visual presentations. Because a large number of data points and different types of data will often need to be presented together (e.g., text and numeric data), researchers first need to carefully select their visualization types (e.g., comparing categories, assessing hierarchies, showing changes over time, plotting connection and relationship, and mapping geospatial data) (Tay et al., 2018). Each visualization type has its own characteristics that can help researchers best translate their data into visual elements. Researchers can use various types of visual presentations, depending on: (1) the analysis goal; (2) interaction (i.e., level of details to be shown); (3) user (i.e., level of users' visual literacy); (4) dimensionality (i.e., number of variables researchers wish to visualize); (5) cardinality; and (6) data type (i.e., types of data to be analyzed) (Golfarelli & Rizzi, 2020). Table 9-2, adapted from Golfarelli and Rizzi (2020), lists different types of visualization from which users can select, depending on these six dimensions.

Table 9-2. Different Types of Visualization

Dimension	Description	Example
Goal		
Composition	Highlight a distinct part of data as a part of a complete dataset	Stacked column chart
Order	Analyze objects by emphasizing their order	Alphabetical list of names
Relationship	Analyze the correlation between two or more objects or variables	Point graph
Comparison	Examine two or more objects or variables to establish their similarities or dissimilarities	Column chart
Cluster	Emphasize data grouping	Dendrogram
Distribution	Analyze how objects are dispersed in space	Histogram
Trend	Examine a general tendency of data variables	Line graph
Geospatial	Analyze data values using a geographic map	Choropleth map
Interaction		
Overview	Display an overview of the entire dataset	Dendrogram
Zoom	Focus on items of interest	Network map
Filter	Quickly focus on a particular item category by ignoring unwanted items	Area chart

Dimension	Description	Example
Details-on-demand	Select an item and get its details	Choropleth map
User		
Lay	Computer-literates who may have trouble in understanding complex visualization	Line graph
Tech	Skilled users with a deeper understanding of analytics	Tree map
Dimensionality		
One-dimensional	A single numerical value or a string	Gauge
Two-dimensional	One dependent variable as a function of one independent variable	Single line graph
n-dimensional	Each data object is a point in an n-dimensional space	Bubble graph
Tree	A collection of items, each having a link to one parent item	Dendrogram
Graph	A collection of items, each linked to an arbitrary number of other items	Network map
Cardinality		
Low	From a few items to a few dozen items	Pie chart
High	Dozen items or more	Heat map
Independent/Dependent Type		
Nominal	Qualitative, each data variable is assigned to one category	Pie chart
Ordinal	Qualitative, categories can be sorted	Column chart
Interval	Quantitative, supports the determination of equality of intervals	Line graph
Ratio	Quantitative, a unique and non-arbitrary zero point	Point graph

Visualization is generally used in tandem with other analytics approaches. For example, O'Halloran et al. (2018) proposed a digital mixed-methods design by integrating data transformation and visualization. This technique involves: *qualitative analysis* → *transformation to quantitative data* → *data mining (quantitative analysis)* → *visualization* → *qualitative exploration.*

Using this design path, qualitative analyses of text, images, and other types of non-numeric data can be transformed into quantitative data using digital tools (e.g., multimodal annotation software). These quantitized results are analyzed using machine-learning techniques. After that, the findings are visualized to help qualitative interpretations and explanations of large datasets. Qualitative and quantitative strands are integrated in relation to the design of the study, the method, interpretation, and reporting (O'Halloran et al., 2018).

To illustrate the use of visualization in mixed-methods research, we use the study reported in Dong et al. (2018). This study qualifies as mixed-methods research because it used both qualitative and quantitative data (i.e., concurrent mixed-methods design). Drawing on systemic functional linguistics (SFL) theory, Dong et al. (2018) proposed a framework that taps into unstructured data from financial social media platforms to assess the risk of corporate fraud. They employed a dimension reduction technique (principal component analysis) for the TF-IDF feature selection. They used support vector machine (SVM) for document classification. For comparison purposes, they also implemented logistic regression (LR), neural networks (NN), and decision tree (DT). They used accuracy, recall, F1 score, and the area under the receiver operating characteristic (ROC) curve (AUC) to evaluate the quality of trained classifiers. They used a web crawling technique to gather financial social media data on the SeekingAlpha platform. They also gathered the financial ratios and text content of the MD&A section from the annual financial statements of the firm. They used the Stanford CoreNLP toolkit to analyze the social media content. Their framework automatically extracted signals, such as sentiment features, emotion features, topic features, lexical features, and social network features, that were then fed into machine learning classifiers for fraud detection. Using the SVM model with the best performance, they investigated each set of social media features independently. They used a line graph to visualize these models (see Figure 9-5). They were able to compare different signals and display the comparisons using the graph. As can be seen in Figure 9-5, reproduced from Dong et al. (2018, p. 475), they found that topic features were most predictive of fraud.

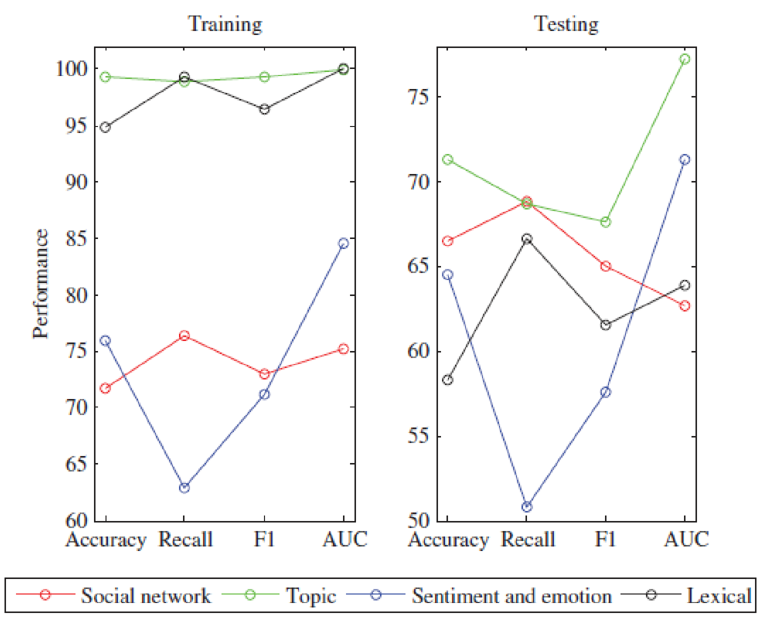

Figure 9-5. Performance of Classification Using Each Set of Social Media Features

Visualization is not only important in presenting data, but also valuable in exploring and analyzing data. The particular strength of visualizations lies in their ability to trigger cognitive responses that are difficult to obtain by other means (Molina et al., 2014). Using visualization in mixed-methods research can transform a researcher from being a passive transmitter of knowledge, who collects and analyzes data, to an active researcher who co-constructs knowledge with participants via visualization (Onwuegbuzie & Dickinson, 2008). This is particularly true for analytics research that deals with big data.

9.2. Building Theory in Analytics Research Using a Mixed-Methods Approach

Although one can use mixed-methods research to test and build theory, when it is applied to analytics research, researchers have a greater opportunity to build theory using large-scale datasets (i.e., data-driven research approach). A mixed-methods approach to analytics research not only allows researchers to observe psychological and behavior elements that could not be observed using conventional quantitative methods, such as a survey, but also enable them to include unconscious behaviors and emotional states of customers or users into the analysis that can hardly be observed using qualitative methods, such as interviews (Kar & Dwivedi, 2020). Findings from analytics techniques, such as natural language processing, can be used to uncover factors or constructs that may be further used for theoretical model development (Kar & Dwivedi, 2020). When researchers employ mixed-methods research in the context of analytics work, they not only report what they observe in the data, but also are tasked to uncover relationships that are hidden in large-scale datasets by analyzing and interpreting data from a pragmatic perspective (O'Halloran et al., 2019). Consequently, a mixed-methods approach in analytics research offers important knowledge and insights that a single method cannot offer.

We propose a framework (see Figure 9-6) to use a mixed-methods approach in analytics research to build theory. First, researchers need to begin with research questions. As we discussed in earlier chapters, research questions should drive the selection of the research method. Although research questions can come from a gap in the literature and conflicts in results in the literature (Creswell & Creswell, 2018), it is common for analytics research to start from data (data-driven) (Maass et al., 2018). Data-driven research uses exploratory approaches to analyze big data to extract scientifically interesting insights (Kitchin, 2014; Maass et al., 2018). Researchers can also combine theory-driven and data-driven approaches to strengthen the outcomes of mixed-methods research. If researchers do not consider domain theory in their analytics research, they can skip the theory step and directly determine the purpose of mixed-methods research (see Chapter 4).

Next, researchers should decide whether they will adopt a mixed-methods monostrand design or multistrand design and determine their mixed-methods research designs (e.g., concurrent or sequential; equal-status or dominant-less dominant status design). After collecting large volumes of data, it may be necessary for researchers to undertake data cleaning based on their research questions and transform the data (say by quantitizing). For example, large volumes of text can be summarized into closely grouped themes (Kar & Dwivedi, 2020). Researchers then move to the validation and data analysis stage. If researchers adopt a mixed-methods multistrand design, they need to state clearly when the mixing takes place (e.g., at the analysis stage and at the inferential stage).

We refer to the integration of findings and meta-inference stage as the theory development block (see Chapter 10 for a discussion of meta-inferences). During this stage, researchers are encouraged to use visualization to draw their theoretical model if they use a data-driven approach. Correlations and patterns that researchers extracted from the analysis of large datasets can yield insights into empirically interesting phenomena, rather than predictions based on prior theory (Maass et al., 2018). Building a cohesive body of knowledge about phenomena should be traced back to an existing theory, when possible, even if the results may not fit the theory. Therefore, the outcomes of analytics research can extend and refine an existing theory or even generate a new theory.

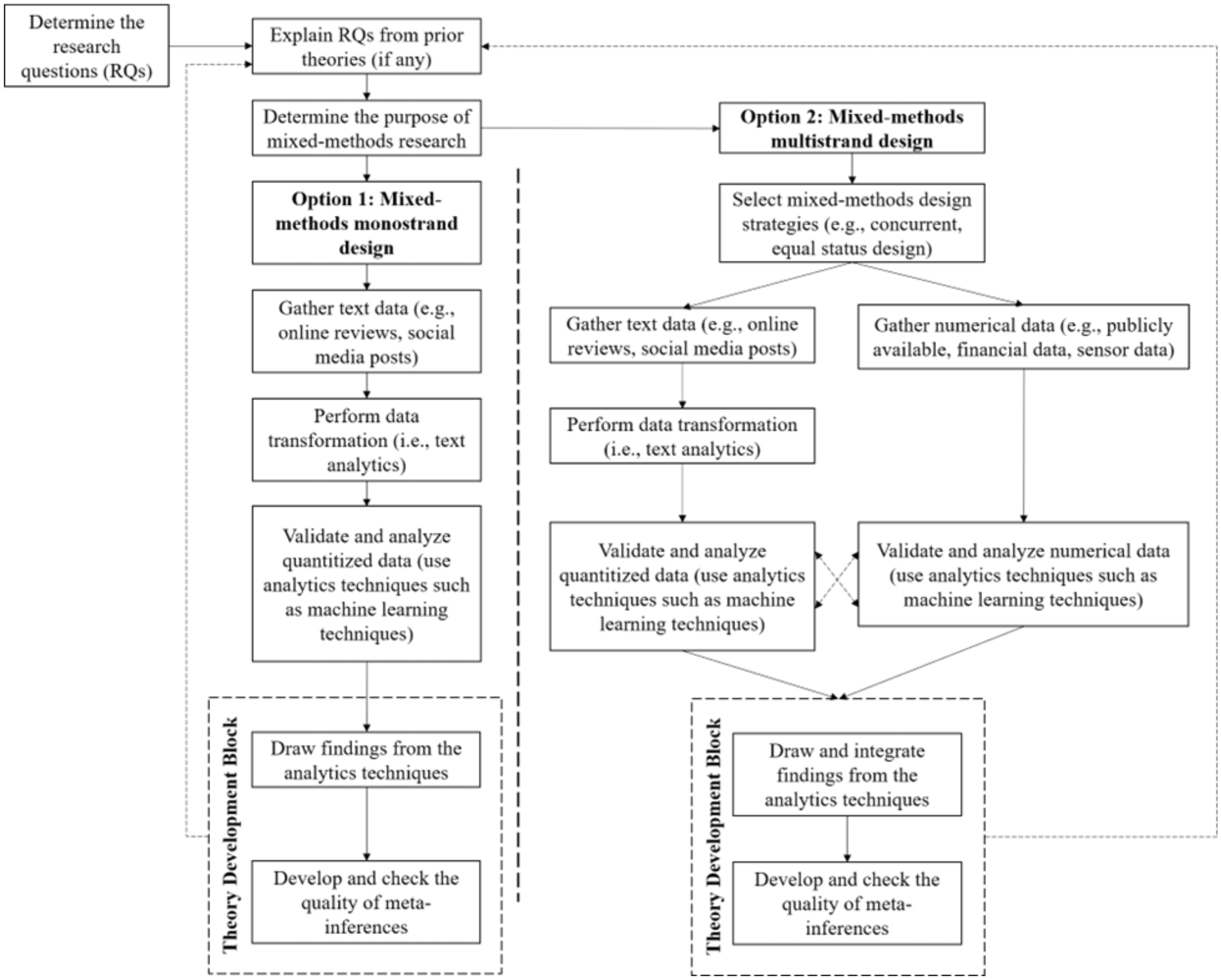

Figure 9-6. Building Theory Using a Mixed-Methods Approach in Analytics Research

Summary

- Big data describes data that are generated from an increasing plurality of sources including Internet clicks, mobile transactions, user-generated content, and social media as well as purposefully generated content through sensor networks or business transactions, such as sales queries and purchase transactions.
- Big data analytics refers to scalable techniques, such as text analytics and web analytics, that enable researchers to process and analyze big data (e.g., digital records and activities from websites and social media including users' online activities and online conversations). Big data analytics include general analytical techniques, text analytics, web analytics, network analytics, and mobile analytics.
- A wide variety of data (e.g., text-based data and numerical data) with high volumes (large-scale data), high velocity (high-speed data), and with a high level of veracity offers a new practice for mixed-methods research. New digital approaches to mixed-methods research include: (1) the use of both text-based data and numerical data; (2) one type of data is analyzed and transformed into another type of data (i.e., *quantitized*—qualitative data are transformed into quantitative data; *qualitized*—quantitative data are transformed into qualitative data); and (3) the use of visualization for analysis of large-scale data.

- Four basic ideas and techniques for big data visualization that mixed-methods researchers can use are: (1) understanding different ways of processing data; (2) visually dealing with a massive number of data points; (3) recognizing attributes in visual presentation; and (4) identifying key features of interactivity and real-time visualization.
- Mixed-methods research provides opportunities for researchers to integrate data-driven and theory-driven approaches to research. Correlations and patterns that researchers extract from the analysis of large datasets can yield insights on empirically interesting phenomena that can be used to refine an existing theory or even generate a new theory.

Exercises

1. Assume your work/research group is tasked with initiating a research project on big data using a mixed-methods approach. Define your research questions and your mixed-methods designs. Based on your research questions, put together a plan on how you would gather and then analyze data. Use Table 9-1 as your guide—you are, of course, not limited to the example techniques listed in that table.
2. Select a mixed-methods research article in your field (or a related field) that utilized big data. What technique did the authors use to gather and analyze their data? Did they state their mixed-methods purpose and design clearly? If not, identify their mixed-methods purpose and design. Explain how the authors answered the research questions using mixed-methods research.
3. Explain the role of visualization in analytics research using mixed-methods designs. Select two or more analytics articles in your field or a related field that used a mixed-methods research approach and explain how the authors used visualization to communicate information/insights about their data.

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CHAPTER 10

GENERATING META-INFERENCES IN MIXED-METHODS RESEARCH

After researchers analyze their qualitative and quantitative data, the next step is to develop meta-inferences. Inferences made on the basis of the results from each strand are synthesized to generate meta-inferences, typically at the end of the study (Teddlie & Tashakkori, 2006). Thus, meta-inferences denote “an integrative view of findings from qualitative and quantitative strands of mixed-methods research” (Venkatesh et al., 2016, p. 436).

A critical aspect of developing meta-inferences includes keeping one’s research questions in the foreground because, at the very basic level, inferences are answers to research questions (Teddlie & Tashakkori, 2010). Researchers need to examine each set of data analysis outcomes separately and evaluate how effectively they answer the relevant research question(s). After each research question is answered, researchers should then compare and contrast the answers to different questions and assess conceptual variations and similarities among them (Teddlie & Tashakkori, 2010). Meta-inferences, therefore, denote a coherent conceptual framework that provides answers to research questions in mixed-methods research (Creswell, 2010).

Researchers generally develop meta-inferences through a different analysis pathway that depends on their mixed-methods design strategies. The three most common pathways are: (1) researchers merge the qualitative and quantitative findings to develop meta-inferences (i.e., merging of qualitative and quantitative inferences → meta-inferences); (2) researchers first develop quantitative inferences, followed by qualitative inferences; meta-inferences are then created based on the qualitative inferences that have been developed by integrating the quantitative inferences (quantitative inferences → qualitative inferences → meta-inferences); and (3) researchers first develop qualitative inferences, followed by quantitative inferences; meta-inferences are then created based on the quantitative inferences that have been developed by integrating the qualitative inferences (qualitative inferences → quantitative inferences → meta-inferences) (Venkatesh et al., 2013). Regardless of the researchers’ paradigmatic stance and purposes of their mixed-methods research, we recommend researchers use the first pathway if they use a concurrent mixed-methods design and the second or third pathways if they use a sequential mixed-methods design..

10.1. Theoretical Reasoning Techniques of Generating Meta-Inferences

Given that meta-inferences are essentially theoretical statements about a phenomenon, including its interrelated components and boundary conditions, the process of developing meta-inferences is conceptually similar to the process of developing theories from observations. The observations here are the findings from the qualitative and quantitative strands (Venkatesh et al., 2013). Beyond induction, theoretical reasoning techniques, such as deduction, the combination of induction and deduction, and abduction, can be used to develop meta-inferences (Venkatesh et al., 2016).

Induction, deduction, and abduction can be distinguished from each other in two important ways: the generality of the explanations they propose and the certainty of knowledge claims they produce (Behfar & Okhuysen, 2018). The differences among these three methods of generating meta-inferences are summarized in Table 10-1 (adapted from Behfar & Okhuysen, 2018).

Table 10-1. Differences Among Induction, Deduction, and Abduction

Type of Reasoning	Relationship between Observation and Theory	Outcome: Strength of the Assertion	Evaluation Criteria for Knowledge Claim
Inductive	Moving from specific cases or observations to general explanation	*Probable knowledge claim* that the hypothesized relationship is consequential and reliable	Does the general observation account for the specific cases? Can the relationships observed in specific incidents generalize to other contexts or relationships?
Deductive	Moving from general explanation to specific prediction	*Certain knowledge claim* that the pattern is predictable or the phenomenon reliably occurs	Was the premise validated? Can the prediction be replicated?
Abductive	Moving from specific observations to particular explanation	*Plausible knowledge claim* for resolving the empirical anomaly	Does the explanation cohere into a testable hypothesis? Does the explanation identify new variables or relationships? Does the explanation carefully document the anomaly?

10.1.1. Inductive Theoretical Reasoning

Inductive reasoning refers to reasoning from a particular observation to a general perspective (Johnson & Gray, 2010). It involves generalizing a theory supported in a specific setting to another context as the theory evolves (Tashakkori & Teddlie, 1998). Inductive reasoning is a theory-building process, starting with observations of specific instances, and seeking to establish generalizations about the phenomenon under investigation (Hyde, 2000). It broadens the meaning of a concept as the phenomenon and individuals under study are embedded in a larger social context (Polsa, 2013). More generally, induction is involved in a range of cognitive activities, such as categorization, probability judgment, analogical reasoning, scientific inference, and decision making (Hayes et al., 2010).

An inductive argument is one in which the premise provides some, but not complete, evidence for the conclusion (Miller, 2003). Toulmin's (2003) work on practical reasoning provides a useful conceptual basis in explaining the process of drawing a theoretical claim using an inductive approach (Ketokivi & Mantere, 2010) (see Figure 10-1). In Toulmin's terminology, grounds constitute the premises of argument (e.g., data, observations, practical premises); claims can be theoretical interpretations or empirical and theoretical generalizations. Grounds and claims appear throughout scientific texts. Finally, warrants—"the practical standards or canons of argument" (Toulmin, 2003, p. 91)—provide the justification for bridging grounds to claims (Ketokivi & Mantere, 2010).

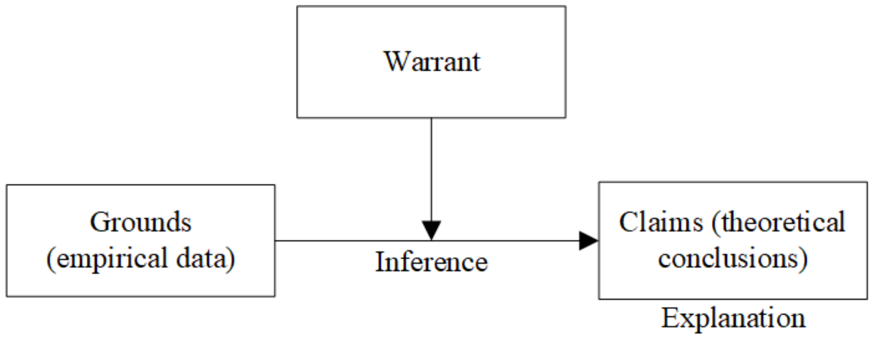

Figure 10-1. Inductive Theoretical Reasoning

Toulmin's framework emphasizes the important distinction between inference and explanation. Glaser (1992) also underscores the importance of separating inference from explanation: what the researcher finds interesting must not interfere with the interpretation of data. Whereas grounds are empirical data, claims are theoretical conclusions. We can think of claims as explanations. Inference, in turn, is the mechanism that bridges the grounds with the claims and warrants are "the essence of inference" (Ketokivi & Mantere, 2010, p. 317). Therefore, induction makes knowledge claims where "it is improbable that the premises be true and the conclusion false" (Hurley, 2000, p. 33; see also Behfar & Okhuysen, 2018, p. 325).

One of the advantages of an inductive approach is its capability to uncover previously unknown aspects of a phenomenon under study (Polsa, 2013). However, inferences generated using an inductive approach often lack the solid normative foundation of deduction and thus are "methodologically incomplete" (Ketokivi & Mantere, 2010, p. 317). Inductive conclusions contain knowledge claims not analytically implied by premises and researchers are only able to observe particular events, not generalities (Ketokivi & Mantere, 2010). Hume (1969, p. 139) underscores this problem of induction by arguing that "*there is nothing in any object, consider'd in itself, which can afford us a reason for drawing a conclusion beyond it;* and, *that even after the observation of the frequent or constant conjunction of objects, we have no reason to draw any inference concerning any object beyond those of which we have had experience*."

Inductive reasoning can be used in both qualitative and quantitative research. For example, Follmer et al. (2018) conducted a qualitative study to investigate how people respond to person-environment misfit in an organization. Based on interviews with eighty-one individuals, they identified three broad responses to the experience of misfit: resolution, relief, and resignation. In this example, the authors established generalizations from a specific sample to a broad, general population. Researchers can also use inductive reasoning in quantitative research. For example, one can use supervised machine learning (ML) methods to discover robust patterns in quantitative data. The patterns identified by ML could be used for exploratory inductive or for post-hoc analysis of regression results to detect patterns that may have gone unnoticed (Choudhury et al., 2021).

The applicability of an inductive approach in both qualitative and quantitative research makes it a suitable inference-generation tool in mixed-methods research. Developing meta-inferences using inductive theoretical reasoning enables researchers to propose theoretical relationships that are both argumentatively plausible and statistically likely (Creswell & Plano Clark, 2018).

10.1.1.1. Applying Inductive Theoretical Reasoning to Draw Meta-Inferences

Klingebiel and Joseph (2016) examined how firms made decisions about the timing of innovations, focusing on the mobile handset industry during the feature-phone era. They conducted a mixed-methods study by conducting interviews with managers at handset manufacturing firms and using quantitative data from secondary sources about their firms' feature entries. They gave equal importance to qualitative and quantitative data, and their objective was to build theory. In developing their meta-inferences, they followed the first analysis pathway (merging of qualitative and quantitative inferences → meta-inferences). They drew their meta-inferences using inductive theoretical reasoning. They developed qualitative and quantitative inferences simultaneously. Meta-inferences were then developed based on the integration of the qualitative and quantitative inferences. Following Toulmin's framework, the authors differentiated inferences (i.e., conclusions based on evidence and reasoning) from explanations (i.e., authors' interpretations of the conclusion). An example of qualitative inferences in their study was "managers at early-mover firms deliberately compensate [for] the commercial uncertainty associated with launching early" (p. 1010), and an example of quantitative inferences was "early movers launch significantly (0.1% level) more features than late movers" (p. 1011). Based on these two inferences, they developed their meta-inference: "collectively, these findings lend support to interviewees' suggestions of greater breadth for early movers" (p. 1011).

In this example, Klingebiel and Joseph (2016) started with grounds (empirical data), then established generalizations about the phenomenon being investigated. In both qualitative and quantitative strands of the research, they employed inductive theoretical reasoning. Based on their meta-inferences, they then made a broader theoretical claim: "Firms with different entry-timing positions deliberately follow different investment strategies: early movers aim for larger, more uncertain returns, while late movers aim for smaller, more certain returns" (p. 1010). They also considered a number of alternative explanations to defend their claim. One was that firms with low capabilities (i.e., firms in the narrow-late cluster) may be constrained by the frequency and speed of feature launch. They argued that this was not the case, however. Their respondents confirmed that most firms could access the base technologies underlying each feature because patents were held not by rivals but by supplier (see p. 1012 for details). A second alternative explanation was from an ecological perspective. They argued that one might suspect specialists to enter earlier into areas close to their core through phones, with advanced technologies catering to their niche's user needs, whereas a generalist might follow only if the new technology shows a propensity to become integrated into mainstream handsets. They argued that this alternative explanation is more likely a conservative bias for breadth-timing nexus because early specialists are unlikely to have broad feature lineups. Their analysis showed that variation in the market orientation variable did not explain heterogeneity in entry timing. They refuted possible alternative explanations by revisiting their results and drew inferences inductively from their datasets. Through the analyses of qualitative and quantitative data and the adoption of inductive theoretical reasoning, they built a theory that demonstrated how firms deliberately self-select into moving early or late.

10.1.2. Deductive Theoretical Reasoning

Deductive reasoning is a theory-testing approach that seeks to test whether the theory applies to specific instances (Hayes et al., 2010; see also Sarker & Lee, 2002). Inferences generated using deductive reasoning are viewed, at least by some, to be stronger than inductive reasoning because by testing a priori hypothesis, "it is impossible for the premises to be true and the conclusion false" (Hurley, 2000, p. 33; see also Behfar & Okhuysen, 2018, p. 325). Whereas inductive reasoning offers a probable explanation, deductive reasoning offers a certain explanation (Behfar & Okhuysen, 2018).

We illustrate drawing inferences using deductive theoretical reasoning in Figure 10-2. In deductive reasoning, researchers start with an abstract, general relationship among concepts based on a theory and then move toward concrete empirical evidence (Neuman, 1997). Thus, in deductive reasoning, there is a well-established role for existing theory because it informs the development of hypotheses and the selection of variables. After researchers develop the hypotheses, they should empirically test them and derive the claims or results based on the empirical evidence. Inference in deductive theoretical reasoning is the mechanism that bridges the theory with empirical evidence. If the theory produces acceptable predictions of the unknown (e.g., correct signs of regression coefficients), the theory is deemed empirically adequate (Ketokivi & Mantere, 2010).

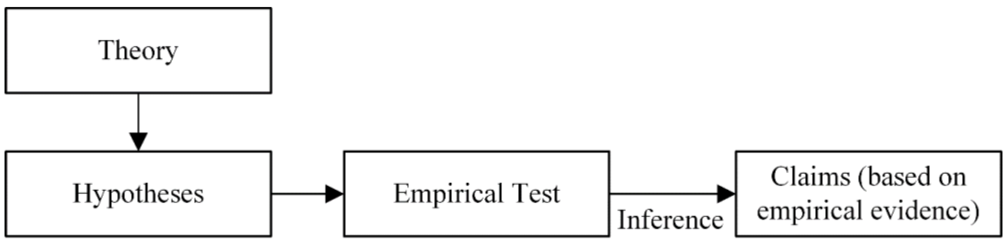

Figure 10-2. Deductive Theoretical Reasoning Processes

The advantage of a deductive approach is that it uses an existing theory and presumes [universal] applicability across contexts. A theory guides the study purposefully in an empirical setting (Polsa, 2013). However, the drawback of this approach is that it is self-evident—its lack of flexibility in addressing and adapting to empirical circumstances does not provide selection criteria for choosing among alternative explanations (Ketokivi & Mantere, 2010; Polsa, 2013).

Deductive theoretical reasoning is commonly used in quantitative research. For example, Chen et al. (2015) drew on dynamic capabilities theory to conceptualize the use of big data analytics as an enterprise dynamic capability that brings competitive advantage to organizations. Using a quantitative survey technique, they tested their model and found support for the theory—an enterprise dynamic capability (i.e., in this case, BDA usage) affects organizational value creation.

Deductive theoretical reasoning can also be used in qualitative research. Patton (2002, p. 253) stated that when conducting qualitative research, "the evaluator may be open to whatever emerges from the data, a discovery or inductive approach. Then, as the inquiry reveals patterns and major dimensions of interest, the evaluator will begin to focus on verifying and elucidating what appears to be emerging—a more deductive approach to data collection and analysis." Theory testing by pattern matching is an example of the use of deductive theoretical reasoning in qualitative research (Campbell, 1975; Sarker & Lee, 2002). At the beginning of the study, a primary theory and at least one competing theory are put forward for testing. The main theory is expressed as a pattern of independent outcomes that are predicted to occur. Researchers then gather case data and compare it to the predictions of the theory and of the counter-theory. Support is demonstrated for the theory if the case data match the predicted pattern of outcomes of theory more closely than they match the predicted pattern of outcomes for the counter-theory (Hyde, 2000). For example, Mikalef et al. (2021) conducted a multiple-case study approach to examine the role of big data analytics in the formation of dynamic capabilities. Drawing on dynamic capabilities theory, they compared the case study data to the predictions of the theory. They found that different combinations of organizational inertia (e.g., economic, political, socio-technical) may hinder the formation of dynamic capabilities, which according to the theory, is built upon three organizational processes: sensing, seizing, and transforming. This example thus demonstrates the applicability of deduction in qualitative research.

10.1.2.1. Applying Deductive Theoretical Reasoning in Mixed-Methods Research

Researchers can apply deductive reasoning when developing their meta-inferences if their goal is to demonstrate how the findings are strongly tied to theories. For example, drawing on expectation-confirmation theory, Bhattacherjee and Premkumar (2004) conducted three studies using a mixed-methods approach to demonstrate how users' beliefs and attitudes changed during the course of their IT usage. Their first and second studies, which were conducted using a quantitative survey, examined the influence of pre-usage beliefs and attitudes on post-usage beliefs and attitudes as well as intention in the end-user training contexts (i.e., rapid application development (RAD) and computer-based training (CBT) contexts). Overall, their quantitative findings support the predictions of expectation-confirmation theory. Two of their many quantitative inferences were "usefulness at time t_2 was explained by disconfirmation beliefs at t_2 and usefulness at time t_1" and "the attitude variance at time t2 was explained by satisfaction at t_2 . . . usefulness at time t_2 . . ., and attitude at t_1" (p. 241). These inferences are theory-driven, generated using a deductive approach.

After analyzing the data from the quantitative studies, they conducted a content analysis of CBT users' qualitative responses to a set of open-ended questions on what they liked or disliked about using CBT, whether their initial expectations from CBT usage were met, and whether they intended to use it again in the future. The qualitative data were content-analyzed into general themes representing the main constructs. In this analysis, expectation-confirmation theory was the main theory driving the qualitative inferences. One of the qualitative inferences was "disconfirmation [influences] later-stage usefulness perceptions and intentions" (p. 247). Although they did not explicitly generate and report their meta-inferences, they used deductive theoretical reasoning to draw their final conclusions (e.g., "IT users' usefulness (the most salient belief driving IT usage) and attitude perceptions tend to fluctuate with time"; p. 249).

10.1.3. Combination of Inductive and Deductive Theoretical Reasoning

Although researchers can adopt either inductive or deductive theoretical reasoning to develop their meta-inferences, we recommend that they use both types of theoretical reasoning (Miller, 2003; Tashakkori & Teddlie, 1998; Venkatesh et al., 2016). A balance of induction and deduction in developing meta-inferences allows researchers to defend both their inference and explanation (derived using an inductive approach) with empirical testing. Similarly, when deductive theoretical reasoning limits researchers from justifying their findings using alternative theoretical explanations, inductive theoretical reasoning may help researchers generate theoretical insights.

10.1.3.1. Applying Both Inductive and Deductive Theoretical Reasoning in Mixed-Methods Research

Califf et al. (2020) conducted a mixed-methods research study to conceptualize a holistic technostress process that included positive and negative components of technostress embedded in two subprocesses: the techno-eustress subprocess and the techno-distress subprocess. The purpose of their mixed-methods research was developmental, and the design was sequential less-dominant qualitative followed by a dominant quantitative investigation. They addressed three research questions: (1) "what are the salient factors that determine technostress in healthcare?" (qualitative research question); (2) "what are the outcomes of the salient factors that determine technostress in healthcare?" (quantitative research question); and (3) "are the factors identified in the qualitative study supported by the results of the quantitative study?" (mixed-methods research question) (p. 849).

They started with a qualitative, interpretive case study involving interviews of 32 nurses. Based on the findings from the case study, the authors built a research model that operationalized the concepts embedded in the holistic technostress model. They then empirically validated the model by analyzing survey data collected from 402 nurses employed in the U.S. Whereas they derived their qualitative inferences using an inductive approach, they used a deductive approach to derive their quantitative inferences. They used the first analysis pathway to derive their meta-inferences (qualitative inferences → quantitative inferences → meta-inferences). One of their many qualitative inferences was "the appraisal of characteristics of HealthTech [are] related to promoting job performance, tasks, and skills" (p. 855). Given the results of their quantitative data analyses were consistent with the qualitative analysis, their quantitative inference regarding the appraisal characteristics was the same as their qualitative inference. Based on both types of inferences, they generated their meta-inferences as follows: "characteristics of the technology that are related to promoting task accomplishment and/or personal development will lead to positive psychological states" and "when nurses view the technology as conducive to completing one's work tasks, they experience positive emotions" (p. 855).

10.1.4. Abductive Theoretical Reasoning

Abductive theoretical reasoning, or *inference to the best explanation*, is "a form of inference that goes from data describing something to a hypothesis that best explains or accounts for the data" (Josephson & Josephson, 1996, p. 5). It was proposed by Charles Peirce to indicate a form of reasoning that moves from observations in a specific situation, information source, or data set to an explanation that accounts for those particular observations (Anderson, 1986; Behfar & Okhuysen, 2018). Abductive theoretical reasoning follows a distinctive rule—for example: (1) D is a collection of data (facts, observations); (2) H explains D (H would, if true, explain D); (3) no other alternative explanations can explain D as well as H does; (4) therefore, H is probably true (Josephson & Josephson, 1996, p. 5). The core idea is that a body of data provides evidence for a hypothesis that satisfactorily explains or accounts for that data (Josephson & Josephson, 1996). Thus, an abductive approach is a kind of theory-forming or interpretive inference. It contributes to the advancement of science by allowing for discovery through the exploration of data to produce plausible explanations (Behfar & Okhuysen, 2018).

Abductive reasoning allows researchers to make a logical connection between data and theory, and is often used for theorizing about surprising events (Teddlie & Tashakkori, 2009). This connection effectively makes inference and theoretical explanation integral parts of abduction

(Ketokivi & Mantere, 2010; Lipton, 2004). As explained earlier, induction emphasizes the distinction between inferences and explanations (see Figure 10-1). Inferences are the mechanisms that bridge empirical data and theoretical explanations, whereas theoretical explanations are an author's interpretations or empirical and theoretical generalizations. According to abductive reasoning, researchers have the authority to select the *best explanation* among the competing explanations, and the criteria for being the best explanation are defined by pragmatic virtues (e.g., interestingness, usefulness, simplicity), not by truth value or even empirical adequacy; inferences and theoretical explanations are seen as integral parts of a single process in abduction (Ketokivi & Mantere, 2010).

The main strength of abduction is that "it is a candid description of how empirical scientists in practice make choices in their reasoning" (Ketokivi & Mantere, 2010, p. 319). Abductive reasoning leads to plausible knowledge claims that are untested, held tentatively, and subject to continuous revision (Behfar & Okhuysen, 2018). Whereas deduction supports its conclusions in such a way that the conclusions must be true, given true premises (i.e., they convey conclusive evidence), abduction produces *fallible inferences*—i.e., researchers consider all possible explanations from the data and then choose one explanation after ruling out other alternative explanations (Josephson & Josephson, 1996). Abduction also produces *ampliative inference*—i.e., at the end of abduction, having accepted the best explanation, researchers may have more information than they had before (Josephson & Josephson, 1996). Unlike inductive reasoning, abduction does not rely solely on empirical data to move from the specific to the more general, and unlike deductive reasoning, theoretical premises do not guarantee the results (Coreynen et al., 2020). Taken together, abduction overcomes some problems associated with induction, which only allows researchers to observe particular events, not generalities. Abduction also addresses some problems associated with deduction, which do not provide researchers with an understanding of how they choose among alternative explanations (Ketokivi & Mantere, 2010). Therefore, abductive theoretical reasoning is a suitable approach to draw meta-inferences in mixed-methods research.

10.1.4.1. Applying Abductive Theoretical Reasoning in Mixed-Methods Research

Huré et al. (2017) conducted a mixed-methods study to investigate omni-channel shopping value (SV). The authors addressed two research questions: (1) "how can omni-channel shopping value be modeled?"; and (2) "how can omni-channel shopping value be accurately measured?" (p. 314). They first conducted a quantitative study to test the appropriateness of their research model, which suggested that offline SV, online SV, and mobile SV influenced omni-channel SV. Some of their quantitative inferences are: (1) the hedonic dimension contributed positively and significantly to offline, online, and mobile SV; (2) the social dimension contributed positively and significantly to the online and offline SV; (3) the joint utilitarian and social dimension contributed positively and significantly to the mobile SV; (4) the utilitarian dimension contributed positively and significantly to the online SV . . . [whereas] this relationship was not significant in the mobile and offline channels; and (5) online and offline SV had significant effects on omni-channel SV, but mobile SV had a negative, albeit nonsignificant, effect on omni-channel SV.

They then conducted a qualitative study (semi-structured interviews) to understand the findings of the quantitative study (e.g., mobile SV had a negative and nonsignificant effect on omni-channel SV). They adopted an abductive theoretical reasoning approach to draw inferences. Consistent with an inductive method, they approached their data with an open mindset, putting aside existing knowledge during the qualitative data collection and analysis. Prior knowledge was used in the second step to discuss the emergent codes and better understand the dimensions of the omni-channel SV. One of their many qualitative inferences was "omni-channel SV as stemming from the SV derived from different patronized touch points [online, offline, and mobile]; the latter themselves are formed by SV sub-dimensions—utilitarian, hedonic, and/or social" (p. 320). This inference was consistent with their quantitative inferences. The abductive approach was particularly useful in providing "the best explanation" to understand why their quantitative study showed a negative, nonsignificant path between the mobile SV and the omni-channel SV. They noted that "the lack of usability of smartphones together with the specialized usages of mobile touch points could explain that even though the mobile SV is identified, the latter was not observed to contribute to the global SV" (p. 322). An abductive approach was effective in this case to solve a practical problem and resolve an anomaly (Tashakkori & Teddlie, 1998).

10.2. Convergence, Complementarity, and Divergence in Meta-Inferences

Findings from mixed-methods research have three possible patterns: *convergence*, *complementarity*, and *divergence* (Erzberger & Kelle, 2003; Venkatesh et al., 2016). If the qualitative and quantitative inferences are consistent, or converge, then meta-inferences strengthen the initial theoretical assumptions (Erzberger & Kelle, 2003). If qualitative and quantitative inferences complement each other, then meta-inferences provide a more complete picture of the empirical domain under study (Venkatesh et al., 2016). If inferences are contradictory, researchers need to resolve the divergent findings to further understand the phenomenon under study. Conflicting evidence between qualitative and quantitative findings and resolving the same are a key value of conducting mixed-methods research.

There are several strategies that can be used to deal with divergent findings: (1) an appraisal of the quality of components of mixed-methods research (i.e., checking for methodological mistakes); (2) reanalyzing existing data and revisiting theoretical assumptions; and (3) collecting and analyzing additional data when needed (Moffatt et al., 2006; Pluye et al., 2009). Divergent findings (i.e., qualitative and quantitative inferences contradict each other) could be because researchers made methodological mistakes at the initial stage of the study or the initial theoretical assumptions are not relevant for the study context (Venkatesh et al., 2016). If the divergent findings are due to methodological mistakes, researchers must engage in a re-examination to determine what issues caused such divergent findings (da Costa & Remedios, 2014; Venkatesh et al., 2016).

If, however, the divergence between qualitative and quantitative inferences can be interpreted in a sense-making plausible manner, researchers should reanalyze the existing data and revisit their theoretical assumptions (Pluye et al., 2009). For example, in investigating the antecedents of technostress in the context of HIT, one of the qualitative inferences of Califf et al. (2020) was "the appraisal of the environmental conditions associated with end-user support activities focused on responsiveness and benevolence will engender positive psychological responses" (p. 855). Their quantitative data analysis led to a contradictory inference: "technical support was found to reduce one's positive psychological response" (p. 855). To find the best possible explanation for this finding, the authors revisited the qualitative data. Their re-examination of the qualitative data led to the following best explanation: "healthcare workers specialize in a domain different from that of technology workers, and, as our qualitative data highlights, believe that patient care is their primary job/responsibility. Owing to significant communication gaps between nurses and technical support (due to different domain expertise), nurses may feel that calling a help desk takes time away from patient care, leads to more frustrating exchanges, and in turn lower their positive psychological responses." (p. 855). In this example, the process of drawing inferences using abduction produced plausible explanations that could be subjected to additional induction and deduction (Behfar & Okhuysen, 2018).

Researchers can also ask new research questions, collect, and analyze new data to further examine conflicting findings (Pluye et al., 2009). By way of illustration, Moffatt et al. (2006), as cited by Pluye et al. (2009), evaluated the impact of welfare rights advice on health and social outcomes among a population aged 60 and over. Separate analyses of the qualitative data (n = 14) and quantitative data (n = 126) revealed divergent findings. Whereas the qualitative findings suggested the relationship was significant, quantitative findings indicated no significant relationship between welfare rights advice and health and social outcomes. These divergent findings led them to collect additional quantitative and qualitative data. They also collected a limited amount of qualitative data on the perceived impact of resources from all participants who had received additional resources. The qualitative and quantitative follow-up data verified the initial findings of each study, suggesting that the positive relationship extended beyond the 14 participants in the initial qualitative study to all those receiving additional resources. They also examined whether the outcomes of the qualitative and quantitative components matched, and they discovered that the outcomes that emerged in the qualitative study contained a number of dimensions not measured in the quantitative study. In this example, the divergent findings led the authors to collect additional data and make further comparisons that led to richer insights both about the research design and about the phenomenon.

Venkatesh et al. (2013) suggest two approaches to develop meta-inferences when qualitative and quantitative inferences are contradictory. First, researchers may use a *bracketing* approach. Bracketing is "the process of incorporating a diverse and/or opposing view of the phenomenon of interest" (p. 39). Bracketing is appropriate when qualitative and quantitative findings are irreconcilable and suggest extreme results—e.g., best-case and worst-case scenarios (Pluye et al., 2009). This approach is consistent with the notion of exploration and exploitation of breakdowns in which empirical findings cannot easily be explained by available theories. The process of a breakdown, along with the abductive reasoning approach, can help researchers resolve the empirical puzzle or anomaly, leading to high-quality meta-inferences. Researchers should use a bracketing approach if their design is a concurrent mixed-methods research design, as bracketing allows a side-by-side, simultaneous comparison of qualitative and quantitative findings.

Second, researchers can use a *bridging* approach—"the process of developing a consensus between qualitative and quantitative findings" (Venkatesh et al., 2013, p. 39). This approach helps researchers understand transitions and other boundary conditions related to their research model and context, and it can be used in any type of mixed-methods design with either deductive, inductive, or abductive theoretical reasoning. Considering the divergent findings of Califf et al. (2020), discussed earlier, they used bridging to develop their meta-inferences. After they reexamined their qualitative data and generated the best possible explanation for their findings, they bridged the gap and developed a meta-inference based on an integration of the divergent findings. Their meta-inference was "healthcare workers who do not perceive end-user support as related to proper and helpful support activities will experience a lowered positive psychological response" (p. 855). This meta-inference acknowledges contradictory or confirmatory elements of findings and leads to a new understanding of the phenomenon under study.

Summary

- The overarching goal of developing meta-inferences is to develop in-depth theoretical understanding that a single study cannot offer.
- The three most common pathways to develop meta-inferences are: (1) merging of qualitative and quantitative inferences → meta-inferences; (2) quantitative inferences → qualitative inferences → meta-inferences; and (3) qualitative inferences → quantitative inferences → meta-inferences.
- The existing theoretical reasoning techniques, including induction, deduction, the combination of induction and deduction, and abduction, can be used to develop meta-inferences.
- Findings from mixed-methods research have three possible patterns: *convergence*, *complementarity*, and *divergence.*
- Three strategies that can be used to deal with divergent findings: (1) an appraisal of the quality of components of mixed-methods research (i.e., checking for methodological mistakes); (2) reanalyzing existing data and revisiting theoretical assumptions; and/or (3) collecting and analyzing additional data.
- Two approaches to developing meta-inferences when qualitative and quantitative inferences are contradictory are bracketing and bridging.

Exercises

1. Select an article in your field that used a mixed-methods research approach. Discuss how the authors developed their qualitative and quantitative inferences. Which theoretical reasoning approach did the authors use?
2. Using the same article, answer the following questions:
   a. Did the authors report meta-inferences in their study? If so, what were they?
   b. If they did not, can you generate a meta-inference from the qualitative and quantitative findings reported in the article?
   c. Did the authors report any divergent findings? If so, how did they deal with such findings?

Note: You can also use other articles in your field or related fields that discuss various types of meta-inferences and use different approaches to generating meta-inferences, as discussed in this chapter, to answer the above two questions.

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CHAPTER 11

MIXED-METHODS RESEARCH PAPER TEMPLATES

Despite the growing interest in mixed-methods research, the issue of how researchers should report their findings in papers, especially for journal submission and subsequent publication, has not been properly addressed (Creswell & Tashakkori, 2007). Once researchers have conducted research using a mixed-methods approach and developed their meta-inferences, the challenge is to effectively communicate the results to the audience. Although there are some guidelines on disseminating mixed-methods research results, including Bryman (2015), Creswell (2015), Creswell and Tashakkori (2007), and Teddlie and Tashakkori (2009), these guidelines do not provide templates on how to organize and structure a paper that uses a mixed-methods approach.

This chapter provides mixed-methods research paper templates that can be used to organize and structure a paper that uses a mixed-methods approach. We first discuss the construction of a mixed-methods paper in six sections: introduction, literature review or theory development, methods, results, discussion, and conclusions—although some variations in the structure of an empirical mixed-methods paper exist depending on its purpose and designs. The sections (including subsections) need not be written in the order in which they are discussed. For example, researchers can go back and forth between the results and discussion sections, or they can combine the data analysis and results sections when necessary. We then present different strategies for structuring a mixed-methods paper to ensure the *purpose* of mixed-methods research is reflected throughout the paper and importantly, drives the structure. General guidance on writing an empirical journal article is available through numerous other sources including chapter 4 in Venkatesh (2021).

11.1. Overview of the Sections of a Mixed-Methods Paper

Here, we describe each of the sections of a mixed-methods paper, with ties to a traditional empirical paper and an emphasis on the unique elements of a mixed-methods paper.

11.1.1. Introduction

A distinguishing feature in the introduction section of a mixed-methods paper is that the authors provide a rationale for the methodological importance (Fetters & Freshwater, 2015). The introduction section generally establishes the need for the research and the appropriateness of mixed-methods research. It must consist of at least four aspects of the study: (1) the topic; (2) research problems (i.e., practical gaps as well as theoretical gaps); (3) research questions; and (4) the purpose of mixed-methods research. As with all research, it is necessary to establish the *relevance* and *importance* of the topic being studied in the introduction section. This includes identifying the problem that needs to be addressed using mixed-methods research and discussing the importance of solutions to this problem (Creswell, 2015). After introducing the topic, researchers should create *a clear picture of the problem or issue* that needs to be addressed using mixed-methods research (Creswell, 2015).

Next, the specific problem is narrowed further into *the questions of the study* (Dahlberg et al., 2010). In writing these research questions, researchers can adopt several different approaches: (1) write separate quantitative and qualitative research questions; (2) write separate quantitative and qualitative research questions, followed by a mixed-methods research question; and (3) write only a mixed-methods research question that reflects the procedures or the content of the study (see Chapter 4 for details). Researchers should order these research questions to reflect the type of mixed-methods design used in the study. After researchers formulate the research questions, they should specifically identify *the purpose of the mixed-methods research*. Identifying the purpose will also help researchers refine their research questions, if necessary (Onwuegbuzie & Leech, 2006). Based on this purpose, the claim for *contributions to theory and practice* should be articulated and expanded later in the discussion section.

Although the structure of the introduction section is the same for different purposes of mixed-methods research, the characteristics of the phenomenon being studied under each purpose can be quite different, and these characteristics should be made clear when researchers identify their research questions. For example, the aspects of the phenomenon being studied with complementarity as the purpose are different, indicating that the qualitative and quantitative strands should be used to examine overlapping aspects of a phenomenon or different aspects of the same phenomenon (Greene et al., 1989). In contrast, a mixed-methods study with a completeness purpose is characterized by the use of qualitative and quantitative methods to investigate two distinct but related aspects of a phenomenon. The characteristics of the phenomenon examined in a mixed-methods study with an expansion purpose is similar to the completeness purpose. The difference is, with an expansion purpose, one uses qualitative and quantitative methods to investigate two somewhat unrelated aspects of a phenomenon (Greene et al., 1989). The goal is to expand or extend our understanding of a phenomenon using different methods. The other mixed-methods purposes (i.e., compensation, corroboration, diversity, and developmental) are often characterized by the use of qualitative and quantitative methods to investigate the same aspects of a phenomenon in different strands of the mixed-methods study. Regardless, the purpose(s) should be clearly reflected in the introduction section.

11.1.2. Literature Review/Theory Development

In this section, researchers should be explicit about their *worldview* (paradigm) and how it informs their mixed-methods research project (Creswell, 2015). The explanation of worldviews or paradigms should be clear on how the theory and rationale for the approach influences the selection of mixed-methods research designs (Dahlberg et al., 2010). The selection of worldviews depends on the researchers' familiarity with different philosophies and which one seems to resonate with their research project (Creswell, 2015). However, these worldviews or paradigms should not be the focus of the discussion in mixed-methods research. Research questions and purposes identified in the introduction section, not paradigms, should drive mixed-methods research.

As noted earlier in Chapter 3, similar to research in general with some additions/differences, if authors conduct theory-driven research and their study has an overall theoretical basis, such theory should be described in this section. However, if authors adopt a data-driven approach or an inductive technique (e.g., use big data analytics techniques to identify patterns that represent relationships among concepts), there might not be a strong theoretical basis for the questions being studied (Maass et al., 2018). Authors are still encouraged to present a relevant literature review that helps to explain what they seek to find in a study (Creswell & Creswell, 2018) and ground their mixed-methods work in the context of relevant prior research. However, significant emphasis on datasets, data analyses, and implications of the findings, rather than on theory development, is an acceptable practice in mixed-methods research with a data-driven approach.

As we discussed in Chapter 3, theory in mixed-methods research is used to explain, predict, generalize, and inform the research questions and hypotheses tested in a study. It is necessary to make theories and their assumptions explicit, describe them in detail, and suggest how they inform a particular phase of a mixed-methods study. If the theory (theories) used in the qualitative component of the study is (are) different from what is used in the quantitative component of the study, researchers should clearly describe and explain the role of each theory. Further, understanding and gaining mastery of the prior research including studies related to the phenomenon under investigation are crucial in making good inferences (Teddlie & Tashakkori, 2009). Regardless of the design approaches to mixed-methods research, a good mixed-methods paper should also include a comprehensive review of others' responses to similar questions about the same or similar phenomenon proposed for the investigation (Teddlie & Tashakkori, 2009).

It is common to provide a hypotheses development sub-section in a theory-testing paper. Each hypothesis should be stated and with sufficient argumentation to support it (Lindgreen et al., 2021). Hypotheses are, and should be, developed from theory. That is, theory is a precondition for deductive inferences. Hypotheses should be carefully developed because they lead to correct operationalization of constructs and choice of research methods (Lindgreen et al., 2021).

11.1.3. Research Methods

The structure of the methods section varies, depending on the purpose of mixed-methods research and consequent methods used. The other two major design elements that influence the structure of this section are *time orientation* (i.e., concurrent and sequential mixed-methods designs) and *status of mixed-methods research* (i.e., equal and dominant-less dominant status designs). We will discuss different structures of the methods section in the *Paper Templates Based on Purposes of Mixed-Methods Research* section of this chapter.

The method section should at least include *sampling design*, *data collection*, and *data analysis strategies* for the qualitative and quantitative strands of the study. A clear rationale for design decisions appropriate for the research project should be provided. In the data analysis subsection, authors should describe the steps they took to analyze data obtained through the data collection strategies. In analytics research, for example, data extraction techniques and algorithms used to analyze data should be explicitly explained. For mixed-methods research articles, explicitly discussing the link between qualitative and quantitative data analysis approaches is particularly important, as it will help establish the strategies for developing meta-inferences at the end of the study (Dahlberg et al., 2010). If researchers use a monostrand design (e.g., transforming qualitative data into quantitative data), they should describe the approach they used to transform the data, and describe how and why such an approach is necessary in the context of their study.

In the method section, authors should explain their mixed-methods research design in detail. A good rule of thumb to make the methods easy to follow is to describe them in the study phases as it happened (Fetters & Freshwater, 2015). A general view regarding the method section, which is widely shared by various bodies including the *American Psychological Association* (APA), is that sufficient method details should be provided so that the research can be replicated. To communicate mixed-methods design to readers, it is helpful to present *a diagram of procedures* (i.e., a figure used to convey specific design details and procedures, including data collection and data analysis techniques) to help readers understand the design. Based on Creswell (2015), there are five essential parts of a diagram of procedures: (1) boxes that show the data collection and analysis for both quantitative and qualitative research; (2) a circle that shows the interpretation phase of a study; (3) procedures attached to both the data collection and analysis phases, shown as bullet points positioned alongside the boxes; (4) products that will result from each phase of data collection and analysis; and (5) arrows that show the sequence of procedures (Creswell, 2015; Ivankova et al., 2006). Using specific shapes (i.e., boxes, circles, and arrows) to convey specific designs and procedures are a recommended practice in mixed-methods research (Creswell, 2015).

Consider, for example, a team of researchers that sets out to understand the mechanisms by which (positive) online reviews influence online purchase decisions. After conducting an initial literature review, they discover that existing theories are insufficient to explain such mechanisms and conclude that a mixed-methods approach is needed to uncover different aspects of customers' online reviews. The purpose of mixed-methods research is complementarity. Here, the qualitative research question is: how do customers use online reviews to determine which product to buy? The researchers decide to collect customer review data of 300 selected products from Amazon. To gain better insights, they also transform the qualitative data into numerical data (i.e., quantitizing) and use the transformed data to examine how online reviews are associated with numbers of purchase transactions for products included in their sample.

In order to understand whether a secondary source of reviews will have an impact on customers' final purchase decisions, the researchers conduct a quantitative study. Specifically, they conduct a 2x2 laboratory experiment by manipulating the number of information sources (one vs. two information sources) and the degree of consistency of the review content across sources (consistent vs. inconsistent conditions). Participants in the two information source conditions are asked to make a purchase decision after they are presented with the first information source. Then, they are presented with the second information source that could be either consistent or inconsistent with the reviews from the first information source. Then, they are asked whether they want to modify their purchase decision. The quantitative research question is: will the presence of competing reviews influence customers' initial purchase decision?

Given the quantitative strand of the study is not dependent on the qualitative strand, they decide to conduct the experiment when they are collecting their qualitative data using a data mining technique (i.e., a concurrent mixed-methods design). After the experiment, they analyze the data quantitatively by performing various statistical analyses. They then merge the findings and explain how the findings from the quantitative strand provide additional insights beyond the findings from the qualitative strand of the study.

The diagram of procedures for this illustrative study is presented in Figure 11-1. The two research strands in this illustration assess similar but different aspects of customer reviews. The qualitative study only focuses on the effect of online reviews from one information source on customers' purchase decisions, whereas the quantitative study assesses different sources of online reviews. One variation within this complementarity purpose is the use of a different type of method to gain additional insights beyond the findings from one method (Venkatesh et al., 2013), which can be characterized with the analogy of "peeling the layers of an onion" (Greene et al., 1989, p. 258). In this diagram of procedures, in addition to displaying qualitative and quantitative data analysis procedures, we convey the mixed-methods data analysis procedures (i.e., using side-by-side comparison, data transformation, and joint display). Such a figure design will be particularly helpful for readers to understand the mixed-methods research.

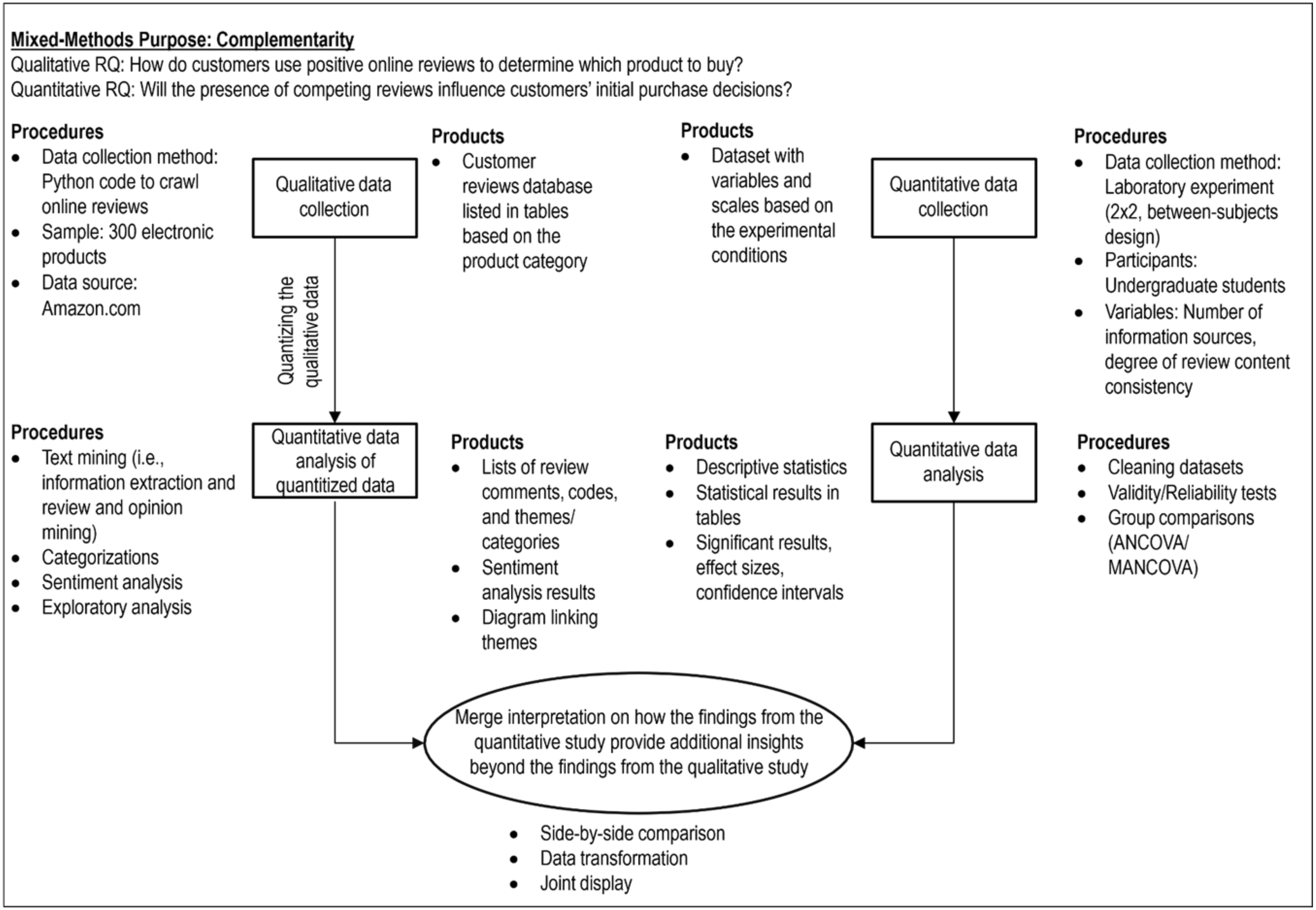

Figure 11-1. A Diagram of Procedure for an Illustrative Study with a Concurrent Mixed-Methods Design

11.1.4. Results

The methodology and results section should have parallel structures (Dahlberg et al., 2010). They share the responsibility for providing information that supports the reliability and validity of the substantive findings (Bem, 2003). The results section can be organized by adding several sub-sections that line up with the data analysis description outlined in the previous section (Dahlberg et al., 2010). Although the content may vary, depending on the type of method researchers use and how detailed the results description should be, this section should include at least *the sample characteristics* (e.g., demographics) and *findings of the qualitative and quantitative data analyses* (i.e., qualitative and quantitative results sections). Although separating the findings of the qualitative and qualitative data analyses is a common practice in mixed-methods research (Creswell & Plano Clark, 2018), integration should take place at one or multiple points over the course of the research process (Creswell, 2015). The qualitative and quantitative results sections help organize the findings, but one or both sections should include some mention of the other section, or comment on how findings from one strand of the study inform, enhance, refine, alter, or contradict the findings from the other strand of the study (Dahlberg et al., 2010), as discussed earlier, and will depend on the purpose of the mixed-methods research.

As discussed previously, integration can happen in several areas of the study: data collection (e.g., researchers collected both open- and closed-ended questions during the survey), data analysis (e.g., researchers quantified the qualitative data), and results. In a mixed-methods study with a corroboration or complementarity purpose, it is common for researchers to show the integration of findings in the results section. Specifically, researchers should bring together the results of the analyses of the quantitative and qualitative data and then compare them side-by-side. In contrast, in mixed-methods research with a compensation, developmental, or expansion purpose, we suggest researchers first present the results of the first strand of the study and use them to explain the results of the second strand of the study. In mixed-methods research with a completeness or diversity purpose, researchers should select their integration method based on their selected design (e.g., if they use a concurrent design, they may integrate their data in the data analysis stage, and then bring together and integrate the qualitative and quantitative findings in the results section).

Teddlie and Tashakkori (2009) suggested that researchers use visual representations (e.g., figures, diagrams) to simplify the complex interrelationships among variables or elements inherent in mixed-methods research. Visual representations can enhance the readability of the study for audiences not used to seeing complex data collection and analysis procedures and interrelated findings (Creswell, 2002). The use of visual representations also allows researchers to effectively communicate their results to practitioners (Teddlie & Tashakkori, 2009).

11.1.5. Discussion

Although the discussion section is a common, standard feature of every social sciences empirical paper (see Bem, 2003), there are additional sections/sub-sections to be included in a mixed-methods paper. In addition to the implications and limitations sections, a mixed-methods paper should include sections/sub-sections on the *qualitative inferences, quantitative inferences*, and especially *meta-inferences*. The qualitative and quantitative inferences can be either combined with the results section or reported separately. In either case, the inferences section should highlight the knowledge contribution of mixed-methods research. Inferences should be based on the findings reported in the results section and interpreted in the context of the research setting (Teddlie & Tashakkori, 2009). When developing inferences, researchers should explain how and why mixed-methods research was needed in order to achieve the initially conceptualized purpose (Dahlberg et al., 2010). It is important to establish the credibility of these inferences by making sure they meet the quality standards of qualitative and quantitative research (i.e., validity and reliability tests) (see Chapters 7 and 8 for details).

One of the most important aspects in mixed-methods research that differentiates it from other research papers is *meta-inferences* (see Chapter 10). In developing meta-inferences, researchers have to integrate the qualitative and quantitative inferences and establish the quality of meta-inferences by examining at least their design quality and interpretive rigor (see Chapter 8). These meta-inferences should provide answers to the research questions. If the qualitative and quantitative inferences are divergent, researchers should investigate the source of the inconsistency and reconcile the differences. Researchers can highlight the differences or similarities between their research outcomes and the past literature upon which they are built. Meta-inferences should advance theory development in the field by adding to the ongoing discussion in the literature on a topic or providing additional insights that have been overlooked or have not been acknowledged (Creswell & Tashakkori, 2007; Venkatesh et al., 2013).

Generally speaking, the majority of social sciences journals will seek both practical implications (i.e., research outcomes relevant to practice) and theoretical implications (i.e., how the findings contribute to theory development in the field) (Rosemann & Vessey, 2008; Whetten, 1989). The implications will differ greatly depending on the audience and stakeholders, and the problem researchers set up as the main context of the study (Dahlberg et al., 2010). These implications should be consistent with qualitative inferences, quantitative inferences, and meta-inferences developed previously.

Next, as Bem (2003) suggested, it is necessary to discuss possible shortcomings of the study. In addition to reporting a study's limitations, researchers should report threats that they encountered over the course of the research process and discuss how they overcome such threats. Remind readers of specific characteristics of the methods used and how the use of mixed-methods research might have strengthened the study's outcomes.

Last, the discussion section should present future research directions. Researchers can identify questions that remain unanswered and that have been raised by the study, along with suggestions for research endeavors that would help in answering them (Bem, 2003). Of course, researchers can also invite others to pick up where they left off (Dahlberg et al., 2010).

11.1.6. Conclusions

This section can begin by stating the most important findings of the work. Researchers should mention that they have achieved their main purpose of conducting mixed-methods research. Additionally, as with all conclusion sections, the golden nuggets (including key implications of the work) should be mentioned and, we might add, with no apologies.

11.2. Paper Templates Based on the Purposes of Mixed-Methods Research

In this section, we provide templates for structuring a mixed-methods research paper based on the purposes of mixed-methods research. As discussed in Chapter 4, there are seven possible purposes of mixed-methods research: (1) *compensation*; (2) *corroboration*; (3) *diversity*; (4) *developmental*; (5) *complementarity*; (6) *completeness*; and (7) *expansion*. We use these purposes, along with the time orientation and the priority of different strands of mixed-methods research, as the bases for presenting templates to structure and write a mixed-methods paper. This section is intended as a summary and overview—and the reader is referred back to the various earlier chapters to best think through the purpose and consequent design strategies.

Each outline we present here follows the shape of an hourglass (as discussed in Bem, 2003; Venkatesh, 2021). It begins with broad general statements, then progressively narrows down to the details of the study, then broadens out again to a more general discussion. To a certain extent, the major aspects of these templates are similar to a conventional social sciences paper. However, the order and some detailed aspects in each section are slightly different, depending on the mixed-methods research purpose and design. These suggested structures are not meant to constrain researchers, and other structures are indeed possible, and we encourage researchers to explore these possibilities.

Sections 11.2.1 through 11.2.7 present an overview of the templates for papers based on each of the seven mixed-methods purposes and the corresponding figures that present the details of the template are shown in Figures 11-2 through 11-8 (and for better pagination, these figures are shown after section 11.2.7).

11.2.1. Compensation Purpose

A mixed-methods study with a compensation purpose is generally conducted when the findings from the initial data collection have been compromised due to weaknesses associated with the method used. Thus, it is common for researchers to decide to conduct such a mixed-methods study after the initial study has been conducted. For this reason, our recommended template for this purpose is based on a sequential mixed-methods design. A suggested outline for mixed-methods research with this purpose is shown in Figure 11-2. Unlike a study with a corroboration purpose, which we discuss next, it is not necessary for a study with a compensation purpose to have an equal status design. If the design is a dominant-less dominant status design, the less dominant strand of the study typically only provides limited contributions to the overall study. Thus, the less dominant strand of the study typically contains errors or major weaknesses that can only be addressed by the dominant strand of the study. We suggest researchers present the results of the study based on the order of their data collection and data analyses procedures, and then present the integration of both types of data during the analysis stage. A table or figure to illustrate the comparison of results will be useful to help readers evaluate whether weaknesses associated with the first method have been properly compensated by the second method.

11.2.2. Corroboration Purpose

A suggested template for a mixed-methods study with a corroboration purpose is shown in Figure 11-3. Our recommended template for this purpose is to follow the logic of convergence embedded in the classic conceptualization of triangulation, as suggested by Greene et al. (1989). This requires the implementation of qualitative and quantitative methods to be different from one another with respect to their strengths and limitations, and both methods are used to understand the same phenomenon (Greene et al., 1989). The most effective way to achieve the corroboration goal is by implementing both qualitative and quantitative methods independently and simultaneously (Greene et al., 1989; Tashakkori & Teddlie, 2008). For this reason, one common way to structure the methods section is to report both the qualitative and quantitative methods sections—researchers can start with either the qualitative or quantitative method, but they should inform the readers that both the qualitative and quantitative strands of the study are conducted concurrently. Although a dominant-less dominant design is possible, we suggest that both strands of the study be weighted equally (i.e., equal status design) to ensure the strengths of both methods are optimized. When presenting the results of a mixed-methods study with a corroboration purpose, we recommend researchers use joint displays or side-by-side comparisons to help readers understand the source of the results. Researchers can then develop both qualitative and quantitative inferences based on the results. In general, the goal of the corroboration purpose is convergence. If the results are divergent, researchers will have to reconcile the inconsistency, as discussed in Chapter 10.

11.2.3. Diversity Purpose

Our suggested template for a mixed-methods research study with a diversity purpose is shown in Figure 11-4. Given the goal of a mixed-methods research project with a diversity purpose is to uncover divergent findings, we suggest the use of multiple theoretical frameworks to maximize the possibility of uncovering inconsistent findings. Researchers can use either a sequential or a concurrent mixed-methods design when they conduct such a study. If they use a sequential mixed-methods design, the order of the study depends on the design investigation strategy (i.e., a sequential qualitative-quantitative design or a sequential quantitative-qualitative design). For example, if a researcher’s goal is to develop a theory that provides a new explanation of the phenomenon under investigation, they can start with exploratory qualitative case studies, followed by explanatory surveys. Researchers can also elaborate the element of priority of methodological approach (i.e., equal status designs and dominant-less dominant status design). However, we recommend an equal status design to ensure both qualitative and quantitative data are emphasized equally when they are used to understand the phenomenon under investigation. Thus, stronger inferences and the balance in results can be achieved when inconsistency exists.

11.2.4. Developmental Purpose

In a mixed-methods research study with a developmental purpose, the results from one method are used to help develop or inform the other method (Greene et al., 1989). Thus, we recommend a template that is based on a sequential mixed-methods research design (see Figure 11-5). By definition, the first component of the study should be implemented first. We recommend a combination of the methods and results sections for each component of the study (i.e., qualitative study and quantitative study sections). The order of the components of the study depends on the design investigation strategies. If the investigation strategy is a sequential qualitative-quantitative design, then researchers should start with the qualitative sampling design, qualitative data collection, and qualitative data analysis procedures sub-sections (e.g., findings from the qualitative component of the study are used to develop survey items for the quantitative component of the study). In contrast, if the investigation strategy is a sequential quantitative-qualitative design, researchers should start with the quantitative sampling design, quantitative data collection, and quantitative data analysis procedures sub-sections (e.g., findings from the quantitative component of the study are used to determine the sampling strategy for the qualitative component of the study). The richness of the methods section also depends on the design status, with greater emphasis placed on the dominant strand of the study if the design is not equal. Researchers also need to be clear on how the results of the two components of the study are related. Thus, researchers should discuss the results of each strand of the study independently and then discuss where the merging takes place (i.e., *quantitative and qualitative results sections*). Although the discussion can be separate, we encourage researchers to integrate the qualitative and quantitative findings using figures or diagrams. Next, researchers should develop inferences for each strand of the study and establish the reliability and credibility of the qualitative and quantitative inferences (i.e., *quantitative and qualitative inferences sub-sections*) before they generate meta-inferences in the discussion section.

11.2.5. Complementarity Purpose

A suggested template for writing a mixed-methods research paper with a complementarity purpose is shown in Figure 11-6. As we discussed in Chapter 5, a concurrent design is the best approach for a mixed-methods study with a complementarity purpose because such a study aims to investigate different aspects of a phenomenon. Thus, the template we provide for a complementarity purpose is based on a concurrent design. The paper's structure could also be influenced by the priority of the two different strands. If researchers use an equal-status design, both the qualitative and quantitative strands of the study should be emphasized equally. In contrast, if researchers use a dominant-less dominant status design, they should place greater emphasis on the dominant strand of the study. In describing each strand of the study, researchers have to describe how participants are sampled, how data are collected, and how they are analyzed. It is also important to explain the rationale for selecting a particular sampling strategy (Collins et al., 2007; Onwuegbuzie & Collins, 2007). Researchers have to explain why they use a specific sampling strategy, how that sampling strategy is supported by theories, and how it is consistent with the purpose of the study (Dahlberg et al., 2010). After describing how the samples are identified/chosen, data collection methods should be explained in this section. Data collection can be categorized into different types of approaches and each approach has to be described in its own sub-section (Dahlberg et al., 2010). In the results section, researchers should summarize their data and report the findings of their analyses. They should address the quantitative, qualitative, and mixed-methods research questions by reporting the results of their main analyses. After researchers discuss their methods and results, they should, in the discussion section, generate their qualitative inferences, quantitative inferences, and meta-inferences. Meta-inferences should be linked back to the research questions in such a way that meta-inferences are the answers to the research questions. After that, researchers should provide their conclusions.

11.2.6. Completeness Purpose

A recommended structure of a mixed-methods research study with a completeness purpose is shown in Figure 11-7. Unlike a study with a complementarity purpose, the qualitative and quantitative components of a study with a completeness purpose cannot stand by themselves. A single method alone is especially insufficient to provide a complete picture of the phenomenon. For this reason, we recommend researchers integrate the qualitative and quantitative data in the data analysis sub-section. Both sequential and concurrent designs are possible. In mixed-methods sequential designs, one needs to complete the first strand of the study, generate inferences from the first strand of the study, and use them to inform the next strand of the study. In contrast, in mixed-methods concurrent designs, one needs to collect qualitative and quantitative data simultaneously and discuss the results of the integrated data analysis. Greater emphasis should be placed on the dominant strand of the study if the different strands are not equal. Meta-inferences developed from a study with a completeness purpose should provide a complete picture of the phenomenon (Tashakkori & Teddlie, 2008; Teddlie & Tashakkori, 2003). Thus, researchers should explain how different research strands help them answer their research questions.

11.2.7. Expansion Purpose

A mixed-methods paper with an expansion purpose can be structured based on a sequential design (Teddlie & Tashakkori, 2009). The aspects of the phenomenon investigated in the qualitative and quantitative strands of the study need to be distinct (Greene et al., 1989). Because the second strand of the study is implemented to expand the findings from the first strand of the study, we recommend researchers present the methods and results sections of the first strand of their study, and then use the inferences from the first strand of the study to formulate the research questions in the second strand of the study (see Figure 11-8). The order is determined by the nature of the investigation (i.e., a sequential qualitative-quantitative or a sequential quantitative-qualitative design). For each strand of the study, researchers should report the *sampling design strategy, data collection,* and *data analysis strategies,* with a greater emphasis given to the dominant strand of the study. Researchers can present the results section after the methods section of each strand of the study, followed by development of inferences and quality assessment of those inferences. Although the analyses of qualitative and quantitative data are usually kept separate in a study with an expansion purpose, a major challenge for researchers is to mix both methods to create meaningful meta-inferences (Greene et al., 1989). To address this issue, we recommend researchers collect both qualitative and quantitative data at multiple points during the study and simultaneously analyze them to gain rich insights into the phenomenon.

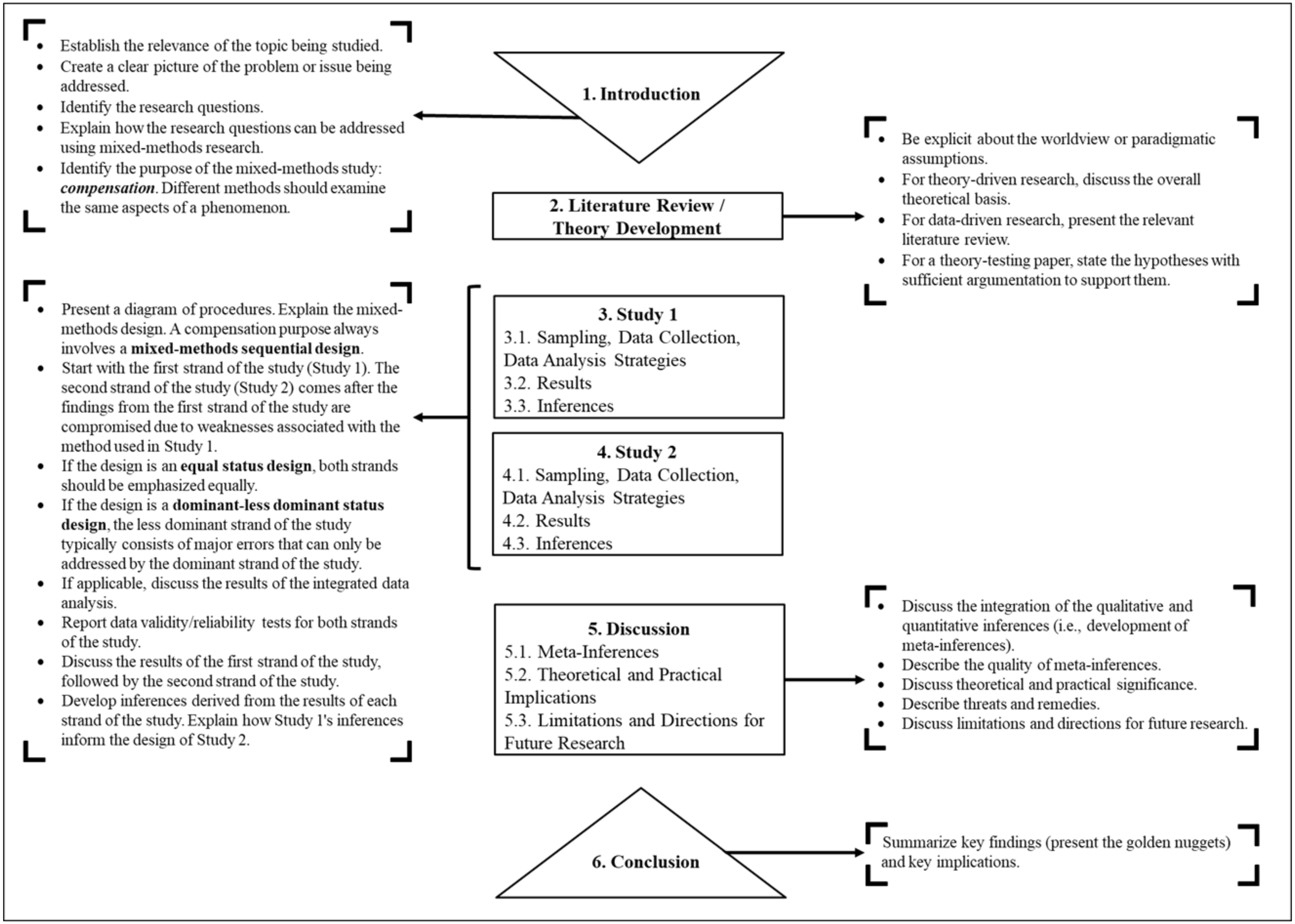

Figure 11-2. Paper Template for Mixed-Methods Research with a Compensation Purpose

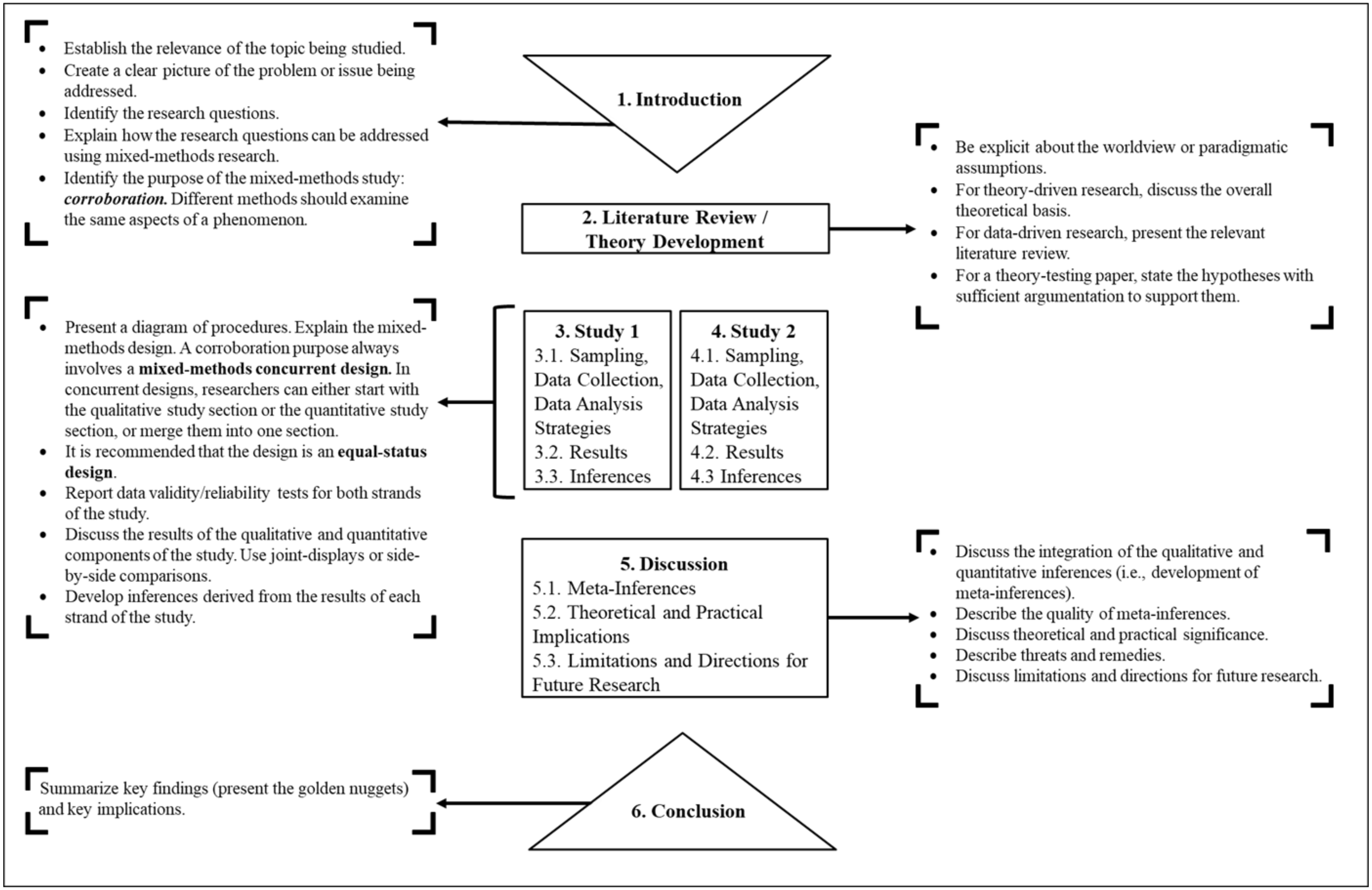

Figure 11-3. Paper Template for Mixed-Methods Research with a Corroboration Purpose

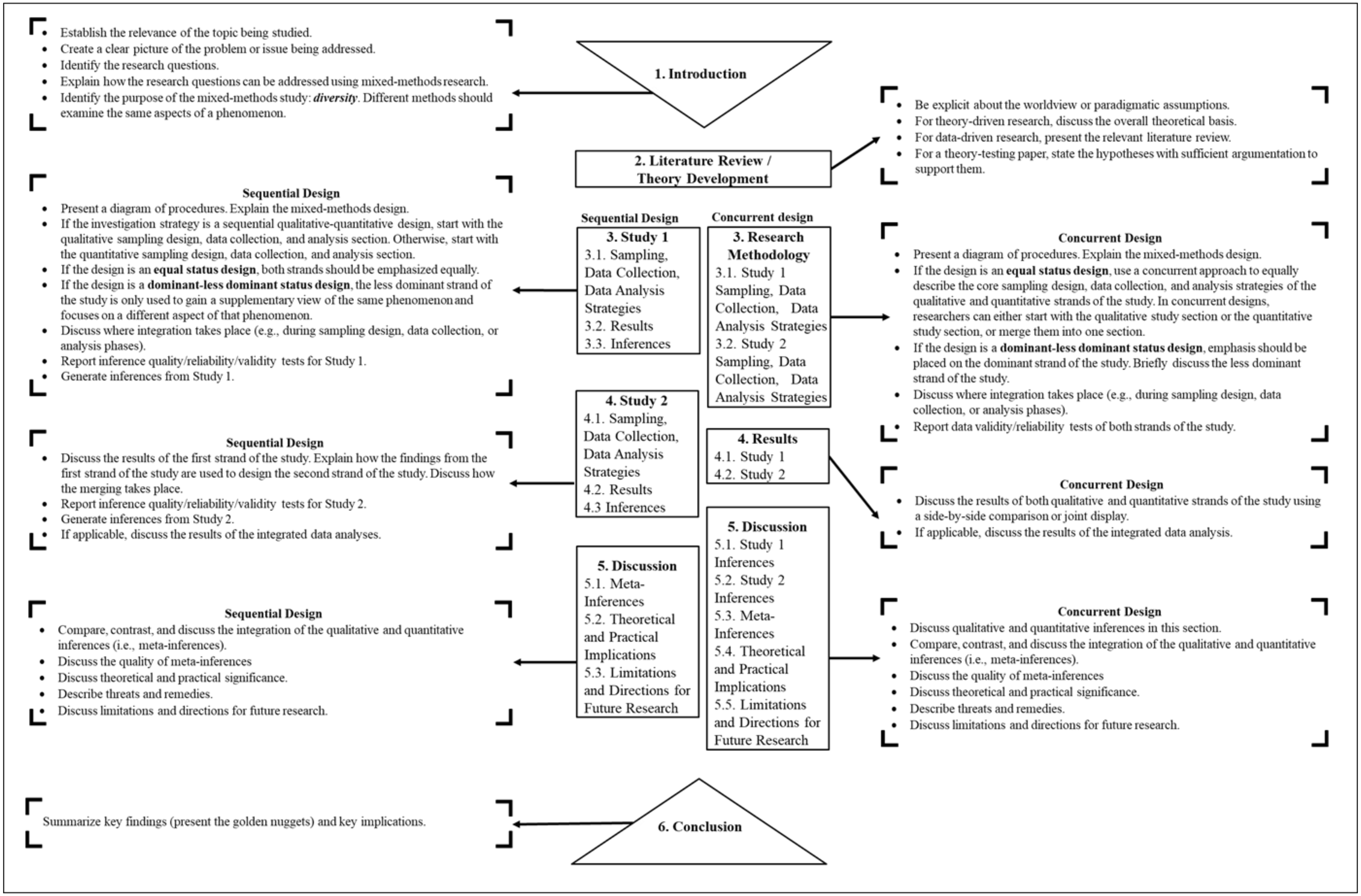

Figure 11-4. Paper Template for Mixed-Methods Research with a Diversity Purpose

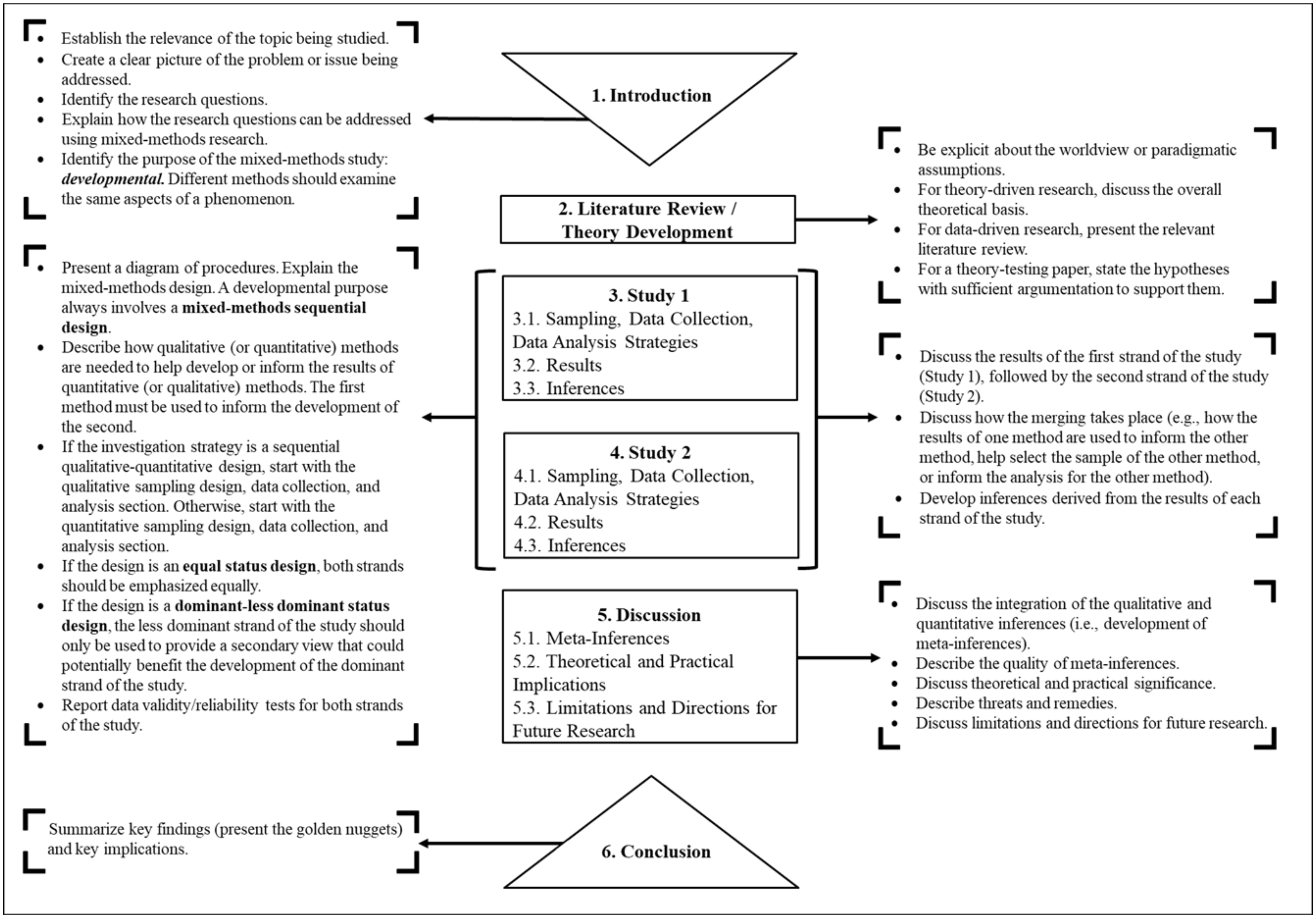

Figure 11-5. Paper Template for Mixed-Methods Research with a Developmental Purpose

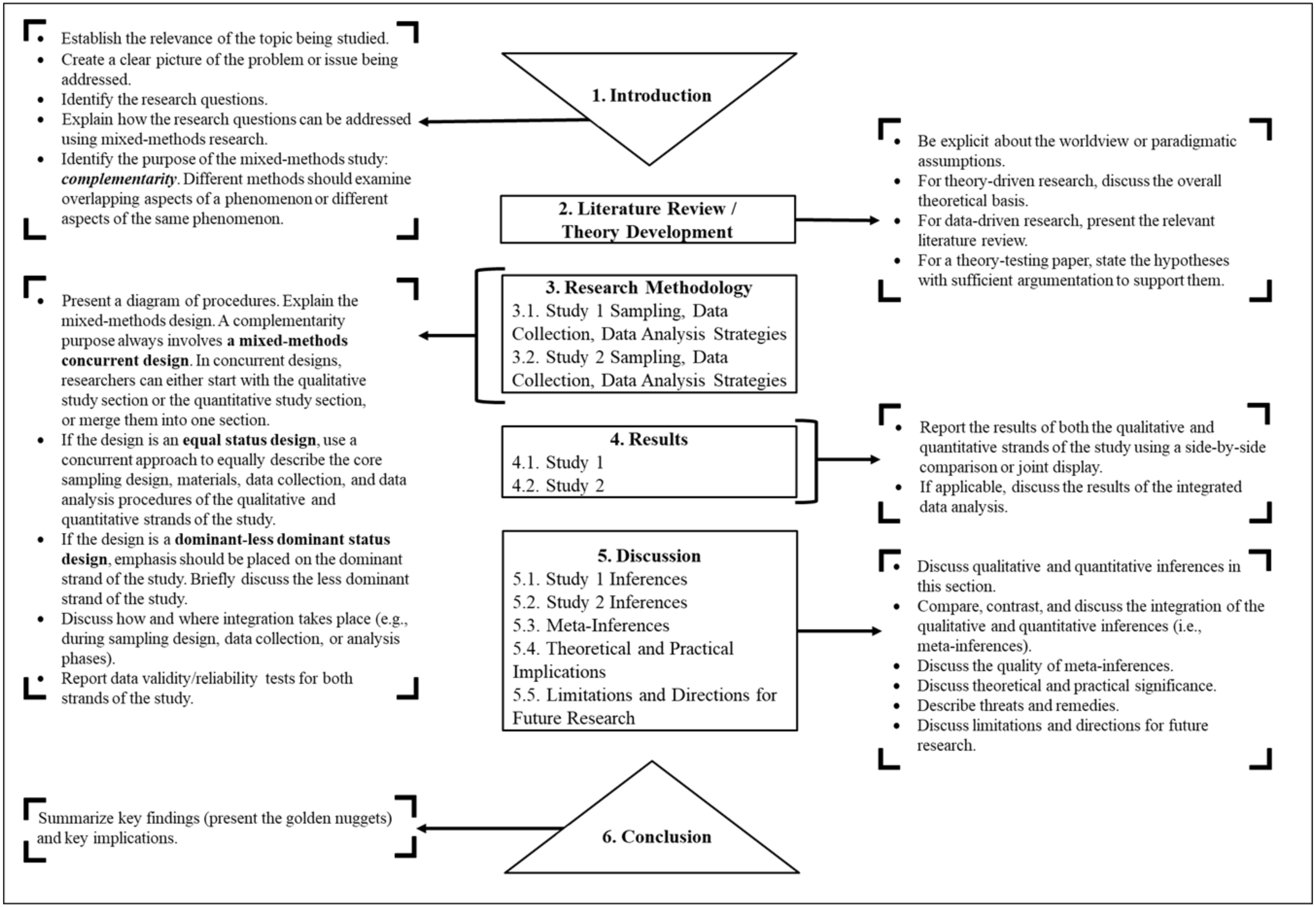

Figure 11-6. Paper Template for Mixed-Methods Research with a Complementarity Purpose

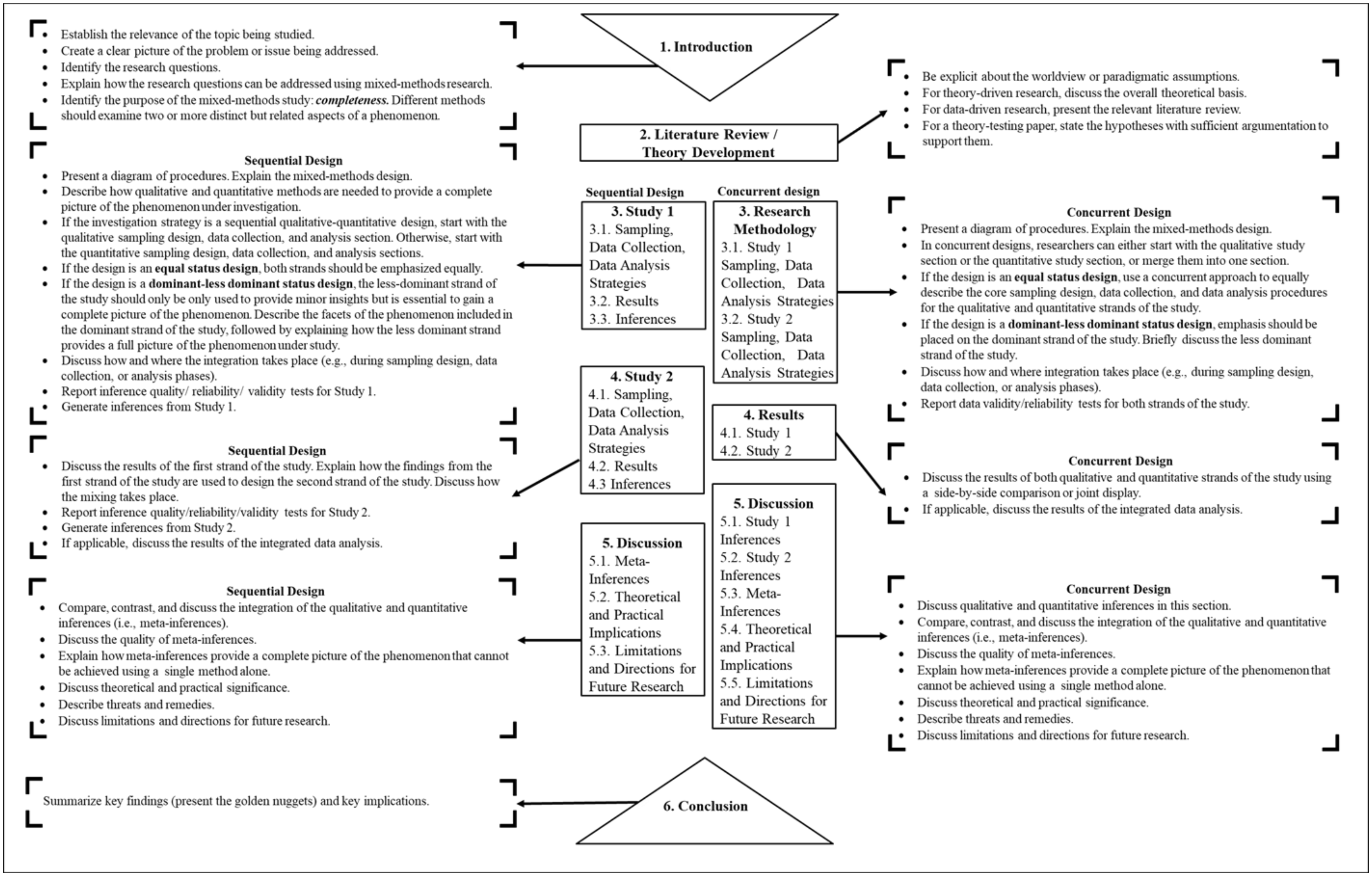

Figure 11-7. Paper Template for Mixed-Methods Research with a Completeness Purpose

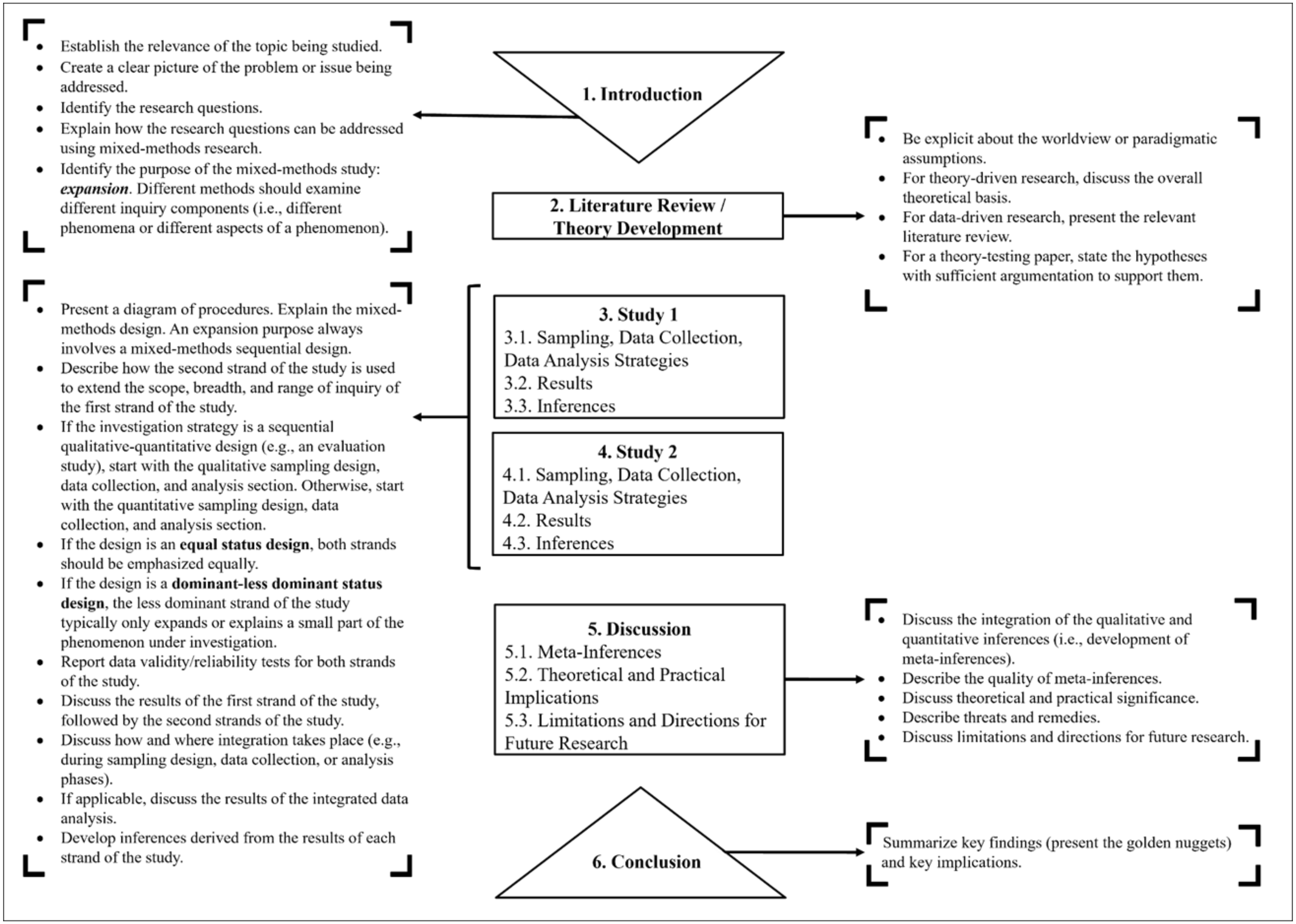

Figure 11-8. Paper Template for Mixed-Methods Research with an Expansion Purpose

Summary

- A mixed-methods research paper should consist of at least six main sections: introduction, literature review or theory development, methods, results, discussion, and conclusions. However, the specific structure of a mixed-methods paper depends on the mixed-methods purpose and related design decisions. Authors should present the details of their mixed-methods designs and report the full results of their mixed-methods research.
    - *Introduction*: Establish the appropriateness of mixed-methods research and relevance of the topic being studied. It should consist of at least four components of the study: (1) topic; (2) research problems; (3) research questions; and (4) purpose(s) of mixed-methods research.
    - *Literature review or theory development*: Be explicit about worldview(s) or paradigm(s) used in the design of a mixed-methods study. If authors use a theory-driven approach, a theory should be used to explain, predict, generalize, and inform research questions and hypotheses tested in a study.
    - *Methods:* Include sampling design, data collection, and data analysis strategies for the qualitative and quantitative strands of the study. Use a diagram of procedures to help readers understand the design.
    - *Results:* Include at least the sample characteristics (e.g., demographics of respondents) and findings of the qualitative and quantitative data analyses (i.e., qualitative and quantitative results sections).
    - *Discussion:* Include *qualitative inferences, quantitative inferences,* and *meta-inferences*. The qualitative and quantitative inferences can be either combined with the results section (earlier) or reported separately in the discussion section. In either case, the inferences should highlight the knowledge contribution of mixed-methods research.
    - *Conclusion:* Summarize the golden nuggets from the work.
- A mixed-methods paper can be structured according to its purpose (i.e., compensation, corroboration, diversity, developmental, complementarity, completeness, and expansion), as well as its time orientation (i.e., sequential and concurrent design) and status of mixed-methods research (i.e., equal status design and dominant-less dominant status design). We presented seven templates that can be used to organize a mixed-methods research paper, and each template is constructed primarily based on the purpose and consequent design strategies underlying the mixed-methods research.

Exercises

1. Develop an outline for your mixed-methods research paper. Discuss and provide the rationale for why the phases are ordered in the sequence you propose.
2. Design a mixed-methods research study that places greater emphasis on the quantitative strand and less emphasis on the qualitative strand of the study. Discuss a structure for the paper (various sections of the paper): introduction, methods, results, and discussion section. *Note:* participants/instructors are encouraged to discuss the variations—in terms of which strand is dominant and what the purpose is—as a basis to understand various possible paper structures.

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CHAPTER 12

GUIDELINES FOR EDITORS AND REVIEWERS

In recent years, we have seen a growing interest in mixed-methods research in several fields and, as we have discussed extensively in earlier chapters, the publication of papers in various journals, including leading journals, that use mixed-methods research approaches. Many scholars are indeed conducting mixed-methods research for the first time, often after having been trained and having experience conducting only either qualitative or quantitative research. Even in teams of researchers, frequently, and any researcher is likely to have typically been trained and consequently possess expertise in only one type of method. At the same time, scholars on editorial boards, who thus may have not conducted mixed-methods research, could be asked to evaluate a mixed-methods methods paper. To this end, in this chapter, we provide guidelines that will assist editors and reviewers in reviewing and judging the quality of mixed-methods research papers.

We provide a checklist of questions that editors and reviewers can use when they review a mixed-methods research paper (see Table 12-1). This checklist is not a rigid standard or requirement for editors and reviewers to use, but it identifies recommended elements for inclusion that we believe to be the most important aspects of an empirical mixed-methods research paper. The checklist provides editors and reviewers, particularly those less familiar with mixed-methods research, a list of criteria to consider in the review process.

Table 12-1. A Checklist of Questions for Reviewing a Mixed-Methods Research Paper

Guideline	Related Chapters	Required/Recommended?	Editor/Reviewer Evaluation
Appropriateness of a mixed-methods approach	4	Providing clear qualitative, quantitative, and mixed-methods research questions is *required* for all types of mixed-methods research designs.	Are the research questions (i.e., qualitative, quantitative, and mixed-methods research questions) provided?
		Providing justification for employing mixed-methods is *required* for all types of mixed-methods research designs.	Are the reasons or justifications for employing mixed-methods research given?
		There are seven purposes of mixed-methods research: compensation, corroboration, diversity, developmental, complementarity, completeness, and expansion. Specifying the purpose(s) of mixed-methods is (are) *required* for all types of mixed-methods research.	Is (are) the purpose(s) of mixed-methods research identified and clearly explained?
		Explaining the benefits of using mixed-methods research is *required* for all types of mixed-methods research.	Are the benefits of using a mixed-methods approach explained?
Paradigmatic stance	2	Mixed-methods research is characterized by paradigm pluralism. The most common paradigmatic stances used in mixed-methods research are pragmatism, critical realism, transformative emancipatory, and dialectic stance. Identifying a paradigmatic approach for conducting mixed-methods research is *required* for all types of mixed-methods research.	Is the paradigmatic approach and its underlying assumptions identified?
Theory in a mixed-methods research paper	3	If authors use a theory-driven approach, a priori theory is *required*. Hypotheses should be developed based on the prior theory used. If authors use a data-driven approach, reviewing relevant literature is still *recommended*, although it is not necessary.	Is prior theory reviewed and properly identified? Are hypotheses developed based on prior theories? If not, is there a suitable discussion of the data-driven approach, with or without the relevant literature review?

Guideline	Related Chapters	Required/Recommended?	Editor/Reviewer Evaluation
Strategies for mixed-methods designs	5	If authors use multiple design elements (e.g., time orientation, strands/phases of research, mixing strategies, priority of methodological approach), they are *required* to explain how different elements are selected and how they are related.	Are various mixed-methods design elements identified and presented in a logical order? Do the authors explain how the decision related to one design element influences another design element?
		As mixed-methods research has emerged as the third research approach, using mixed-methods nomenclature is *required*.	Do the authors use mixed-methods nomenclature, especially in designing their mixed-methods research?
		Aligning mixed-methods design strategies with the purpose(s) of mixed-methods research is *required* for all types of mixed-methods research.	Are the strategies aligned with the purpose(s) of conducting mixed-methods research?
Strategies for collecting and analyzing data	6, 7, 9	Specifying the procedures for qualitative and quantitative data collection and analysis is *required*. Authors should be able to explain how their data collection and analysis procedures are related to their chosen designs (e.g., if the authors use a qualitative-quantitative mixed-methods sequential design, they analyze the qualitative data first followed by quantitative data).	Are the procedures for qualitative and quantitative data collection including sampling strategies discussed?
			Are those procedures related to the chosen design?
			Are the procedures for qualitative and quantitative data analyses discussed?
	8, 11	Having a diagram of procedure helps authors communicate their designs to readers. It is *recommended* that authors use a pictorial representation (visual model) to illustrate their data collection and analysis strategies. This will be particularly helpful until the standards and expectations related to mixed-methods research are widely understood.	Is a visual model (a diagram of procedure) presented to illustrate the strategies for collecting and analyzing data?

Guideline	Related Chapters	Required/Recommended?	Editor/Reviewer Evaluation
		Regardless the types of mixed-methods research design authors use, it is *required* that authors present and explain the results of the mixed-methods data analysis (e.g., how to mix and embed the qualitative and quantitative analyses).	Are the results of the qualitative, quantitative, and mixed-methods data analyses discussed?
		Different types of display can help authors describe their findings. It is *recommende*d that authors use a data display technique (e.g., table, matrix) to communicate their findings.	Is a table, matrix or visual structure (e.g., joint display) used to illustrate the integration and interpretation of the qualitative and quantitative findings?
		Authors are *required* to report the accepted criteria for the qualitative and quantitative strands of the study (i.e., design validity, measurement validity).	Are the procedures for and results of validation discussed for the qualitative and quantitative strands of the study?
Development of meta-inferences	8, 10	Authors are *required* to properly develop qualitative and quantitative inferences. These inferences should meet the quality standard (inferential validity).	Are qualitative and quantitative inferences properly developed?
			Do qualitative and quantitative inferences meet the quality standard?
		Explaining how inferences are generated (i.e., deductive, inductive, abductive) is *required* for all types of mixed-methods research.	Do the authors explain how inferences are generated (i.e., inductively or deductively, or both)?
		Meta-inferences are the core of mixed-methods research. Authors are *required* to generate and report meta-inferences.	Are meta-inferences developed and reported?
			Do the authors explain how meta-inferences are generated?
		Authors are *required* to assess the quality of meta-inferences using two quality criteria: design quality and interpretive rigor (see Chapter 8).	Is the quality of meta-inferences properly assessed?
		If findings from the qualitative and quantitative strands of research are contradictory (i.e., divergent findings), authors are *required* to resolve the divergent findings.	Do the authors reconcile divergent findings (if any)?

Guideline	Related Chapters	Required/Recommended?	Editor/Reviewer Evaluation
Additional elements	11	Making sure the narrative structure of the paper is related to the design strategies is *required*. The discussion section should articulate how the use of a mixed-methods research approach provides a greater understanding of the phenomenon of interest (linking the discussion back to the goal of conducting mixed-methods research).	Is the narrative structure of the paper related to the design strategy (e.g., qualitative and quantitative strands of research are discussed simultaneously in a concurrent mixed-methods design)?
			Does the discussion section articulate how the use of a mixed-methods research approach advances the understanding of the phenomenon of interest?
			Does the discussion section include implications of the integrated findings?

12.1. Appropriateness of a Mixed-Methods Approach

The first step editors and reviewers should do when they review a mixed-methods research paper is to check whether mixed-methods research is appropriate for the inquiry (Venkatesh et al., 2013). For example, if the theoretical or causal mechanisms underlying a submitted manuscript is clear and the research objective is to replicate an existing finding, then mixed-methods research may not be a suitable approach or at least not necessary—in such a case, a length to contribution ratio assessment is warranted for the additional space the reporting of mixed-methods research will necessarily take. A journal that values the robustness brought forth by a mixed-methods research approach (purpose: compensation) would value such a paper and likely value it different from a journal that focuses on novelty and would feel mixed-methods research is appropriate only when the purpose is something other than compensation or corroboration. Where relevant, it is appropriate for authors to state quantitative questions, qualitative questions, and mixed-methods research questions. Editors and reviewers should ensure research questions drive the methodology selection. For example, if the objective of research is to identify and test theoretical constructs and mechanisms in a new context, then an exploratory qualitative, followed by an explanatory qualitative (i.e., sequential design) is appropriate (Venkatesh et al., 2013)—here, the purpose will be developmental.

Editors and reviewers should further ensure the statements about value and rationale for the choice of mixed-methods research are included in the paper (Creswell & Creswell, 2018). Editors and reviewers may not be familiar with different mixed-methods research purposes. We urge them to review and be familiar with the seven purposes of mixed-methods research described in chapter 4, and evaluate how the overall research questions and objectives fit with one or more of these purposes. Absent a clear fit, it is likely that mixed-methods research is not appropriate or at least not necessary (Venkatesh et al., 2013). In the spirit of writing for the understanding of the readers, especially until the norms related to mixed-methods research and the templates for how such a paper is structured are widely understood, editors and reviewers should also make sure that authors convey the benefits of using a mixed-methods approach.

12.2. Paradigmatic Stance

This issue perhaps poses the biggest challenge and associated risk in moving mixed-methods research papers to publication. Authors for their part should strive to provide information on their stance, and editors and reviewers should importantly keep an open mind. Given worldviews or paradigms influence how theory and rationale for a mixed-methods approach influences the selection of mixed-methods research designs (Dahlberg et al., 2010), editors and reviewers should examine the appropriateness of paradigmatic assumptions that authors use in their paper. More importantly, editors and reviewers should understand that each research paradigm has its strengths and limitations. We encourage them to be open-minded and embrace the use of multiple paradigms in mixed-methods research. For example, if authors use the paradigm of positivism in their quantitative strand of the study and interpretivism in their qualitative strand of the study, then their work should be evaluated based on these multiple paradigms. We underscore that the paradigmatic stance should not be an obstacle in conducting or publishing mixed-methods research. Authors' methodological selection that will follow from the paradigm choice should then be evaluated based on the research questions they are trying to answer (Tashakkori & Teddlie, 1998).

12.3. Theory in a Mixed-Methods Empirical Paper

As discussed in Chapter 3, as with most social sciences papers, theory is an important part of a mixed-methods research paper. If authors use a theory-driven approach, editors and reviewers should ensure that they include and use prior theory appropriately in their manuscript. Even if a paper is data-driven (e.g., authors use big data analytics techniques to generate a theory), editors and reviewers should ensure that an appropriate literature review (any relevant theories and prior studies), if applicable, is presented—although such prior work may not be sufficient to explain the phenomenon of interest.

12.4. Strategies for Mixed-Methods Research Designs

Editors and reviewers should ensure that authors present and explain their mixed-methods research design and the rationale for choosing it. Although selecting all the elements of mixed-methods design strategies are not necessary, a detailed discussion of the primary strategies (i.e., time orientation, priority of methodological approach) should be made clear to readers. Editors and reviewers should expect authors to name the specific type of design used so the research can be replicated. Because mixed-methods research is considered a distinct methodological approach, editors and reviewers should ensure that authors use appropriate, consistent nomenclature in discussing their mixed-methods design.

It is important to ensure that the mixed-methods design strategies are aligned with the mixed-methods purpose(s). The purpose(s) of mixed-methods research should inform and guide the mixed-methods design (Greene et al., 1989). For example, as we discussed in Chapters 5 and 11, if the purpose of mixed-methods research is developmental, then a mixed-methods sequential design is more suitable than a concurrent design. This perspective stems from the pragmatic foundation for conducting mixed-methods research—the research problems, purpose, and questions should drive the design selections. Editors and reviewers should also ensure that authors explain how one design element decision influences another design element decision (e.g., given mixing takes place at the inferential stage, authors decide to adopt a partially mixed concurrent equal status design).

12.5. Strategies for Collecting and Analyzing Data

In reviewing the procedures, editors and reviewers should ensure that authors report the strategies for collecting and analyzing their data in detail. Because multiple types of data are collected, separate descriptions of methods are needed when they differ. There should be detailed and thorough descriptions of the separate quantitative and qualitative methods, including specific forms of quantitative and qualitative data collection and analysis techniques (e.g., procedures, sample size, types of analysis) (Fetters & Freshwater, 2015). Editors and reviewers should also ensure that authors develop and report strategies for the mixed-methods data analysis in which both qualitative and quantitative data are rigorously analyzed so that useful and credible inferences can be derived from each type of data analysis (Venkatesh et al., 2013). Authors should include a visual depiction or diagram, such as a joint display, in their paper, especially if it will help readers better understand the findings (Fetters & Molina-Azorin, 2019).

As part of evaluating data collection and analysis procedures, editors and reviewers should ensure that authors follow and report the quality metrics tied to each strand of research. For example, for quantitative research, ensure that authors report at least the reliability, internal and discriminant validity; and, for qualitative research, ensure that authors report credibility and dependability (Teddlie & Tashakkori, 2009). For big data analytics research, it is critical for editors and reviewers to assess data extraction techniques and algorithms used to analyze data using various validation techniques (e.g., sensitivity analysis).

Note that the order and structure of a mixed-methods study are dependent on the underlying mixed-methods design (see Chapter 11). For example, let's say a paper reports mixed-methods research with a completeness purpose. The authors may have used a large-scale survey to gather quantitative data and used the survey's findings as a basis for qualitatively interviewing several informants to further examine the phenomenon under investigation. In this case, it may make more sense to present the quantitative procedures first. Editors and reviewers should ensure that authors are transparent in the details of the methods. One way to review the data collection and analysis strategies is by using a diagram of procedures, as discussed in Chapter 11. A diagram of procedures provides critical information that portrays the quantitative and qualitative data collection sequencing, data collection procedures, integration, and outcomes of the various stages or steps (Creswell, 2015).

12.6. Development of Meta-Inferences

Given meta-inferences are the outcomes of mixed-methods research, editors and reviewers should be aware of the importance of meta-inferences in mixed-methods research. If authors fail to provide and explain meta-inferences, then the key objective of conducting mixed-methods research is not achieved (Venkatesh et al., 2013). Because meta-inferences are generated by integrating qualitative and quantitative inferences, editors and reviewers should ensure all the generated inferences meet the quality criteria, as discussed in Chapter 8. Specifically, inference quality should be assessed for the overall findings from mixed-methods research (i.e., meta-inferences). Editors and reviewers should ensure that authors provide an explicit discussion and assessment of how they have integrated findings from the quantitative and qualitative strands of the study (see Chapter 8).

Authors must explain how inferences are generated. As mentioned in Chapter 10, the process of developing meta-inferences is conceptually similar to the process of developing theories from observations. Thus, if authors use any of the theoretical reasoning techniques (e.g., induction, deduction, abduction), they should explicitly state those techniques. Specifying the use of theoretical reasoning also helps confirm the role of theory in the paper. Such discussions will help readers understand whether meta-inferences are consistent with the research objectives and help the research/paper make substantial theoretical contributions (Venkatesh et al., 2013). We encourage editors and reviewers to refer to Chapter 10 about how to develop high-quality meta-inferences.

As we discussed in Chapter 10, when researchers integrate qualitative and quantitative methods, one of the following three outcomes may arise: (1) qualitative and quantitative results may be *convergent*; (2) qualitative and quantitative results may relate to different aspects of the same phenomenon and thus they may be *complementary*; and (3) qualitative and quantitative results may be *divergent* (Brannen, 2005; Erzberger & Kelle, 2003; Teddlie & Tashakkori, 2009). When the findings are convergent, meta-inferences strengthen the initial theoretical assumptions that were used to structure the research process (Erzberger & Kelle, 2003). When the findings are complementary, meta-inferences provide a more complete picture of the empirical domain under study, which cannot be achieved by a single method alone (Erzberger & Kelle, 2003). However, when the findings are divergent, meta-inferences are means to find new, better, complete and/or contingent explanations for the phenomenon under investigation (Erzberger & Kelle, 2003). Editors and reviewers should ensure that authors provide sufficient explanations for divergent findings (e.g., reanalyzing existing data and/or revisiting theoretical assumptions).

12.7. Additional Elements

In addition to the primary aspects of mixed-methods research we discussed earlier, editors and reviewers should ensure that the narrative structure of the paper is related to the design strategies (e.g., qualitative and quantitative strands of research should be discussed simultaneously in a concurrent mixed-methods design). For example, the discussion section should follow the sequence of procedures used in the mixed-methods design. It should also reflect the implications of findings from the two different research strands. Editors and reviewers should ensure the narrative flows logically and makes sense (Fetters & Molina-Azorin, 2019).

Editors and reviewers should ensure that the discussion section articulates how the use of a mixed-methods research approach advances the understanding of the phenomenon of interest. The findings should be linked back to the research questions and the discussion should include the implications of the integrated findings. If authors use a data-driven approach, they are expected to specify how their contribution has refined existing theory or generated new theory.

Summary

This chapter provides a checklist of questions that editors and reviewers can use when they review a mixed-methods empirical paper. The criteria include:

- *Appropriateness of a mixed-methods approach:* Ensure research questions drive the method selection and the purpose of mixed-methods research is clearly stated.
- *Paradigmatic stance:* Ensure an explicit discussion of paradigmatic assumptions.
- *Theory:* Ensure that there is an appropriate discussion and use of prior theory.
- *Strategies for mixed-methods research designs:* Ensure the presentation and explanation of the mixed-methods research design and the rationale for choosing it.
- *Strategies for collecting and analyzing data:* Ensure the details needed to demonstrate the strategies for collecting and analyzing their qualitative and quantitative data are presented.
- *Development of meta-inferences:* Ensure meta-inferences that meet quality standards are presented.
- *Additional elements:* Ensure that the narrative structure of the paper is related to the design strategies and that the discussion section articulates how the use of a mixed-methods research approach advances the understanding of the phenomenon of interest.

Exercises

1. Select a mixed-methods research paper in your field and review that paper using the guidelines provided in this chapter. What recommendations do you have for the authors?
2. *Peer-review exercise:* If you are asked to develop and write a mixed-methods paper in your class, exchange feedback on your in-progress paper with your classmates. Review your classmates' in-progress papers using the guidelines we discussed in this chapter. What recommendations do you have for your peers?

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CHAPTER 13

CHALLENGES AND STRATEGIES IN CONDUCTING, WRITING, AND PUBLISHING MIXED-METHODS RESEARCH

In this chapter, we discuss a number of challenges in conducting, writing, and publishing a mixed-methods research paper. Despite the various benefits that can be derived from mixed-methods research, there are some challenges associated with this methodology including: controversies related to the paradigmatic and philosophical issues in mixed-methods research; the use of, and rationale for, mixed-methods research; the nomenclature, design, and classification issues in mixed-methods research; problems with integration; team selection and resource issues surrounding mixed-methods research; and problems with presentation of findings (Halcomb, 2019; Teddlie & Tashakkori, 2003, 2009, 2010). In this chapter, we detail these challenges and provide recommendations to address them (see Table 13-1).

Table 13-1. Challenges and Strategies in Conducting Mixed-Methods Research

Category	Challenge	Strategy
Paradigmatic and philosophical issues	The debate over the issues of the *incompatibility thesis*—i.e., it is inappropriate to mix qualitative and quantitative methods due to fundamental differences, e.g., epistemological, between the paradigms underlying those methods?	Move away from “metaphysical paradigms” (i.e., the concept of paradigms used by purists who link assumptions of their chosen paradigm with methodological traditions) to paradigms as shared beliefs in a research community (i.e., pragmatism).
Paradigmatic and philosophical issues	If researchers try to combine two or more different paradigms, whether those paradigms can be given equal weight. It they can, a challenging issue may arise if the findings from one method contradict the findings from another method. Lack of commonality in researchers’ standpoints about mixed-methods research.	Take a comprehensive, new epistemological position—knowledge gained from qualitative and quantitative approaches should not be seen as irreconcilable pools of knowledge, but as different positions on a continuum of knowledge. Be more open-minded, reviewing more exemplary mixed-methods studies, and selecting one or two and use them as the “gold standard” for guiding the research process.
Research questions and rationale for mixed-methods research	Assess the suitability of using mixed-methods research in one’s study.	Ensure research questions drive the methodological selection, not the other way around.

Category	Challenge	Strategy
Research questions and rationale for mixed-methods research	Formulate appropriate research questions that leverage the synergy of integrating qualitative and quantitative data, without expanding the scope of the study beyond the optimal.	Anticipate changes that may take place during the study (e.g., during the preliminary analysis, especially in a sequential mixed-methods design) and be open to emerging research questions without expanding the scope of the study beyond the optimal. If it is deemed necessary to expand the research scope, researchers are encouraged to gather more resources, if available, or reallocate existing resources to accommodate the changes.
Nomenclature, design, and classification	Researchers are faced with a challenge of examining different types of mixed-methods designs from various resources (e.g., books and journal articles) and selecting one that suits their research purpose.	Review different design elements discussed in this book, select those most salient to their study and then explain those dimensions in their mixed-methods design section of the paper; use the decision choice model discussed in chapter 5.
Integration	Ensure a proper integration of findings across methods, especially when it comes to data integration.	Use a diffraction approach involving reading data across methods while allowing data to cohere or not.
Team selection	Mixed-methods research requires methodological expertise in multiple areas.	Form a strong research team consisting of individuals with various methodological backgrounds and expertise; gain sufficient knowledge in both qualitative and quantitative research before undertaking a mixed-methods research project.
Required resources	Mixed-methods research requires more resources (for data collection, management, and analysis) than single-method research.	Careful planning and preparation are critical.
Presentation of findings	A large volume of data generated by mixed-methods research can create a challenge in the analysis and reporting process.	Use templates for publishing mixed-methods research discussed in chapter 11; if authors encounter issues with a journal's page limits, report details of the study in appendixes or as supporting materials for review.

13.1. Paradigmatic and Philosophical Issues in Mixed-Methods Research

Although mixed-methods research allows researchers to combine and integrate different methodologies, one challenge they will face in conducting mixed-methods research is the debate over the issues created by the *incompatibility thesis*—i.e., it is inappropriate to mix qualitative and quantitative methods due to fundamental differences, e.g., epistemological, between the paradigms supposedly underlying those methods (Howe, 1988; Salehi & Golafshani, 2010)? The debate is at the root of mixed-methods research that the quantitative-qualitative dichotomy should remain intact because each method has distinct assumptions about the phenomenon being studied (Salehi & Golafshani, 2010; Tashakkori & Teddlie, 2003). True believers of each method (e.g., constructivists, interpretivists, positivists) argue that different methods and their findings must remain independent, claiming, for example, interpretivism is a qualitative paradigm and "accommodation between paradigms is impossible" as it leads to "vastly diverse, disparate, and totally antithetical ends" (Guba, 1990, p. 81). "Both sets of purists view their paradigms as the ideal for research, and, implicitly if not explicitly, they advocate the incompatibility thesis" (Azorin & Cameron, 2010, p. 97). The quantitative and qualitative debate has been so divisive that some journals have established their reputation around one specific methodology (either-or, but not both).

One way to overcome the paradigmatic challenges is to move away from metaphysical paradigms (i.e., the concept of paradigms used by purists who link assumptions of their chosen paradigm with methodological traditions) to "paradigms as shared beliefs in a research community" (Teddlie & Tashakkori, 2010, p. 14). Such a view supersedes the qualitative/quantitative dichotomies of induction/deduction, subjectivity/objectivity, and context/generality (Morgan, 2007). As we discussed in Chapter 2, mixed-methods research emphasizes *paradigm pluralism*—the belief that a variety of paradigms may serve as the underlying philosophy for the use of mixed-methods research (Teddlie & Tashakkori, 2010). Among other paradigmatic stances, the paradigm of pragmatism is the most common philosophical underpinning of mixed-methods research. Pragmatism rejects the "either-or" decision associated with the paradigm wars (Morgan, 2007; Tashakkori & Teddlie, 2003); it accepts the use of multiple methods in one research project and emphasizes the importance of research questions over methodologies (Tashakkori & Teddlie, 2003).

Pragmatism also opens a range of new opportunities for thinking about classic methodological issues in social sciences (Morgan, 2007). In general, we recommend researchers, editors, and reviewers adopt a "contingency theory for [a] research approach selection" (Johnson & Onwuegbuzie, 2004, p. 22) that accepts that qualitative, quantitative, and mixed-methods research are all superior [or at least appropriate] under different circumstances. It is the researcher's task to examine the specific contingencies and make a decision about which research approach should be used in a specific situation (Johnson & Onwuegbuzie, 2004). For researchers wishing to adopt this approach, we suggest they read about the paradigm of pragmatism discussed in Chapter 2 (see also Morgan, 2007; Tashakkori & Teddlie, 2003; Teddlie & Tashakkori, 2010).

If researchers try to combine two or more different paradigms, some other concerns include whether those paradigms and more appropriately, the methods chosen can be given equal weight (Foss & Ellefsen, 2002). Even if researchers give equal weight and value to both methods by arguing the weaknesses of one method can be compensated by the strengths of another method, a challenging issue may arise if the findings from one method contradict the findings from another method (Salehi & Golafshani, 2010). One way to overcome this challenge is by taking a comprehensive, new epistemological position. Such an alternative position suggests that "within a complex and differentiated reality, we need different and various types of knowledge" (Foss & Ellefsen, 2002, p. 244). Knowledge gained from the qualitative and quantitative methods should not be seen as irreconcilable pools of knowledge but as different positions on a continuum of knowledge. We discuss several different strategies that authors can use to deal with divergent findings in Chapter 9.

Lastly, the lack of commonality in researchers' standpoints about mixed-methods research can hinder the research process (Salehi & Golafshani, 2010). For example, some believe that mixed-methods research is to serve the quantitative paradigm while relegating the qualitative paradigm to secondary status (Denzin & Lincoln, 2005), whereas others believe that mixed-methods research should include mixing in all stages of the study. This lack of communality can cause some confusion about the nature of mixed-methods research. To overcome this challenge, researchers are encouraged to be more open-minded, reviewing more exemplary mixed-methods studies, and selecting one or two and using them as "gold standard" for guiding the research process. Several examples with various purposes have been discussed earlier and are summarized in Table 13-2, which include the chapters in the book where we use those examples as illustrations.

Table 13-2. Examples of Mixed-Methods Studies in Various Social Science Disciplines

Author(s)	Journal Name	Title	Chapters
Battilana et al. (2015)	*Academy of Management Journal*	Harnessing productive tensions in hybrid organizations: The case of work integration social enterprises	4, 5
Brickson (2005)	*Administrative Science Quarterly*	Organizational identity orientation: Forging a link between organizational identity and organizations' relations with stakeholders	4, 5
Califf et al. (2020)	*MIS Quarterly*	The bright and dark sides of technostress: A mixed-methods study involving healthcare IT	7
Dong et al. (2018)	*Journal of Management Information Systems*	Leveraging financial social media data for corporate fraud detection	9
Sarker et al. (2018)	*Information Systems Research*	Work-life conflict of globally distributed software development personnel: An empirical investigation using border theory	3
Sonenshein et al. (2014)	*Academy of Management Journal*	It's not easy being green: The role of self-evaluations in explaining support of environmental issues	4, 7, 8
Stewart et al. (2017)	*Academy of Management Journal*	Those with the most find it hardest to share: Exploring leader resistance to the implementation of team-based empowerment	1, 3, 4, 5, 6, 7, 8

Author(s)	Journal Name	Title	Chapters
Vergne (2012)	*Academy of Management Journal*	Stigmatized categories and public disapproval of organizations: A mixed-methods study of the global arms industry, 1996-2007	1
Walsh (2014)	*Journal of Strategic Information Systems*	A strategic path to study IT use through users' IT culture and IT needs: A mixed-method grounded theory	2
Zhang and Venkatesh, (2017)	*MIS Quarterly*	A nomological network of knowledge management system use: Antecedents and consequences	2

13.2. Research Questions and Rationale for Mixed-Methods Research

Another challenge facing some researchers is assessing the suitability of using a mixed-methods approach in their work. Some researchers adopt a mixed-methods research approach because they believe mixed-methods research is a new approach to doing research, although a careful investigation of their research questions suggests that a mixed-methods approach is not needed to answer the research questions. As we discussed in earlier chapters, a mixed-methods project must start with a research question (or a set of research questions) that drives method selection. Social sciences researchers do consider mixed-methods as a new method to address complex research questions (Salehi & Golafshani, 2010), but they should provide solid reasons for choosing a mixed-methods approach and the value it will bring to answer research questions. Some scholars report using a mixed-methods approach simply to improve the probability of publishing their manuscripts, while in reality, such an approach is not necessary and may initially create a practical problem—the rationale given for the mixed-methods approach may not match the actual objective (Bryman, 2006).

If mixed-methods research is deemed appropriate, another common challenge faced by researchers is "how to formulate appropriate research questions that leverage the synergy of integrating quantitative and qualitative data, without expanding the scope of the study beyond the optimal" (Teye, 2012, p. 385). The combination of both qualitative and quantitative methods can easily broaden the scope of research. For example, Teye (2012) reported that when he conducted mixed-methods research to study forest policy formulation and implementation in Ghana, he had to conduct more in-depth interviews than originally planned because the target group he initially planned to interview was different from the group he encountered in the field. He had to broaden the research scope, generate more data, and spend more time to analyze the data. To overcome the challenge associated with the research scope, researchers should anticipate changes that may take place in the field and be open to emerging research questions without expanding the scope of the study beyond the optimal. However, if it is deemed necessary to expand the research scope, researchers are encouraged to gather more resources, if available, or reallocate existing resources to accommodate the changes.

13.3. Nomenclature, Design, and Classification Issues in Mixed-Methods Research

Issues regarding the language of mixed-methods research (i.e., nomenclature) (Teddlie & Tashakkori, 2010), design, and classification have changed over time but still need discussion and development (Teddlie & Tashakkori, 2009). For example, although typologies are important (see section 2, Chapters 4-9), mixed-methods typologies with both overlapping and divergent components and/or different names and labels can be a challenge to researchers (Teddlie & Tashakkori, 2010) (e.g., a mixed-methods convergent parallel design is the same as a concurrent design). Due to a significant number of taxonomies, categorizations, and terminologies surrounding mixed-methods research, researchers utilizing a mixed-methods approach are faced with the challenge of examining different types of mixed-methods designs from various resources (e.g., books, journal articles) and selecting one that suits their research purpose.

We recommend several strategies to overcome this challenge. First, in this book, we discussed different mixed-methods designs from which researchers can select, and we proposed a more unified framework that is meant to guide researchers, editors, and reviewers in conducting, evaluating, and publishing mixed-methods research. We encourage researchers to review different design elements discussed in this book, select those most salient to their study, and then explain those dimensions in the mixed-methods design section of their paper. Second, for researchers who are new to mixed-methods research, this diversity can be overwhelming (i.e., too many options on how to plan a mixed-methods study). Our approach with a detailed decision choice model (for example, see Figure 5-7) is systematic and covers most types of mixed-methods research. In our approach to identify the mixed-methods design, we have treated research questions and purposes as separate from the design, data collection and analysis techniques, and inferential stages. This separation is intended to flexibly guide researchers from one stage of the mixed-methods research to the next stage of the research—often, without being trapped in complex definitions and design selections.

13.4. Problems with Integration of Findings in Mixed-Methods Research

Ensuring a proper integration of findings across methods is one of the biggest challenges in mixed-methods research (Bryman, 2006; Teye, 2012). Results can be integrated at both the analysis and interpretation stages. In most cases, however, results are integrated only at the level of interpretation (Bryman, 2006; Caracelli & Greene, 1993; Teye, 2012). Only a few studies have reported integration at the analysis stage (Uprichard & Dawney, 2019). Effective data integration requires a well-considered approach that "knows when to synthesize some findings (because they are equivalent and commensurate) and when to respect and investigate contradictory findings (because the contradiction reflects epistemologically based differences that cannot be resolved empirically, only conceptually)" (Fielding, 2012, p. 125). Here, we first discuss the problems associated with data integration (i.e., integration at the analysis stage).

Instead of "adding up" data, where findings of one method are considered alongside findings of another, data integration goes beyond just reporting the findings of both approaches and considers the interaction of data during the analysis (Uprichard & Dawney, 2019). The goal of data integration is to produce a more comprehensible object—the extent to which data from different methods can be interpreted together in a meaningful way. Two most common data integration techniques are: (1) combination of data types within different types of analyses (e.g., using categorical or continuous variables both for statistical analysis and for comparing coded qualitative data); and (2) conversion of data (i.e., quantitizing or qualitizing) (Fielding, 2012). Indeed, there must be a clear rationale for using such techniques.

Data integration can, however, be problematic when objects examined in the qualitative strand of the study are different from the quantitative strand of the study. As such, different methods may produce "cuts" (i.e., findings from different methods are completely different and do not fit together) (Uprichard & Dawney, 2019). For example, Ling and Pang (2021) studied a social justice problem of poverty in the context of financial education with Hong Kong early adolescent ethnic minority students. They used a vignette-based methodology to gather data in a mixed-methods design study. The study consisted of three phases. Phase 1 (baseline) consisted of pre-surveys using quantitative and qualitative methods and individual interviews. The findings of Phase 1 informed the design of new financial lessons and vignettes, which were piloted and implemented in Phase 2 (intervention). Phase 3 (follow-up) involved evaluations using qualitative and quantitative surveys. The authors argued that "[q]ualitative data enable in-depth investigation into the financial beliefs and behaviors of underrepresented groups", whereas "[q]uantitative data provide objective evidence for program evaluation" (p. 3). For most parts of the analysis, the authors conducted a content analysis of the qualitative data and then transformed the results into quantitative data. They also performed statistical analyses of the quantitative data. Although the findings revealed the lessons' positive impact (i.e., the intervention group showed a significant increase in long-term financial planning strategies than the control group did), most students (both in the intervention and control groups) did not have a budget plan. The mixed-methods data analyses demonstrated that students in the intervention group did not show any improvement in their saving behavior although their financial planning strategies seemed to improve. These findings demonstrate "cuts" that reveal different aspects of the same phenomenon (or multiple phenomena) that do not cohere and cannot be integrated. The authors explained the conflicting findings using three perspectives of finance research: traditional finance, behavioral finance, and cultural finance. Whereas traditional and behavioral finance concerns with individuals' saving behaviors, cultural finance extends such individual behaviors to the family's saving behaviors. The authors' intervention in their quantitative strand of the study was designed to directly affect the students' financial literacy, not that of their families' financial literacy. In other words, the conflicting findings were due to two different aspects of the phenomenon being investigated in the same study.

Uprichard and Dawney (2019) recommended a method called *diffraction* as a way to integrate qualitative and quantitative data that are not coherent. In diffraction, mixed data, objects, and methods coproduce one another; "[T]he ontology of the data, the object, and methodological approach become as important as their epistemologies" (p. 26). Thus, diffraction precludes the option of using mixed data to illustrate, enrich, or verify each other as an effort to "entail the 'holding still' of one and a refusal to see the research object as a messy, processual entity" (p. 27). A diffraction approach involves reading data across methods while allowing data to cohere or not. If not, it will produce seemingly conflicting findings that should be explained using different narratives. We encourage a careful reading of Uprichard and Dawney (2019) for a more detailed discussion on diffraction.

13.5. Team Selection in Mixed-Methods Research

Team selection issues surrounding mixed-methods research can also create challenges in writing and publishing mixed-methods research paper. Specifically, mixed-methods research requires methodological and philosophical expertise in multiple areas—rather than conducting social impact interviews to learn about individuals' experiences with an intervention program or conducting a survey to learn about the impact of technology adoption, researchers need to conduct both interviews and surveys. We encourage researchers to form a strong research team consisting of individuals with backgrounds and expertise in different types of methods. Moreover, we strongly recommend that researchers, especially Ph.D. students, first gain sufficient knowledge in *both* qualitative and quantitative research (e.g., by taking courses or attending workshops in various research methods) before undertaking a mixed-methods research project.

13.6. Required Resources for Mixed-Methods Research

Collecting two different types of data and/or a subsequent large volume of data means that the resources required for data collection, management, and analysis are also greater for a mixed-methods project (Halcomb, 2019; Halcomb & Andrew, 2009). A further consideration is the time required to complete a mixed-methods project. For example, in a project with a sequential design, significantly more time is required (compared to a single method project or a concurrent mixed-methods project) to collect and analyze the first data set prior to commencing the collection of the subsequent data (Halcomb, 2019). Similarly, in a concurrent project, sufficient time and resources are required to facilitate collection of two sets of data at the same time (Halcomb & Andrew, 2009). These logistics challenges can be overcome by careful planning and preparation (e.g., secure sufficient resources to collect and analyze both qualitative and quantitative data; create a timeline for data collection and analysis).

13.7. Presentation of Findings in Mixed-Methods Research

A large volume of data generated by mixed-methods research can create a challenge in the analysis and reporting process (Halcomb, 2019). To overcome this challenge, we provided a number of templates for publishing mixed-methods research in Chapter 11. In addition, a challenge can arise if a manuscript does not fit within a journal's word/page limits, particularly when there is a need to describe data collection and data analysis in detail for both methods. If that's the case, one approach is for authors to report details of their study in appendixes or supplementary materials for review. A second approach, though sub-optimal, is to publish the results of each study separately, incorporating the meta-inferences into the second study. Finally, we encourage journals to be flexible regarding their page limits for a mixed-methods research paper, as such papers necessarily tend to be longer due to the method details, analysis/results details, and meta-inferences. This will ensure that a mixed-methods study is transparent and can be carefully evaluated.

Summary

Challenges in conducting, writing, and publishing mixed-methods research include: the paradigmatic and philosophical issues in mixed-methods research; the use of, and rationale for, mixed-methods research; the nomenclature, design, and classification issues in mixed-methods research; problems with integration of findings in mixed-methods research; the team selection and resource issues surrounding mixed-methods research; and problems with presentation of findings in mixed-methods research. The key issues in each of these are described below:

- *Paradigmatic and philosophical issues in mixed-methods research:* move away from "metaphysical paradigms" (i.e., the concept of paradigms used by purists who link assumptions of their chosen paradigm with methodological traditions) to "paradigms as shared beliefs in a research community"; use a contingency approach; take a comprehensive, new epistemological position; and be more open-minded by reviewing more exemplary mixed-methods studies to address the lack of commonality in researchers' viewpoints about mixed-methods research.

- *Research questions and rationale for mixed-methods research:* provide solid reasons for choosing a mixed-methods approach and the value it will bring to answer the research questions.
- *Nomenclature, design, and classification issues in mixed-methods research:* review different design elements that we discuss in this book, select those most salient to their study, and then explain those dimensions in the mixed-methods design section.
- *Problems with integration of findings in mixed-methods research:* use a diffraction method to integrate qualitative and quantitative data that are not coherent.
- *Team selection in mixed-methods research:* form a strong research team consisting of individuals with various methodological background and expertise; gain sufficient knowledge in both qualitative and quantitative research before undertaking a mixed-methods research project.
- *Required resources for mixed-methods research:* carefully plan and prepare a timeline for execution.
- *Presentation of findings in mixed-methods research:* use the templates for publishing mixed-methods research discussed in chapter 11.

Exercises

1. Among the challenges of conducting, writing, and publishing mixed-methods research discussed in this chapter, which challenges do you think are the most commonly experienced by researchers in your field? Based on your understanding of your field, propose recommendations to overcome those challenges.
2. Select one published mixed-methods article in your field. Did the authors discuss challenges they encountered in the paper? If so, what are those challenges? If not, what challenges seem likely, given the paper's context and content?
3. By the end of this chapter, you should have designed and maybe even conducted your own mixed-methods project. From your own experience, identify challenges you encountered, especially those not discussed in this chapter? What is your plan for addressing them (or how did you address them)?

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His articles have been cited about 175,000 times and about 60,000 times per Google Scholar and Web of Science, respectively, with an h-index of 88 and i-10 index of 150. He has been recognized to be among the most influential scientists (e.g., Clarivate, Thomson Reuters' highlycited.com, Emerald Citations, SSRN, PLoS Biology). For example, in an article in *PLoS Biology* (Iaonnidis et al. 2019), using citation data from 1996-2022 and a standardized metric that was a composite of six citation metrics, he has a career ranking of 422nd out of ~8 million scientists across all scientific fields and 1st out of ~17K scientists in information systems; in previous annual updates, he was similarly ranked in the top-1000 out of ~8 million active scientists across all scientific fields. His papers are among the most cited in the various journals: *Information Systems Research* (2000), *Decision Sciences* (1996, 2008), *MIS Quarterly* (2003, 2012), and *Management Science* (2000). In 2012, his *Decision Sciences* (2008) was among the fifty papers to receive Emerald's Citations of Excellence award—in 2014, this paper was selected to be among only thirty-five most-cited papers across fifteen years of this award; this paper, along with the *Decision Sciences* (1996), were the top-two most-cited papers published in *the journal,* with the 2008 paper also being the most downloaded. In 2016, his *MISQ* (2013) was selected to be among the fifty papers to receive Emerald's Citations of Excellence award. In 2017, his *Journal of Operations Management* (2012) paper was selected for the Ambassador award for citations over a five-year period. In 2008, his *MISQ* (2003) paper was identified as a current classic by *Science Watch* (a Thomson Reuters' service), and since 2009, it is the most influential article in one of the four *Research Front Maps* in business and economics.

He has taught a wide variety of undergraduate, MBA, exec MBA, Ph.D., and executive courses. Student evaluations have rated him to be among the best instructors at the various institutions, and he has received teaching awards at the school and university levels. He has performed extensive administration and service. At Arkansas, he served as the director of the information systems Ph.D. program for two terms (2004-'09; 2011-'15), with the latter term including him serving as chair of the Walton College Ph.D. committee. During his term as director, he led a transformational effort that produced the top-two most-productive information systems assistant professors graduating since 2000 (see Chen et al. 2015, *Communications of the AIS*). At Maryland, he was the Director of the MBA Consulting Program and led undergraduate curriculum revision efforts. He has served on several committees at the university, school and department levels. In 2009, he launched an IS research rankings web site, affiliated with the Association for Information Systems (AIS), that has received many accolades from the academic community including *AIS' Technology Legacy Award*. He is serving or has served on the editorial boards of the several journals including the *ISR*, *Journal of the AIS*, *Journal of Operations Management*, *Management Science*, *MISQ*, *Organizational Behavior and Human Decision Processes*, and *Production and Operations Management.*

Susan (Sue) Brown is the Stevie Eller Professor and department head of Management Information Systems in the Eller College of the University of Arizona. She joined the Eller College as an associate professor in 2005. She completed her PhD at the University of Minnesota and an MBA at Syracuse University. Prior to receiving her MBA, she worked as a programmer/analyst and IS manager in a hospital. Her research interests include individual motivations for and consequences of IT use, mediated interactions, diffusion of misinformation, and research methods. She has received funding for her research from the National Science Foundation, and other public and private organizations. Her work has appeared in leading journals in information systems and management including *MIS Quarterly, Information Systems Research*, *Organizational Behavior and Human Decision Processes*, *Communications of the ACM*, *Journal of Management Information Systems*, and *Journal of the Association for Information Systems*. She has served as an Associate Editor at *MIS Quarterly*, *Information Systems Research*, *Journal of the Association for Information Systems*, and *Decision Sciences* and as a Senior Editor at *MIS Quarterly.* She is currently coeditor-in-chief of *AIS Transactions on Replication Research* and a senior editor at *Information Systems Research.* She has been active in the information systems community, serving as a faculty mentor for doctoral, junior faculty, and mid-career faculty consortia multiple times. She currently co-chairs the doctoral consortium at HICSS. Recently, she served as co-chair of the 2022 AMCIS in Minneapolis. She has received awards for her teaching, research, and service activities. In 2016, she received the AIS (Association for Information Systems) Sandra Slaughter Service award, in 2017, she was named a fellow of the AIS, and, in 2022, received a Woman of Impact Award at the University of Arizona. In 2024, she will become the 14th Editor-in-Chief of *MIS Quarterly*.

Yulia Sullivan is an Associate Professor of Information Systems and Business Analytics (ISBA) at Hankamer School of Business, Baylor University. She earned her Ph.D. degree in information systems from the University of North Texas, USA. Her research interests encompass a diverse range of topics, including cognitive information systems, the value of IT for organizations, artificial intelligence & ethics, human-computer interaction, and research methods.

Dr. Sullivan has published in premier outlets, such as *MIS Quarterly*, *Journal of the Association for Information Systems*, *Journal of Business Ethics*, *Annals of Operations Research*, and *International Journal of Information Management*, among others. She has also presented her research at many international conferences, including the International Conference on Information Systems and the Hawaii International Conference on System Sciences. In recognition of her exceptional research contributions, Dr. Sullivan was honored with the Habicht Early Career Research Award in 2023 by Hankamer School of Business at Baylor University.

Beyond her research, she plays a significant role in the academic community as an editorial board member of the Responsible Research in Business & Management (RRBM), an international non-profit organization dedicated to promoting credible and valuable research in the business and management disciplines. She also currently serves as the Undergraduate Program Director for the ISBA department at Hankamer School of Business.

Dr. Sullivan's dedication to education and teaching is equally noteworthy. She has been recognized for her significant influence on students' educational journeys and, more broadly, on their lives. In 2022, she earned a nomination for the Excellence in Teaching Award for tenure-track faculty. Furthermore, she has been consistently chosen as a favorite professor by numerous student organizations over the years.