1

Introduction

Common Threads among Techniques of Data Analysis

MELISSA HARDY AND ALAN BRYMAN

In deciding the mix of topics to include in this *Handbook*, we wanted to provide a wide range of analytic options suited to many different research questions and different data structures. An early decision was to include both 'quantitative' and 'qualitative' techniques in a single volume. Within the current research environment, practitioners can hardly fail to notice the schism that exists between camps of qualitative and quantitative researchers. For some, this division is fundamental, leading them to pay little attention to developments in the 'other' camp. Certainly the assumption has been that practitioners of these different approaches have so little in common that any text on data analysis must choose between the two approaches rather than include both in a single text.

We believe that reinforcing this division is a mistake, especially for those of us who practice in the behavioral and social sciences. Discipline boundaries too often act as intellectual fences beyond which we rarely venture, as if our own field of research is so well defined and so much ours that we can learn nothing from other disciplines that can possibly be of use. Many of us may remember our first forays into literature searches on a given research topic, which we too often defined in the narrowest of terms, only to learn from our advisors that we had missed mountains of useful publications arrayed across a variety of fields, time periods, and (perhaps) languages. One of the major costs of dividing and subdividing fields into an increasing number of specializations is that we may inadvertently limit the kinds of intellectual exchanges in which we engage. One learns more from attempting to view a subject through a variety of different lenses than from staring at the same page through the same pair of glasses. And so it can be with analytic techniques.

Researchers run the gamut from technical experts who speak in equations and spin out table after table of numerical results to those who have tried to devise an alternative to page enumeration, so averse to 'numbers' were they. Most of us are somewhere in the middle, interested in a particular research question and trying to formulate as systematic and as persuasive an answer as possible.

Both approaches attempt to 'tell a story' from the data. Quantitative researchers generally refer to this process as hypothesis testing or 'modeling' the data to determine whether and to what extent empirical observations can be represented by the motivating theoretical model. Qualitative researchers may or may not invoke models. Whether the method of *analysis* will be quantitative or qualitative is not so much an issue of whether the information/data at hand are organized through classifications, rank-ordered relative to some notion of magnitude, or assessed at the interval or ratio level of measurement. The choice can involve assumptions about the nature of social reality, how it should be studied, the kinds of research questions that are of interest, and how errors of observation, measurement, estimation, and conclusion should be addressed.

Because this is a text in data analysis rather than data collection, each author assumes a certain structure of data and a certain range of research questions. To be sure, many decisions have been made before the researcher begins analysis, although active researchers seldom march through the stages of design, data collection, and data analysis as if they were moving through security checkpoints that allowed mobility in only one direction. Instead, researchers typically move back and forth, as if from room to room, taking what they learn in one room and revisiting what was decided in the previous room, keeping the doors open.

However, if the researcher is relying on secondary data – data collected to serve a broad range of interests, often involving large national samples – key features such as the sampling design and questionnaire must be taken as given, and other types of information – how long it took the respondent to settle on a response, whether the respondent took some care to frame the response within a particular context even though what was recorded was simply a level of agreement with a statement, for example – are not retrievable. Researchers who collect their own data use a variety of sampling procedures and collection tools that are designed to illuminate what they seek to understand and to provide information best suited to their research interests. But once the data are in hand, the evidence that may be required to address the research problem will be limited to interpretations, reconfigurations, or creative combinations of this already collected information.

This distinction between measuring amounts and distinguishing categories is sometimes referred to as the distinction between quantitative and qualitative variables, and it is only one of the arenas in which 'quantity' and 'quality' are counterposed. Another contrast that is made between qualitative and quantitative approaches involves the use of *statistical* methods of analysis, where quantitative implies using statistics and qualitative, in some quarters, means eschewing statistical approaches. But not all research that is classified as quantitative relies only on statistical approaches. Certainly in coding interview information, any researcher must make decisions about the boundaries of classification, must determine 'like' and 'unlike' things, and these decisions are already shaping any analysis that will follow. In similar fashion, not all qualitative researchers reject statistics, although reliance on inferential statistics is not common. Does the fact that a researcher calculates a correlation coefficient or bases a conclusion on differences in the counts of events suddenly toss the research into the quantitative camp? Does it matter, so long as the procedures are systematic and the conclusions are sound?

THE BASICS

We begin the volume with some basic issues that require a researcher's attention. The novice researcher is often dismayed when first using a given data set, since the correspondence between the concepts he or she has in mind is seldom there simply to be plucked from a list. Issues of reliability and validity loom large in the enterprise of analysis, for the conclusions that can be drawn on the basis of an analysis, regardless of how simple or complex, are contingent on the utility of the information on which the analysis is based. It is the instrumentality of measurement – measure as organizing tool that relates observation to concept to theory – that is a common thread of all analysis. Having made that most fundamental recognition, however, we must also note that it is often through debates over procedures of *analysis* that concerns about the limitations of measurement are played out. The value of a measure is its utility for improving our understanding of some social process, whether such a measure emerges through the manual sifting of data, or whether it serves as the framework for data collection.

Defining variables is therefore an exercise in establishing correspondence. Part of our everyday activities involves organizing the steady flow of information that our senses feed to our brains. The manner in which we accomplish this organization is not a random process. Rather, we categorize, we classify, we monitor frequency and intensity, we note repetition, stability, change, and amount of change, along a variety of dimensions. We fudge the boundaries of these categories with phrases such as 'kind of' and 'sort of'. And whereas our classification schemes may be quite functional for our own use, they may not sit well with the schemes others use.

In our everyday conversations we either gloss over disagreements, or we may pursue the issue by defending how we make sense of a situation. But in taking this next step, we move closer to scientific practice, in that our original statement must then be argued on the basis of empirical evidence, rules of assignment, what counts as 'similar' versus 'different', and which traits trump others in making such assignments. In other words, such statements – such classifications – have to be reproducible on the basis of the rules and the evidence alone. Then the issue is how convincing others find our approach.

Once we have defined the terms of our analysis, the temptation for statistical analysts is to move quickly to the most complex procedures, but that step is premature. We can learn much by studying the distributions of the variables we observe. And once we have good basic information on the univariate distributions, we should spend some time examining simple associations among variables, two at a time. Although this stage can be time-consuming, it is essential to gradually build our understanding of the data structures on which more complex associations will rely. These insights prove valuable when one must translate the finding into some reasoned argument that allows others to grasp what has been learned.

THE UTILITY OF STATISTICS

In many of these early chapters, basic statistical procedures are explained and illustrated. As Duncan (1975: 4) noted:

> There are two broad kinds of problems that demand statistical treatment in connection with scientific use of [models] … One is the problem of inference from samples … Statistical methods are needed to contrive optimal estimators and proper tests of hypotheses, and to indicate the degree of precision in our results or the size of the risk we are taking in drawing a particular conclusion from them. The second, not unrelated, kind of problem that raises statistical issues is the supposition that some parts of the world (not excluding the behavior of scientists themselves, when making fallible measurements) may realistically be described as behaving in a stochastic (chance, probabilistic, random) manner. If we decide to build into our models some assumption of this kind, then we shall need the aid of statistics to formulate appropriate descriptions of the probability distributions.

A major benefit of even 'fallible' measurement as the method of organizing our observations within some comparative framework is that it serves as a tool of standardization, which provides some assurance that both we, as well as others who attempt to replicate our work, can reliably identify equivalences and differences. 'Better' measurement is often taken to mean 'more precise' measurement, but the increase in precision must have utility for the question at hand; otherwise, such efforts simply increase the amount of 'noise' in the measure. For example, a public opinion researcher may decide that she can better capture variability in people's view of a certain taxation policy by moving beyond a Likert scale of agreement or disagreement to a set of possible responses that range from 0 (I see no redeeming value in such a policy) to 100 (I see this policy as the perfect response to the need). In testing this new measurement strategy, however, the researcher may discover that the set of actual responses is far more limited than the options available to respondents and, for the most part, these responses cluster at the deciles (10, 20, 30, …, 90); the respondents effectively reduce the choice set by focusing on multiples of 10 rather than increments of one. However, the researcher may also observe the occasional response of 54 or 32. What is she to make of that additional variability? Can she be confident that the difference between a response of 32 and one of 30 represents a reliable distinction with regard to tax policy? Or is the 32 response perhaps more a reflection of 'a tendency toward non-conformity'?

But this issue of precision/reliability/variability is not in itself a function of a statistical versus a non-statistical approach. The issue of precision, as Duncan notes, is one of assessing the likelihood of erroneous conclusions and the role played by 'chance' in our research activities. Error is inescapable. Error as mistaken observation, error as blunder, error as bias – how do we systematically manage error within the range of techniques available to us? The question at hand is how we manage error when using 'quantitative' or 'qualitative' techniques of analysis.

In sum, any analysis of data, however it proceeds, is a sorting process of information that contains errors – however it was collected. Further, this sorting process by which we sift 'good' information from 'error' also allows us to sort for logical patterns, for example, Y only occurs when X is present, but when X is present, Y does not always occur. And by identifying certain patterns, noting their frequency, determining the contexts under which they occur always, sometimes, or never, we make sense of the data. And that is our goal – to make 'sense' of the data.

SIMILARITIES BETWEEN QUANTITATIVE AND QUALITATIVE DATA ANALYSIS

It is easy to assume that the different preoccupations and inclinations of their respective practitioners mean that as research strategies, quantitative and qualitative research are totally different. Indeed, they *are* different, reflecting as they do distinctive intellectual traditions. However, this does not signal that they are so different they do not share any common features. It is worth reflecting, therefore, on the ways in which quantitative and qualitative data analysis may be said to have common characteristics. In doing so, we begin to raise issues about what data analysis is and also what constitutes a good data analysis, whether quantitative or qualitative.

Both are concerned with data reduction

Although data analysis is something more than data reduction, it is also true to say that paring down and condensing the vast amounts of data that we frequently collect in the course of fieldwork is a major preoccupation of all analysts. Indeed, it would be surprising if this were *not* the case since dictionary definitions of 'analysis', such as that found in *The Concise Oxford Dictionary*, refer to a process of resolving into simpler elements. Therefore, to analyze or to provide an analysis will always involve a notion of reducing the amount of data we have collected so that capsule statements about the data can be provided.

In quantitative research, we are often confronted with a large array of data in the form of many cases and many variables. With small amounts of quantitative data, whether in terms of cases or variables, we may be able to 'see' what is happening. We can sense, for example, the way in which a variable is distributed, such as whether there is bunching at one end of the scale or whether a particular value tends to recur again and again in a distribution. But with increasing numbers of cases and variables our ability to 'see' tails off. We begin to lose sight of what is happening. The simplest techniques that we use to summarize quantitative data, such as frequency tables and measures of central tendency and dispersion, are ways of reducing the amount of data we are handling. They enable us to 'see' our data again, to gain a sense of what the data show. We may want to reduce our data even further. For example, we might employ factor analysis to establish whether we can reduce the number of variables that we are handling.

Similarly with qualitative data, the researcher accumulates a large amount of information. This information can come in several different forms. Ethnographers are likely to amass a corpus of field notes based on their reflections of what they heard or saw. Researchers who use qualitative interviews usually find that they compile a mountain of transcripts of tape-recorded interviews. As Lee and Fielding remark in Chapter 23, the transcription of such interviews is frequently the source of a major bottleneck in qualitative research, because it is so time-consuming to produce. However, transcripts frequently constitute a kind of double bottleneck because, in addition to being time-consuming to generate, they are daunting to analyze. Most approaches to analyzing ethnographic fieldnotes, qualitative interview transcripts, and other qualitative data (such as documents) comprise a coding approach that segments the textual materials in question. Not all approaches to qualitative data analysis entail this approach; for example, narrative analysis, which is discussed in Chapter 29 by Czarniawska, involves a preference for emphasizing the flow in what people say in interviews. But whatever strategy is adopted, the qualitative researcher is keen to break his or her data down so that it is more manageable and understandable. As Lee and Fielding show, the growing use of computer-aided qualitative data analysis software is a means of making that process easier (in terms of the coding, retrieval, and management of data) in much the same way as statistical software can rapidly summarize large quantities of data.

Both are concerned with answering research questions

While the precise nature of the relationship between research questions and data analysis may be different among quantitative and qualitative researchers, both are concerned with answering research questions. In quantitative research, the stipulation of research questions may be highly specific and is often translated into hypotheses which are outlined either at the beginning of an investigation or as we begin to analyze our data. This process is often depicted as indicative of the hypothetico-deductive method with which quantitative research is often associated. Stipulating research questions helps to guide the collection and analyses of data, but having such organizing questions also serves to ensure that the research is about *something* and that the something will make a contribution to our understanding of an issue or topic.

Qualitative researchers are often somewhat circumspect about devising research questions, or perhaps more precisely about the timing of their formulation. In qualitative research there is frequently a preference for an open-ended strategy so that the meaning systems with which participants operate are not closed off by a potentially premature confinement of what should be looked at. In addition, qualitative researchers frequently revel in the flexibility that the open-endedness offers them. Consequently, it is not unusual to find accounts of the qualitative research process which suggest that the investigation did not start with any concrete research questions. Not all qualitative research is like this; many practitioners prefer to begin with the relatively clear focus that research questions provide. Nonetheless, there is a strong tradition among practitioners which enjoins them not to restrict their field of vision too early in the research process by orienting to research questions. Some versions of grounded theory, for example, specifically encourage the deferment of research questions, as Pidgeon and Henwood observe in Chapter 28. But all this is not to say that research questions do not get asked in some versions of qualitative research. Instead, they tend to emerge in the course of an investigation as the researcher gradually narrows the area of interest. The research questions may even be developed into hypotheses, as in grounded theory. Deferring the asking of research questions has the advantage for qualitative researchers of enabling them to develop an understanding of what is important and significant from the perspective of the people they are studying, so that research questions that may be irrelevant to participants are less likely to be asked, if it is the perspective of relevance that matters. It also offers greater flexibility in that interesting insights gleaned while in the field can be used as a springboard for new research questions.

Thus, while the stage at which the formulation of research questions occurs frequently differs between quantitative and qualitative research, and the nature of the research questions may also be somewhat different, data analysis is typically oriented to answering research questions regardless of whether the research strategy is quantitative or qualitative.

Both are concerned with relating data analysis to the research literature

This point is closely related to the previous one but nonetheless deserves separate treatment. An important aspect of any data analysis is to relate the issues that drive and emerge from it to the research literature. With quantitative data analysis, the literature tends to provide an impetus for data analysis, in that it is invariably a key element in the formulation of a set of research questions. Quantitative research papers typically conclude by returning to the literature in order to address such issues as whether a hypothesis deriving from it is confirmed and how far the findings are consistent with it.

With qualitative data analysis, the existing literature may help to inform or at least act as a background to the analysis. This means, for example, that the coding of transcripts or fieldnotes will be partly informed by the literature. Existing categories may be employed as codes. In addition, the qualitative researcher will typically seek to demonstrate the implications of an analysis for the existing literature.

Thus, practitioners of both research strategies are highly attuned to the literature when conducting data analysis. This feature is indicative of the fact that practitioners are equally concerned with making a contribution to theory through their data analysis.

Both are concerned with variation

Variability between cases is central to quantitative data analysis. The goal of quantitative data analysis is to capture the amount of variation in a sample and to explain why that variation exists as it does and/or how it was produced. An attribute on which people (or whatever the nature of the cases) do not vary, and which is therefore a constant rather than a variable, is typically not of great interest to most analysts. Their toolkit of data analysis methods is geared to variability rather than to its absence. As noted above, even the most basic tools of quantitative data analysis – measures of central tendency and dispersion – are concerned to capture the variability that is observed.

But variation is equally important to qualitative researchers when they conduct their analyses. Variation is understood somewhat differently from quantitative research in that it relates to differences one observes but to which one does not necessarily assign a numerical value, but it is nonetheless central as an observation of relative magnitude (e.g., respondents differed more in their opinions on this than on that). In the course of carrying out an analysis of qualitative data, the researcher is likely to be attending to assorted issues that reflect an interest in variation: Why does a particular activity or form of behavior occur in some situations rather than others? Why are some people excluded from participation in certain activities? To what extent do differences in certain kinds of behavior vary because of the different meanings associated with the behavior in certain situations? How and why do people's behavior or meaning attributions vary over time? These are common issues that are likely to arise in the course of qualitative data analysis, and all of them relate in some way to variation and variability. The idea that meaning and behavior need to be understood contextually (e.g., Mishler, 1979) implies that the researcher is forced to consider the implications of contextual variation for his or her findings.

Conversation analysis might be assumed to belie this point about qualitative data analysis in that its emphasis on the ordered nature of talk in interaction could be taken to imply that it is a lack of variation that is of concern. However, the conversation analyst is also concerned with such issues as *preference organization*, which presumes that certain kinds of responses are preferred following an initial utterance and is at least implicitly concerned with the exploration of variation. Similarly, an interest in the use of *repair mechanisms* in conversations would seem to imply a concern with variation and responses to it. Thus, once again, while it is addressed in different ways in quantitative and qualitative data analysis, the exploration of variation is an important component of both strategies.

Further, an initial understanding of patterns of variability may inform the collection of data. In the formal application of sampling theory, populations may be viewed as comprised of different strata, and each stratum may be assigned a different sampling ratio. In this way, the researcher ensures that sufficient variability of important minority characteristics occurs in the sample. Similarly, in deciding where and whom to observe, qualitative researchers may choose sites and/or groups they expect to differ, thereby building into the research design variability of observed behavior and/or observational context.

Both treat frequency as a springboard for analysis

That issues of frequency are important in quantitative data analysis is neither surprising nor illuminating. In the course of quantitative data analysis, the practitioner is bound to be concerned with issues to do with the numbers and proportions of people holding certain views or engaging in different types of behavior. The emphasis on frequency is very much bound up with variation, since establishing frequencies is a common way of expressing variation.

However, frequency is a component of qualitative data analysis as well. There are two ways in which this occurs. Firstly, as some commentators remark when they write up their analyses, qualitative researchers often use quantitative terms, such as 'most', 'many', 'often', and 'sometimes' (Becker, 1958). In many ways, these are very imprecise ways of conveying frequency and, given their ambiguity, it is usually difficult to know what they mean. Qualitative researchers are not alone in this regard, however. In spite of the fact that they use apparently more precise yardsticks for gauging frequency, quantitative researchers also resort to such terms as embellishments of their quantitative findings, although the actual values are generally reported as well. Moreover, when quantitative researchers do employ such terms, they apply to widely different indicators of frequency (Ashmore et al., 1989). Silverman (1985) recommends that qualitative researchers use limited quantification in their analyses rather than rely excessively on vague adjectival terms.

Frequency can be discerned in relation to qualitative data analysis in another way. As Bryman and Burgess (1994) observe, when they code their unstructured data, qualitative researchers are likely to rely on implicit notions of frequency. This can occur in at least two ways. They may be impressed by the frequency with which a theme appears in their transcripts or fieldnotes and may use this as a criterion for deciding whether to apply a code. Themes that occur very infrequently may be less likely to receive a distinct code. In addition, in developing codes into concepts or categories, they may use frequency as a method of deciding which ones are worth cultivating in this way.

Both seek to ensure that deliberate distortion does not occur

Although few social scientists nowadays subscribe to the view that we are objective, value-free observers of the social world, this recognition makes it more important that we proceed in ways that are explicitly defined and therefore replicable. There is evidence in certain quarters of the emergence of avowedly partial research. For example, Lincoln and Guba (1985) recommend that one set of criteria by which research should be judged involves the issue of *authenticity*. This set of criteria relates to the political dimension of research and includes such principles as *catalytic authenticity*, which enjoins researchers to ask whether their research has motivated members to engage in action to change their circumstances, and *tactical authenticity*, which asks whether the research has empowered members to engage in action. In spite of the use of such criteria, which are political in tone and which are a feature of much writing from a feminist standpoint, qualitative researchers have not suggested that the distortion of findings during data analysis should accompany political ambitions. There are plenty of opportunities for researchers to twist findings intentionally during data analysis – whether quantitative or qualitative. However, by and large, they are committed to presenting an analysis that is faithful to the data. Of course, there is a far greater recognition nowadays that both quantitative and qualitative researchers employ a variety of rhetorical strategies for convincing readers of the authenticity of their analyses (see Bryman, 1998, for a review of some of these writing techniques). However, this is not to suggest that data analysis entails distortion, but that through their writings researchers have to win over their readers to the credibility of what they are trying to say. In essence, what is guarded against in most quantitative and qualitative data analysis is what Hammersley and Gomm (2000) call *willful bias*, that is, consciously motivated misrepresentation.

Both argue the importance of transparency

Regardless of the type of research being conducted, the methodology that is used should not eclipse the data, but should put the data to optimal use. The techniques of analysis should be sufficiently transparent that other researchers familiar with the area can recognize how the data are being collected and tested, and can replicate the outcomes of the analysis procedure. (Journals are now requesting that authors provide copies of their data files when a paper is published so that other researchers can easily reproduce the analysis and then build on or dispute the conclusions of the paper.) Whether they also agree about what those outcomes mean is a different issue. Much of the disagreement that occurs in the research literature is less with analysis-as-process and more with the specification or the context in which the question is being addressed and the interpretation of the findings. In arguing a certain 'story line', a quantitative researcher may try to demonstrate the 'robustness' of findings by showing that certain key results persist when evaluated within a variety of contexts of specifications.

If we take as an exemplar of quantitative research the analysis of national survey data, transparency in the data collection process is generally high. Sampling procedures are well documented; comparative analysis of how the sample compares to the population on known characteristics is reported; the researcher is provided with a codebook and questionnaire that provide details about the questions asked, the range of responses given, and frequency distributions, so researchers can be confident they are reading the data correctly. Improvements in computer technology have made this process considerably easier, faster, and more reliable. In addition, the general availability of software packages to perform a wide range of analyses removes the mystery of what algorithm was used and what calculations were made.

But one issue of 'transparency' in quantitative research involves the use of statistical tools that, from some perspectives, 'distance' the researcher from the data. For example, missing values are imputed, cases are weighted, parameter estimates have confidence intervals that change with each specification, sometimes achieving the status of statistical 'significance' and sometimes falling short. Estimates of effects to the first, second, occasionally third decimal point – how can anyone 'see' the original data behind this screen of computational complexity? But to say that the procedures are sufficiently complex to require computer assistance in their application is *not* to say that they are opaque. The sampling framework that generates the case weights is derived from sampling theory, an ample literature that provides rules for both selection and adjustment, as well as the likely consequence of proceeding other than 'by the rules'. The algorithms on which sample estimates are based are derived from estimation theory, their properties tested through simulations and statistical experiments so that researchers can understand the conditions under which their use will yield desirable and reliable results. The process is neither convoluted nor impenetrable, but it is complex, and it is reasonable to assume that practitioners who use quantitative methods are not always well acquainted with the details of sampling, estimation, or statistical theories that provide the rationale for the practice. To acknowledge that building an understanding of the theoretical foundations for this practice is a challenging task is one thing; to reject this literature because it is challenging is quite another.

With qualitative research, an absence of distance and, until rather recently, limited use of technological innovation for organizing and analyzing information can create a different dilemma for replication. Observational data may rely on one person's recollections as fieldnotes are written; transcriptions of taped interviews or coded segments of videotape that anyone can evaluate provide more the type of exactitude that many quantitative types find reassuring. And clear rules that govern who, what, and when we observe; justifications for the chosen procedure over alternatives; rules of coding; logical relationships; analytical frameworks; and systematic treatments of data can combine to produce consistent and reproducible findings.

Conversation analysis (Chapter 26) takes a somewhat different line on this issue from most forms of qualitative data analysis, in that practitioners have always exhibited a concern to demonstrate the transparency of their data and of their analysis. Qualitative researchers generally have few guidelines about how to approach their data other than the need to address their research questions through their data. One of the great appeals of grounded theory (Chapter 28) has been that it provides a framework, albeit at a far more general level than statistical techniques provide, for thinking about how to approach qualitative data analysis. It is also worth bearing in mind that one of the arguments frequently employed in favor of computer-assisted qualitative data analysis is that it forces researchers to be more explicit about the way they approach their data, so that, in the process, the transparency of the analytic process may be enhanced.

Indeed, we begin to see here some of the ways in which quantitative and qualitative data analysis differ. Not only is there a difference in most instances in the transparency of the process, but also quantitative data analysts have readily available toolkits for the examination of their data. Conversation analysis comes closer to a toolkit approach than many other forms of qualitative data analysis, although semiotics (see Chapter 25) and to a certain extent discourse analysis (see Chapter 27) come close to providing this kind of facility. A further difference is that in analyzing secondary data, quantitative researchers usually conduct their analyses at the end of the research process, since data collection occurred elsewhere. However, in analyzing primary data, both quantitative and qualitative researchers intersperse data collection with data analysis. Quantitative researchers need to pilot-test their measures to ensure that the information collected meets criteria of both validity and reliability. And many writers on qualitative data analysis, particularly those influenced by grounded theory, advocate that data collection and analysis should be pursued more or less in tandem. As Coffey and Atkinson (1996: 2) suggest: 'We should never collect data without substantial analysis going on simultaneously. Letting data accumulate without preliminary analysis along the way is a recipe for unhappiness, if not total disaster.' Coffey and Atkinson (1996: 2) go on to say that there 'is no single right way to analyze data'. While this comment is made in relation to the analysis of qualitative data, it applies equally well in relation to quantitative data analysis. On the other hand, there are plenty of ways in which data can be wrongly or inappropriately analyzed, and a book such as this will help to steer people away from potential mistakes.

Both must address the question of error

The manner in which quantitative and qualitative approaches manage the effects of error may well be the most central point of difference. Quantitative research can be viewed as an exercise in managing error, since variability-as-observed-difference is both a function of empirically distinct characteristics and error in the empirical process of observing those distinctions. One context in which the utility of statistical information and the acknowledgment of error come into conflict is the courtroom. Statisticians asked to give expert testimony are inevitably asked by opposing counsel whether they are 'certain' of their findings. Regardless of whether they acknowledge a 5% margin for error, a 1% margin for error, or a 0.1% margin for error, they can never say with absolute certainty that 'this' occasion cannot possibly be an error. In contrast, for many years eyewitness testimony was the gold standard of evidence, since a 'good' eyewitness would deny uncertainty, testifying to no doubt, no possibility of error – testifying with certainty. And so they may have believed. But the frequency with which recently utilized DNA evidence is proving exculpatory has given everyone pause. If we cannot trust our own eyes, how can we be sure of anything? One answer is that absolute certainty was always an illusion, whether it was asserted in scientific enterprise or everyday life. Even so, we know many things, and in so knowing, we can accomplish many tasks. And in trying to accomplish, we can learn much more. So if our choice is between drowning in doubt or acting on best information, we act. Neither judge nor jury can ever be certain, in the sense that they cannot claim that error is impossible; but they can draw conclusions by weighing the evidence. And so they do.

Within the framework of behavioral and social science, both quantitative and qualitative analysts acknowledge that error is an unavoidable aspect of data collection, measurement, coding, and analysis procedures. And both agree that error cannot always be assumed to be random, such that the summary influences of error on our conclusions simply 'cancel out'. Much of the development in quantitative research that has occurred over the past three decades has been oriented toward better managing error. In particular, attention has been focused on developing procedures to address error as a confounding source in the data while preserving the substantive focus and the structural relations of interest. In fact, we can look at the chapters in this text as representing advancements in the analysis of error.

The early chapters on constructing variables, describing distributions, and dealing with missing data involve the exposition of techniques for using already collected bits of information and combining them, reconfiguring them, transforming them in ways that create a better match between the measure and the concept. The variance has been called the 'mean squared error' because it provides the average weighted distance of observations from the midpoint of the distribution. This measure of inequality, of observed difference, provides the problematic for further analysis designed to answer the question: what produced the differences?

Missing data can create problems of error, since the missing information may occur at higher frequency in one or another part of the distribution (creating truncated distributions), or the pattern of missing data may be correlated with other factors. Chapter 4, on inference, underscores the complications introduced by sampling error, or generally by procedures designed to allow statements about the whole using only partial information. What this and other early chapters share is an emphasis on process. Dealing with missing information through some kind of imputation procedure requires that we theorize about the process that created the data gaps in the first place. Why do some people answer this question, while other respondents refuse? What is it about the question, the kind of information the question tries to elicit, and the known characteristics of the respondent that makes 'refusal' more likely?

For example, collecting income information is notoriously difficult. People generally consider their household income or the amount they have saved or invested to be private information. Although respondents often like to offer their opinions, they are less pleased – and sometimes angered – by questions of 'fact' that appear to invade their privacy. But techniques for collecting information in wide categories, coupled with information about relationships among observed characteristics of respondents and the piece of missing information, have allowed improvements in imputations. To ask someone to report last year's gross annual income may elicit a refusal. But to follow up with a question that asks the respondent to report whether it was 'above $50 000' creates a benchmark. Once the respondent supplies that first benchmark, it is often possible to channel them through a progressive series of categories, so that the gross annual income is eventually known to be between $25 000 and $35 000. The exact income is still 'missing', but imputation procedures can now utilize the range of values in which it falls.

In similar fashion, Chapter 4 links the adjustments we make for sampling error (e.g., the building of confidence intervals around estimates by using information on the error of those estimates) to the selection procedures that generated the sample (the part) from the population (the whole). Again, we rely on the theory of probability to move from the population to the sample, and then again to move back from the sample estimate to the population parameter. If the selection process was not according to some known probability process, then probability theory is of no use to us, and we are left with a description of a set of observations that do not generalize to any known population. Later chapters on selection models take these issues further by suggesting approaches that explicitly model mechanisms of sample selection as part of the system of equations testing structural relationships.

The process of constructing variables also introduces error. Are single indicators sufficient? If we combine indicators, what type of weighting scheme should we employ? And even at our best, we realize that there is some slippage between the concepts as abstractions and the variables that we use as the informational repositories of their meaning. But errors in measurement attenuate measures of association, making it more difficult to take that next step of describing underlying processes that produce what we observe. And in trying to represent that process, we are limited to our success in finding information that maps well the conceptual space we have defined. Missing pieces of information – missing for everyone rather than missing selectively – create specification error, which can introduce bias into our conclusions. The chapters on regression, structural equation models, models for categorical data, etc. all address these issues of error that complicate the task of the researcher, providing guidance on proper procedures when we attempt to explain the variability in dependent variables measured in different ways (e.g., by interval scale, by dichotomy, by polytomous classification) and within different levels of complexity (e.g., single equation versus multiple equation models motivated by concerns of endogeneity).

And if we are really interested in the underlying process, don't we need to look at process? In other words, shouldn't we be analyzing longitudinal data, following individuals over time so we know how changes in one aspect of their lives may be linked to subsequent changes in other aspects of their lives? But then we have the complication of correlated errors, since multiple observations on one respondent are likely to be characterized by similar observational errors at each point in time. Or perhaps our longitudinal frame should be the comparison of same-aged people over time to determine whether opinions in the aggregate have changed over time, for example? Further, as social scientists, we know that context is important, that processes may unfold one way under one set of circumstances, but unfold differently under different organizational or institutional constraints. How do we analyze information that describes the individual *within* the organizational context? Over time? These are the issues that event-history models, hierarchical linear models, panel models, latent curve models, and other advanced techniques were designed to address.

The more complicated the questions we ask, the more complicated the error structure with which we must deal, but we are not without tools to tackle these tasks, although the tools become more complicated as well. Any carpenter who wants to saw a board into two pieces has a variety of tools at his or her disposal, the simplest being a handsaw. But to cut designs into the wood, or dovetail a joint, or fit rafters on a double-hipped roof, requires more sophisticated tools to produce the desired outcome.

In qualitative research, error has not been a notion that has great currency. Indeed, some qualitative researchers argue that the very idea of error implies a 'realist' position with which some versions of qualitative research, particularly those influenced by postmodernism (see Chapter 30), are uncomfortable. For these qualitative researchers, it is demonstrating the credibility of findings that is likely to be of roughly equivalent concern (Lincoln and Guba, 1985), although it may be implicit in some notions of validity in qualitative research (e.g., Kirk and Miller, 1986). Demonstrating credibility takes many forms, but a major feature is being able to show a close correspondence between one's data and one's conceptualization, a concern which can be translated into quantitative research as concerns with 'goodness of fit', or how well the theoretical model fits the empirical information.

For those who use statistics, the 'fit' can be assessed as prediction successes versus prediction errors. But interpreting whether a given level of fit, a given value of the statistic, is persuasive evidence of the correctness of the theory is open to dispute. And the terms of dispute on this point are likely to be similar for both qualitative and quantitative researchers. Are your observations consistent with the predictions of the theory? Has the information been properly classified? Have you ignored other things that could change this picture? Do I believe your story? In both types of research, the richer the data, the more persuasive the conceptualization is likely to be.

Moreover, for the qualitative researcher, the emerging concepts must be demonstrably located in the data. The quantitative researcher refers to this as operationalization – whether the empirical variables fit the theoretical concepts. In the process of sorting through the vast amounts of information, many qualitative researchers must inevitably classify, which means they determine categories and group what they observed into 'like' and 'unlike' observations. Is there only one way this can be accomplished? Most researchers from either camp would answer 'no'. So both types of researchers may be accused of category 'errors', in that someone else working with these same observational data may define groups differently. Disputes such as these are not uncommon.

Has the researcher ignored something 'important' in his or her analysis? Not intentionally, but someone with a different perspective may argue a different 'story' by picking up a feature that the first researcher failed to consider. Quantitative researchers refer to this as specification 'error', which simply means that in developing your story, you have left out something relevant. This error of omission is among the most serious in quantitative research, since it means that the evidence on which you are basing your conclusions is incomplete, and it is difficult to say how the story may change once you take this new twist into account.

These sources of 'error' in qualitative and quantitative research – observational error, classification error, and specification error – can be introduced through the choices made by the researcher, who may fail to pick up important cues from his or her research participants or may misread in conceptual terms what is happening. Thus, even though error is a term that is unlikely to sit easily with the way many, if not most, qualitative researchers envision their work, it is not without merit. A major difference is that the quantitative researcher turns to sampling, measurement, and estimation theory to mathematically formalize how error is assessed and addressed; the qualitative researcher generally relies on rules of logic, but not on mathematics. Both researchers, however, must rely on argument and the strength of evidence they muster from their data to convince others of their story.

The trick for the qualitative researcher is one of balancing a fidelity to the data (in a sense, a commitment to naturalism) with a quest to say something meaningful to one's peers (in other words, to conceptualize and theorize). The advantage of fidelity to the data is that the researcher's emerging conceptual framework will be relatively free of error, but the problem is that it may be difficult to appear to have done anything other than act as a conduit for the world-view of the people who have been studied. The corollary of this position is that qualitative researchers must be wary of conceptualizing to such an extent that there is a loss of contact with the data, so that the credibility of their findings is threatened and therefore error creeps in.

ORGANIZATION OF THE BOOK

It is with the kinds of issues and considerations outlined above that the authors of the chapters in this volume have sought to come to terms. The quantitative–qualitative research distinction partly maps onto the organization of the book, but only partly. On the face of it, qualitative data analysis is covered in Part V. However, content analysis is essentially a quantitative approach to the analysis of unstructured or qualitative data, while the chapters in Part I on feminist issues in data analysis (Chapter 6) and historical analysis (Chapter 7) transcend the distinction in having implications for and elements of both quantitative and qualitative approaches to data analysis. Part I provides some of the foundations of data analysis – the nature of distributions and their analysis; how to construct variables; the nature of observational and statistical inference; what missing data are and their implications; and, as has just been remarked upon, feminist issues and historical analysis.

Part II teaches the reader about the single-equation general linear model, its extensions, and its applicability to particular sorts of research questions. Although called the 'linear' model, it can accommodate a variety of functional forms of relationships, which can be used to test whether an association is monotonic, curvilinear, or proportional, for example.

Part III addresses the issue of studying change. Whereas in cross-sectional analysis we can describe how the outcome is associated with certain characteristics, in longitudinal analysis we introduce the timing of the outcome relative to the timing of changes in the characteristics. Introducing time into the research design creates another layer of complications, which must be addressed through both theory and technique. It also requires a different data structure, which factors time into both the procedures and the content of data collection.

Part IV introduces the reader to some recently developed but well-established approaches to data analysis. Many of these approaches address the issue of endogeneity, which is the complication that some of the factors we view as predictors of a certain outcome are also at least partly determined *within* the same system of relationships. In such circumstances, single-equation models are not sufficient.

Part V, as previously noted, is devoted to the analysis of qualitative data. In Chapter 23, some of the main elements of qualitative data analysis are outlined, along with the issues involved in the use of computer software for the management and analysis of qualitative data. Chapter 24 deals with content analysis, which, although an approach for the analysis of qualitative data, employs an analytic strategy that is very much in tune with quantitative research. Chapters 25–27 deal with approaches to qualitative data analyses that emphasize language and its significance in the construction of social reality. Chapter 28 discusses grounded theory, which has been referred to several times in this introduction and which has become one of the major frameworks for organizing qualitative data analysis. Chapter 29, in presenting narrative analysis, provides a discussion of an approach that is attracting a growing number of adherents and which in many ways provides an alternative to the coding approach to the initial analysis of qualitative data that is characteristic of grounded theory and many other approaches to the analysis of qualitative data. Finally, Chapter 30 provides an outline of the highly influential postmodernist approach, particularly in relation to qualitative data. In many ways, the postmodernist mind-set entails an inversion of many of our cherished beliefs about how social research should be carried out and about how to understand its written products.

SUMMARY

The approaches explicated in this *Handbook* are not exhaustive of the range of approaches available to the researcher. As we explained earlier, we chose to build on basics, yet address some of the most difficult and complicated issues researchers face. Some of the most recent innovations in approaches are, at best, mentioned parenthetically, with reference to other sources of information the interested reader is encouraged to pursue. Our goal is to help readers do 'good research'.

Good research shares some common features. It does not violate ethical guidelines. It is not based on 'fictionalized' data, but rather on information collected according to rules of observation and recording. It describes with fidelity and, at its best, explains how what was observed came to be as it was rather than otherwise. In building this text, we hope to allow interested researchers to learn from one another about a wide range of approaches to data analysis. New techniques are in the process of development; techniques already in use find new advocates and new critics. Here is a place to take up the journey.

REFERENCES

Ashmore, M., Mulkay, M. and Pinch, T. (1989) *Health and Efficiency: A Sociology of Health Economics*. Milton Keynes: Open University Press.

Becker, H.S. (1958) 'Problems of inference and proof in participant observation', *American Sociological Review*, 23: 652–60.

Bryman, A. (1998) 'Quantitative and qualitative research strategies in knowing the social world', in T. May and M. Williams (eds), *Knowing the Social World*. Buckingham: Open University Press.

Bryman, A. and Burgess, R.G. (1994) 'Reflections on qualitative data analysis', in A. Bryman and R.G. Burgess (eds), *Analyzing Qualitative Data*. London: Routledge.

Coffey, A. and Atkinson, P. (1996) *Making Sense of Qualitative Data: Complementary Research Strategies*. Thousand Oaks, CA: Sage.

Duncan, O.D. (1975) *Introduction to Structural Equation Models*. New York: Academic Press.

Hammersley, M. and Gomm, R. (2000) 'Bias in social research', in M. Hammersley (ed.), *Taking Sides in Social Research: Essays in Partisanship and Bias*. London: Routledge.

Kirk, J. and Miller, M.L. (1986) *Reliability and Validity in Qualitative Research*. Newbury Park, CA: Sage.

Lincoln, Y.S. and Guba, E. (1985) *Naturalistic Inquiry*. Beverly Hills, CA: Sage.

Mishler, E. (1979) 'Meaning in context: is there any other kind?', *Harvard Educational Review*, 49: 1–19.

Silverman, D. (1985) *Qualitative Methodology and Sociology: Describing the Social World*. Aldershot: Gower.