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Computer-Assisted Integration of Mixed Methods Data Sources and Analyses

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Computer-Assisted Integration of Mixed Methods Data Sources and Analyses

PatBazeley

Objectives

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This chapter has one primary learning objective:

- to improve the level and quality of integration in, and thus inference from, mixed methods studies.

It also has a number of contributory sub-objectives:

- to stimulate readers to think more adventurously about the possibilities for analysis inherent in their mixed methods data;
- to introduce a range of software tools that will assist readers who wish to extend their practice and skills in data management and analysis; and
- to review approaches to, and ideas and suggestions for, ways of integrating data and analyses that are supported by software.

New tools within analysis software, developed in response to the growing interest in mixed methods research, facilitate and extend possibilities for working with mixed data types and analysis methods. This chapter considers the opportunities software presents the researcher working to integrate data and analyses in answering questions asked in the social and behavioral sciences.

The Challenge of Integration

Integration of mixed data sources and approaches to analysis occurred in classic community studies and in evaluation research through much of the last century. All mixed methods studies, by definition, attempt some form of integration, but in the latter years of the last century, debates about commensurability of paradigms created anxiety for many researchers about integrating the various strands of a mixed (or multi-) method research project before they reached the point of drawing conclusions. Currently, specific disciplinary expectations (particularly evident in health and education) as to what constitutes “gold standard” scientific evidence continues to downplay the value of evidence derived from qualitative sources. These theoretical positions combine with practical difficulties involved in collecting, managing, and analyzing multiple sources to limit the extent to which researchers effectively integrate various components of their mixed methods studies (Bryman, 2007; O'Cathain, Murphy, & Nicholl, 2007). As noted by Greene (2007), the interaction challenge in integrated designs remains undertheorized and understudied; I would suggest that the level of integration in many (if not most) mixed methods studies remains underdeveloped.

This chapter takes as its starting point the assumption that integration of data and analyses is not only acceptable but often necessary for achieving project goals, and it looks at how such integration might be facilitated by use of computer software. For current purposes, and borrowing from previous work by Bryman (2007), Woolley (2009), Moran-Ellis et al. (2006), and Yin (2006), I define integration in mixed methods thus:

> Integration can be said to occur to the extent that different data elements and various strategies for analysis of those elements are combined throughout a study in such a way as to become interdependent in reaching a common theoretical or research goal, thereby producing findings that are greater than the sum of the parts.

My approach to integration recognizes “the reality that there can be many different ‘mixes’ or combinations of methods” (Yin, 2006, p. 41) and rejects a clear differentiation between qualitative and quantitative methods or approaches to research (Bergman, 2008). In describing their approach to concept analysis as an integrative mixed method, Kane and Trochim (2007) suggest:

> Rather than simply combining qualitative and quantitative methods, [concept analysis] challenges the distinction between these two and suggests that they may indeed be more deeply intertwined. In some sense it is a method that supports the notion that qualitative information can be well represented quantitatively and that quantitative information rests upon qualitative judgment. (p. 177)

This is an opinion that is somewhat reflective of a much earlier statement by Fielding and Fielding (1986):

> Ultimately all methods of data collection are analysed “qualitatively,” in so far as the act of analysis is an interpretation, and therefore of necessity a selective rendering, of the “sense” of the available data. (p. 12)

If *quantitative* and *qualitative* are poles on a multidimensional continuum rather than distinct entities, as is now widely recognized, then emphasis on the separate definition of these components and a requirement for inclusion of both in a mixed methods study can create unhelpful boundary issues and further impede analytic integration.

The issue for researchers struggling in their attempt to integrate the different strands of their projects is compounded for those who also have a limited understanding of qualitative methodologies, such that they do little more than descriptively identify themes when working with text-based data, or simply use them to find "juicy quotes" to illustrate their statistical results (Bazeley, 2009a). Likewise, those with limited statistical understanding are prone to ignore the assumptions associated with particular statistical procedures and to draw inappropriate conclusions from their data, or they are simply unaware of the possibilities that statistical analyses can offer. Traditional research training in qualitative and/or quantitative methods, in addition, rarely engages with methodological developments that do not fit neatly into either of those boxes, such as Q methodology, social network analysis, or use of fuzzy logic or qualitative comparative analysis. One of the clear challenges in integrating data and analyses, therefore, is in having the breadth and depth of individual or team-based knowledge and skills on which to draw when undertaking a mixed methods study.

Strategies for Integration

Analytic strategies, particularly decisions about the level of integration in mixed methods studies and the point at which it might occur, are very much related to issues of research design and purpose (Maxwell & Loomis, 2003). "Methodology is ever the servant of purpose, never the master" (Greene, 2007, p. 97). The primary purposes for integrating methods, in Greene's analysis, are complementarity and initiation, with the latter being particularly served by dialectically integrated paradigmatic and methodological approaches.

In recent decades, mixed methods theorists have begun to identify a range of integrative design strategies for working with mixed data sources and complex questions (Creswell &

specifically through analysis, rather than as a conclusion to analysis (Bazeley, 1999, 2006, 2009b, 2009c; Caracelli & Greene, 1993; Teddlie & Tashakkori, 2009). Two primary processes—combination and/or conversion—run through most integrative strategies (Bazeley, 2006), and computer software assists integration primarily through providing ways in which quantitative and qualitative data can be combined or converted.

Software for Mixed Methods Analysis

Software for separately analyzed quantitative and qualitative components in a mixed methods study is widely available and can be used as suits the regular preferences of the researcher. Mixed methods researchers wanting to integrate different types of data within their analyses can find assistance also from a number of these software packages, as well as from some more specialist programs. Most of the software described below does not prescribe use of a particular methodology or method of analysis (within its broad domain) but rather provides tools for application to the researcher's chosen approach to analysis.

Available programs that are of assistance to the mixed methods researcher can be broadly classified into three groups: general purpose spreadsheets and databases; programs designed primarily for qualitative data analysis but which provide for combination or conversion of data; and add-on text-analysis modules for statistical programs, which categorize text data and then combine it into statistical analyses. In addition, there is an increasing range of software developed for specific purposes, often inherently involving mixed methods (Teddlie & Tashakkori, 2009).

Software developers respond to user demand: Recent developments in software reflect the growing acceptance of the integration of qualitative and quantitative data and analyses as a legitimate approach to handling data. These developments also offer exciting new possibilities for researchers wishing to explore the limits of what can be achieved with computer software as a tool. From a technical point of view, integrating qualitative and quantitative data is no longer difficult, providing one is reasonably comfortable with computers and with moving between a range of software packages. Yet, there are surprisingly few published studies reporting results from projects that make more than very elementary use of the capacity to integrate data and analyses using computers.

General Purpose Spreadsheets and Databases

Spreadsheets and databases are widely available as components in general purpose office suites. Excel, for example, is often used in research as a data recording tool; as an intermediary for transferring numeric data from one program to another; for simple calculations such as sums, means, and percentages; for production of cross-tabulations (pivot tables); and for charting data. Often the handmaiden to other software, spreadsheets and databases also have some specific functions of value to mixed methods researchers.

Both text and numeric data can be recorded within a spreadsheet, making it a useful tool for mixed methods tasks that involve synthesis of varied forms of data from a range of sources, and one that is quite straightforward to use. A database can be used similarly, with the advantage of being able to handle larger text fields and queries across related tables, but it is somewhat more complex to set up and use. Columns are created to cover all issues to be explored and aspects of concern that might impinge on those, while numeric or summary data or brief quotes from each source or case are entered in each row. These do not need to be ordered in any particular way. Once entered, data can be sorted, resorted, or filtered on the basis of included numeric or categorical variables to reveal patterns across all responses (Bazeley, 2006; Niglas, 2007). New categories or issues can be added during the process if found to be necessary by adding an additional column, or additional categorization of the text summaries can be completed during analysis to allow further sorting and examination of relationships between categories.

Statistical Packages

Statistical software typically provides an extensive range of visualization tools to assist the quantitative researcher to see patterns in and interpret their data, including charts of various types, box plots, scatterplots, dendrograms, and dimensional plots.

Several statistical programs provide additional modules designed to auto-code responses to open-ended questions for statistical analysis. SPSS Text Analysis for Surveys (http://www.spss.com) creates modifiable categories based on regularly co-occurring words from short-answer text responses using natural language processing, allowing the researcher to rapidly categorize a large set of data and combine it with the precategorized or scaled responses from the same survey in regular statistical routines. WordStat (http://www.provalisresearch.com) can be used with either short answers or longer passages of unstructured text (up to 10 Mb). Starting from an automated content analysis of words in the text, the user sets up rules and so builds up dictionaries for categorizing the data. These rules can be stored for future use with further sets of data. Relationships between the coded content of documents and information stored in categorical or numeric variables can be rapidly explored using exploratory data analysis or graphical tools.

Qualitative Data Analysis (QDA) Software

Authors using manual methods for coding the qualitative data component of their mixed methods study typically describe an exhaustive process of reading, re-reading, and checking transcribed text to arrive at a series of themes and subthemes, with the description of these themes being presented as the analysis of the data. With computer-based coding, the researcher can separately identify, on the same passage, a range of contextual, action, responsive, or other factors, with any of these codes used in any combination, as appropriate, across any of the data. As soon as data are coded in this way, almost limitless possibilities for review, sorting, sifting, combination, and comparison of text segments become available, with original source context available as required (Bazeley, 2007).

Tools developed primarily (or initially) for analysis of qualitative data, but which have now developed specific capacities for integrative mixed methods analyses, include NVivo (http://www.qsrinternational.com) and MAXQDA (http://www.maxqda.com). QDA Miner (http://www.provalisresearch.com) has been developed as the qualitative coding component of a larger suite (including WordStat) purposively designed for application within mixed methods analyses. EthnoNotes (http://www.ethnonotes.com) is a multi-user, multiplatform

Web-based application (purchased on a project/user/time basis), which has also been developed specifically for use in mixed methods applications.

Facilities currently offered to the mixed methods researcher by these programs include

- auto-coding tools to facilitate sorting of open-ended responses from structured surveys;
- integration of quantitative (variable) data with coded (thematic) qualitative data for matrix-based comparative analyses of coded text;
- conversion of qualitative coding to variable data;
- export of matrix-based data reflecting detail of associations between codes; and
- visualization tools.

Programs Supporting Particular Mixed Methods Applications

These software programs are designed with particular methodological purposes in mind, rather than for general application to a broader range of projects and purposes.

QCA—Qualitative Comparative Analysis

QCA refers to a set of configurational comparative methods based on the logic of set theory and using Boolean algebra applied to small or moderate-size sets of categorized data. Data are organized as configurations in a "truth table," used to build explanatory models for a given outcome. The original QCA software, developed for dichotomized ("crisp set" or csQCA) data, remains DOS based. More recent developments, however, include and extend crisp set QCA analysis to analysis of multivalue data (TOSMANA, for mvQCA) and fuzzy-set data (FSQCA, for fsQCA). An overview of software on http://www.compasss.org/pages/resources/software.html provides links to (free) download sites for TOSMANA, FSQCA, and a QCA module in R, as well as other resources for users.

Software for Social Network Analysis

Raw data for social network analysis, generated from reports of specified types of contacts between members of a network, is entered into a simple matrix showing who connects with programs. Members of the network may be individuals or organizations or other entities that connect to each other in some way. Mathematical indices for centrality, density, and connectivity (among others) for networks or for the individuals within them can be calculated using, for example, UCINET6 (http://www.analytictech.com/ucinet6/ucinet.htm). Pajek (http://pajek.imfm.si/doku.php?id=pajek)—Slovenian for spider—has been designed for analysis and visualization of large networks. NetDraw (packaged with UCINET) provides direct graphical representation of networks created using either UCINET or Pajek. Increasingly, researchers are developing a range of add-on modules for specialist analyses, for example, using analyses of triads to measure closure and brokerage as aspects of social capital (Prell & Skvoretz, 2008).

GIS Software

Software for geographic information systems (GIS) links physical, demographic, statistical, and social data by plotting them onto maps and so adds a spatial dimension to social science projects. Commercial GIS software suites appropriate for social science researchers include ArcGIS (http://www.esri.com) and MapInfo (http://www.mapinfo.com). Each of these suites provides core components with add-on modules for special purposes; additional specific purpose modules are often developed and made available free or at low cost from other users. Other programs such as Intergraph and Autodesk serve more specific industrial and commercial markets. Some GIS freeware and add-ons, offering more limited functionality than the commercial programs, are also available: Lists can be found at http://opensourcegis.org; and http://www.freegis.org; with reviews at http://www.spatialserver.net/osgis.

The release of Google Earth (http://earth.google.com) has also brought a new visualization dimension to research, with the capacity to build links to locational images into any qualitative program that allows either external hyperlinks, or for images to be imported as data sources, or both (e.g., Atlas.ti, MAXQDA, NVivo).

Data Management in an Integrated Project—Combining Diversity, Complexity, and Flexibility

Those working with mixed data sources are likely to be dealing with complex data sets in which there are multiple sources of varying types of data for each case, possibly from different time periods, and perhaps with cases embedded within cases. Computers come into their own when it comes to data management, as they can reliably keep track of sources, their content, and their connections (see Box 18.1). The range of data types that can be managed within analysis software is ever increasing. Until the turn of the century, few analysis programs could import and work with anything other than plain (ASCII) text or numbers, often with severe limitations on size of files. Many programs now have capacity to import and work with HTML, .pdf, audio, video, and image files as well as numeric, tabular, and rich-text data, within the one project, and to combine variable-based data with text records.

Along with managing complex data, exploratory research typically requires flexibility, for example, to modify coding, and even design, as it proceeds. Even in theory-testing projects, changes to design and coding frequently become necessary in response to data gathering. Qualitative software, in particular, allows for flexibility in developing and changing the structure and content of coding systems. In most programs, it is also possible to code on from already coded data, that is, to generate new, finer categories from material already coded at initial broad or automated coding categories, to identify and code additional aspects not previously noticed or considered, or to recode segments in response to development in conceptualization through the project. Typically, qualitative software also assists the researcher to keep a careful audit trail of the changes made.

Box 18.1: Managing a Complex Set of Data in a 10-year Retrospective Longitudinal Evaluation Project

Green Valley was built as a public housing estate on the southwest fringe of Sydney in the social and economic disadvantage close to a rapidly developing business center. For the past 10 years, the Centre for Health Equity, Training Research and Evaluation (CHETRE), jointly sponsored by the University of New South Wales and the Sydney South West Area Health Service, has been implementing and evaluating community development initiatives within this area. Over that period, results of regular surveys of residents, interviews with a range of stakeholders, and various sources of documentary evidence have been gathered. As part of my role in CHETRE, I have been asked to conduct a retrospective longitudinal study to examine the ebbs and flows of these varying initiatives over time and their impact on community capacity, health, and well-being through that period and to build a model that can guide future planning.

Starting from a box of reports, brochures, news clippings, and other documentary sources, along with a set of files comprising reports, interviews, and statistical databases, I am building a database in NVivo to manage and analyze this data, along with relevant literature. As a first step, every source of data will be recorded in the database, along with variable information pertaining to its type, date, and program and, where appropriate, with demographic data relating to the community role and other relevant aspects of the person(s) from whom it came (treated as attributes in NVivo). Word, .pdf, and multimedia files can be imported as internal sources; any documentary material that cannot be scanned and imported can be recorded as an external source, along with its attributes and its physical location. Hyperlinks to original sources and other files (e.g., SPSS databases or output files) can be stored for immediate access if needed.

The second step will be to work through this data, using NVivo's coding system to effectively index the contents of all the material (including external files). Coding will provide instant access to all material on each condition, action, person, issue, or outcome being considered. Essential components of this second step will be to keep an audit trail of processes used and changes made and to record in memos any queries or ideas prompted by reviewing the data.

The third step builds on the careful foundational work done during the previous two and is enormously facilitated by having done that work using software. Now, using query arising by examining patterns in the intersections of coding categories; trends over time or differences in perspective depending on role or gender or age can be examined by examining the patterns of intersection of coding categories with attribute data; analyses can be restricted to subgroups of the population or particular periods of time by creating sets of data based on attribute values; exceptions can be examined; and so on—all tasks that would be extremely difficult to do using manual methods with such a large and diverse body of data. In addition, information from the qualitative database can be exported for use in other software applications to allow network analysis, locational analyses, or further statistical analyses.

Integrating Numeric or Categorical Variables with Unstructured Data

The majority of mixed methods studies involve having more than one type of data, gathered concurrently or sequentially from the same sources or from different sources. The timing of collection and capacity for matching the sources both have implications for the degree to which analyses of the different components can be integrated. Responses obtained through surveys comprising both open and closed questions, for example, provide data where matching is readily available and integration during analysis is straightforward. Combinations of surveys or questionnaires with interviews or other separately gathered sources may be more problematic in this regard, and often, integration occurs only after completion of analysis of the separate sources, at the point of interpreting conclusions.

Whether one is using qualitative analysis software or software designed to automatically categorize text responses, the clear analytic advantage of using software is its capacity to sort coded text by categorized responses or background variables—whether these be demographic information, responses to questions asking for opinions or experience, or ratings given in response to scaled items. Linking these responses on an individual basis facilitates a richer and potentially more valid analysis (Box 18.2). Variations in responses can be better understood, and anomalies and alternative explanations examined. Matching in theoretical development through better understanding the conditionality or consequences of responses.

Box 18.2: Untapped Potential Impacts on Analysis Quality

The current distress levels of long-term survivors of lung cancer were investigated by Maliski, Sarna, Evangelista, and Padilla (2003). Those with lower levels of distressed mood spoke more positively as a group about five central themes of existential issues—health, self-care, physical ability, adjustment, and support (each described in detail)—than did those who scored higher on distress. Although this information is useful, the authors matched the qualitative data on a two-group basis only to depression scores, ignoring physiological measures such as spirometry results, even though these were described in detail in the method, and also ignoring a stated association of depression scores with racial and educational differences. A comparison of their five central themes using linked data that incorporated these variables may have led them to entirely different conclusions.

Permission to match data gathered at different times is increasingly an issue resulting from human ethics committees' requirements for preservation of anonymity for those responding to surveys or questionnaires. The best strategy is to ask respondents to provide necessary contact information at the end of the questionnaire or survey, if they are prepared to be followed up, along with permission to do so. If necessary, a code name can be used for matching. A critical element is that this issue has to be thought through *before* conducting the first data collection.

Methodological issues raised by combining categorical or numeric variables with text or visual data vary depending on the purpose—complementarity (the most common purpose) is generally unproblematic, for example—and are primarily related to issues raised by different sampling regimes, distributions, and sizes. Researchers interpreting the numeric output from a comparative analysis of text based on quantitatively defined groups must remain conscious of the sample size within each of the compared groups; otherwise, they risk misinterpreting the displayed results. It is also very easy to misinterpret the significance of differences when numbers are small, especially for those who have not had training in statistical procedures and assumptions.

Combining Mixed-Form Survey Data

Surveys or questionnaires employing both closed and open-ended questions are a common source of mixed data (Bryman, 2006). In its most elementary form, combination occurs where a closed question is followed up with a request to respondents to provide comment, explanation, or illustration of their answer. Matching categorical or numeric and text responses on an individual basis is not a problem in this setting, as the different forms of data are obtained at the same time. Comments can then be sorted by the categorized responses to provide illustrative material to assist in interpreting what each response really meant to the survey respondents. Researchers can use the open responses to provide illustrative quotes for their primary statistical analyses, and the direct link between the two data forms allows for a more detailed assessment of other relationships between the text and numeric components of the data, such as through comparative analyses (Box 18.3).

Box 18.3: Linking Text and Numeric Data from a Survey

A combination of Stata and NVivo was used by Ford (2006) to analyze closed and open-ended responses to a survey instrument in her doctoral study of nurses' care of patients who use illicit drugs. Free text responses about the interpersonal constraints these patients imposed on their therapeutic nursing role were provided by 311 of the 1,605 respondents. Ford used this data in two different ways: She used the statistical data to compare those who wrote about their experience with those who didn't, and she then used demographic and other closed responses, imported into NVivo, as a basis for comparing the kinds of issues that these nurses raised.

Nurses who added free text responses were more likely than others to be in high-contact (i.e., clinical) areas of practice and reported more episodes of extended care for patients who were illicit drug users; that is, the issues raised by the survey were more salient for them than for others. They were also younger and less experienced than the remainder of the lower motivation and satisfaction. The specific therapeutic concerns they expressed were about patient aggressiveness, manipulation, and irresponsibility, and they reported frustration with the patient, fear in their role, and pessimism about the usefulness of therapeutic interventions.

Those practicing in different areas expressed unique challenges in response to these patient behaviors, which required different nursing care and which engendered different attitudes. Midwives dealt with manipulative patients and aggressive partners but were particularly concerned about and frustrated with mothers' irresponsibility in the context of "putting a baby in the mix." The attitudes of those working in emergency to people coming into their care were impacted by the short-term nature of a relationship in which they also frequently experienced aggression and manipulation. They were most angered, however, by drug users' irresponsibility toward others harmed by their actions and were frustrated by not seeing any long-term outcomes for the patient from the experience or their care. In contrast, in a medical/surgical practice setting where there was an extended period of time-intensive contact, patients' continued aggressive and manipulative behavior created staffing and care issues.

Decisions about what software to use for linking and analyzing text and numeric data in surveys will depend on the volume and depth of the data, as well as on available or preferred programs. Simple comparative sorts of text responses to particular questions according to values on a categorical variable can be achieved in any spreadsheet or database, but researchers will be quickly overcome by large or complex data sets if that is their only tool. QDA software has the added advantage, for more complex responses, of allowing for revised coding of those responses to more detailed categories, perhaps revealing new concepts that are expressed across responses to a number of questions. Text at these new codes also is able to be compared across categorical variables, while the new categories generated can be exported as variable data back into the quantitative database. For large data sets, software that automates categorization of short-answer responses for inclusion in the statistical database, supplemented by reviewing a sample of responses in each category, may be the most appropriate solution.

Combining Surveys with Interviews or Other Unstructured Data

Use of follow-up interviews to corroborate, illustrate, or elaborate on the meaning of categorized or scaled responses to survey questions continues to be the most common data-gathering strategy employed by mixed methods researchers (Bryman, 2006). Alternative quantitative sources, such as administrative data or biophysical measures, might be obtained in association with interview responses or with reports, filmed observations, or other unstructured data. Spreadsheets, databases, and auto-coding modules for statistical software are even less helpful for handling the qualitative material in these types of projects, however: Analysis of interview or other free text or visual data is a task that benefits particularly from use of QDA software. Coding of this data might proceed on an emergent basis, or it might be directed by the issues and categories raised in or by a prior survey; software can be used flexibly in either way.

The issues in relating quantitative to qualitative data are similar to those for mixed-form surveys. Benefits from these analyses extend beyond detecting simple patterns of association with subgroups to raising questions for further exploration about other relationships. In addition, such analyses provide insights regarding dimensionalization of concepts and the potential to validate scaled measures and to identify and explore deviant cases.

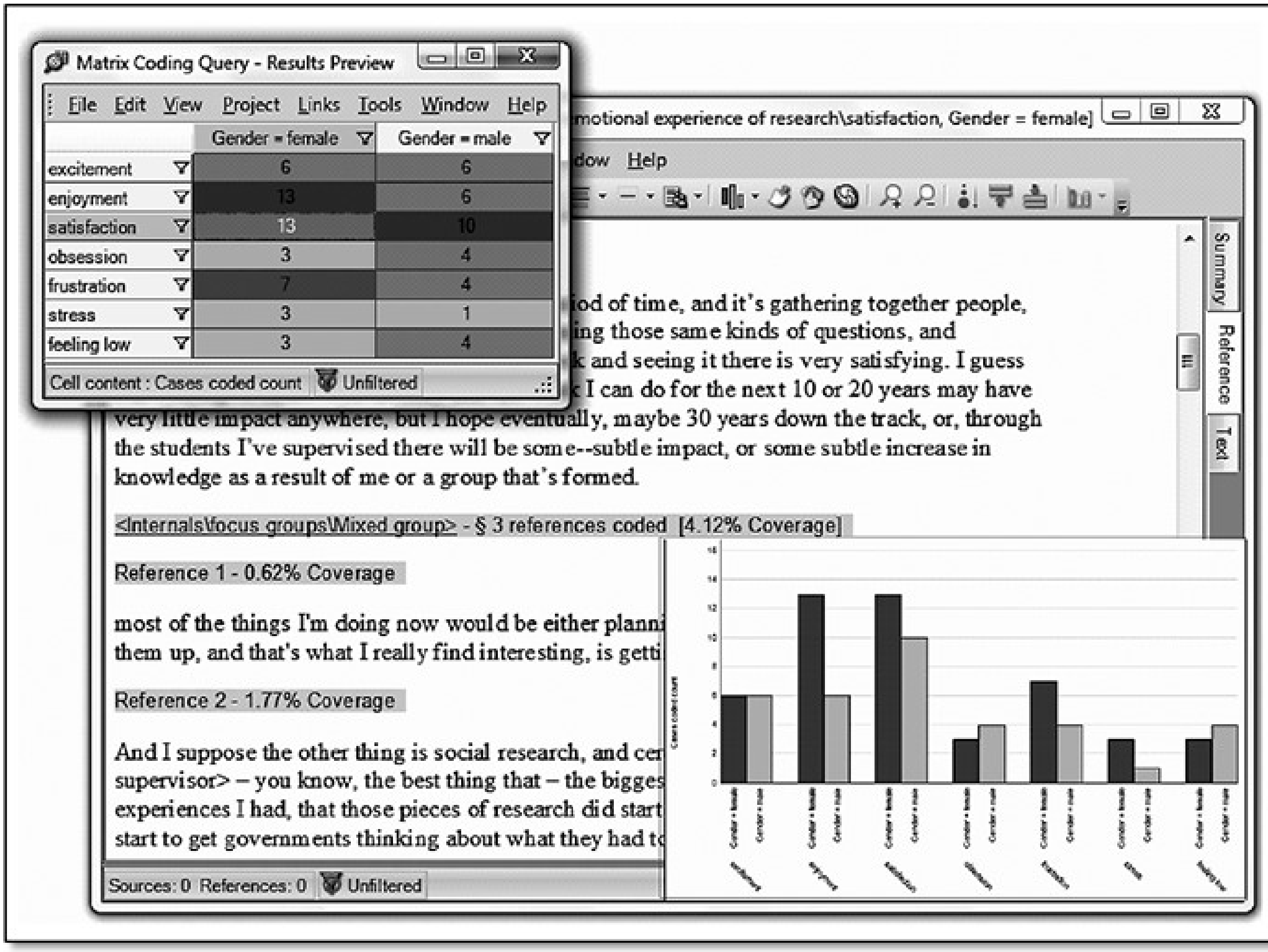
Comparative Analyses Using Mixed Data

The assumption being tested through the comparative process is that a person's gender, or age, or role (or whatever it is that has been included) is relevant to whatever the person might say on the topic(s) of interest. Even in a primarily qualitative project, it is usually relevant to include at least some basic demographic variables in the analysis mix. In a simple extension of this principle, responses to precategorized questions (such as yes/no, or often/sometimes/never) or scaled measures (e.g., level of satisfaction, scores on a measure of social alienation) may also be relevant to the interpretive analysis of the qualitative data. Categorical or numeric variables can be set up and applied interactively within most QDA spreadsheet, or SPSS via Excel), making it very easy to include them in a database with text responses.

Integrative and analytic capacity might be enhanced where quantitative (e.g., demographic) information is simply available for viewing alongside retrieved text segments within a qualitative database, but the real comparative value from inclusion of quantitative data comes about through actual sorting of coded data according to values of a variable. QDA programs differ with regard to the ease with which these comparisons can be obtained, the kind of information generated by them, and the capacity to use the results from them in further analyses. Most, however, are moving to a standard where the comparative data for a range of values can be generated through a single query process, with results presented in a matrix display, rather than having to request data for each possible combination separately. Each alternative component of the information provided in a matrix resulting from this type of query (numeric display, found text) adds to the analytic picture, with numeric patterns showing “how many” and comparative texts showing “in what way.”

Output from a comparative query in NVivo, for example, shows initially as a numeric display in which each cell of the matrix shows the number of sources containing text segment(s), which are identified at the same time by the code specified in that row and the attribute value specified for that column. The display can be changed to show the number of cases, passages, or words coded within each cell, if required. Shading can be used to highlight the relative density of coding across the cells. These tabular displays can be filtered by a row or column variable, exported in Excel format for further statistical analysis, or displayed (and exported) as a chart. Most critically, double-clicking on any cell will reveal the actual text passages meeting both row and column specifications (Figure 18.1).

Figure 18.1 Comparative Matrix Output From NVivo



Click here to download

Often, comparative analyses will simply reveal that some groups talk about a particular topic more often than others, or that different groups talk about different topics or raise different issues (as was the case in Ford's [2006] analysis discussed in Box 18.3). At times, however, a review of the sorted text reveals that different groups talk about the same topic in quite different ways—regardless of whether or not there were differences in how many talked about it. These differences may be revealing of dimensions within the concepts being coded or may suggest other conditions that are influencing the theme being examined. NVivo was used, for example, to compare expressions of satisfaction gained from doing research for male and female social scientists and scientists (Bazeley, 2007). About equal proportions within each gender and discipline group reported satisfaction. Whereas differences in the sorted text were not apparent for gender, comparisons across discipline suggested that scientists were likely to refer to the sense of agency they experienced in doing research,

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expressing satisfaction. These groups, therefore, gained satisfaction from different sources—a dimension of satisfaction not previously considered but one that is highly relevant to considerations of motivation for engaging in research.

In addition, instances where individuals go against a trend can be readily identified and explored in detail. From the examination of gender and discipline differences in satisfaction, two social scientists (one male, one female) also expressed agency, while one scientist expressed neither agency nor achievement as a component of satisfaction. These cases could be identified, revealing that the two social scientists both worked in experimental psychology (more akin to science than social science), and the one scientist's current work was as much to do with recording the history of science and with designing educational materials as with being a scientist. It could be argued, then, that rather than contradicting the observed trend, these apparently discrepant cases added confirmation.

There are often marked inconsistencies in the way that people complete scaled items in questionnaires (Green, Statham, & Solomou, 2008). Where qualitative data can be gathered and used in association with scores derived from a quantitative scale, comparative analyses can make a contribution to understanding and verifying the meaning of the points on the scaled measure. Using software, it is a straightforward task to identify whether differences in scores are reflected by comparable differences in the text. This adds a quite different approach to complement traditional validity testing of scales using confirmatory factor analysis or multiple correspondence analysis.

Pattern Analyses Involving Mixed Data

Comparative analyses can be extended to include examining the pattern that emerges when, say, coded observational data is compared with interview data. Assuming the two sets of data can be linked on a case-by-case basis, and use of software, multiple comparisons can be quickly generated with a high degree of specificity. Thus, in an educational setting, the relationship between codes based on a teacher's observations about particular children and those based on the child's written or artistic work could be examined. Rather than seeking the combination of a code *and* a value of a variable or another code, in this case, the

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when they were *near* children's codes, with near being defined as “for the same case.” The range of software capable of these types of analyses, which involve associations based on proximity between one code and another code, and of identifying and exploring converse cases, is more limited than for analyses that involve direct combination (intersection) of codes with other codes or variable data.

Transforming Qualitative Coding for Further Analysis

Coding information derived from qualitative sources converts to numbers in a variety of forms, from simple counts to variable codes to measures of association, using a variety of methods. Text analysis modules linked to statistics programs are specifically designed to incorporate coded open responses into the statistical database, to be included with the quantitative variables. QDA software will generally provide counts; some will export document-based coding and/or case-based coding, while those that have a matrix function will usually also export results as shown in the matrix display. These exported data can then be imported, where appropriate, into a spreadsheet or statistical software.

When qualitative coding is used as the basis for statistical analysis, there is an advantage in that the researcher does not have to predetermine the categories to be used for that analysis, but when talk or text is reduced to categorical codes or numbers, the danger is that much of the meaning will be lost. With the use of software to generate codes for statistical analysis from qualitative material, text associated with those codes is retained in a readily accessible way. This assists interpretation of patterns during the process of analysis, validation of conclusions through checking findings back against the qualitative data, and initiation of further qualitative analyses or re-analyses.

Qualitative data might be transformed, or quantitized, to facilitate merging and comparison of different data sources or to allow exploratory, explanatory, comparative, predictive, or confirmatory statistical analyses (Sandelowski, Voils, & Knafl, 2009). Quantitizing data is not an end in itself, but “a means of making available techniques which add power and sensitivity to individual judgment when one attempts to detect and describe patterning in a

Counts from Qualitative Data

Simple frequencies generated from qualitative data have been used in a variety of ways in mixed methods projects, such as for counting themes, analyzing talk, and making comparisons. Counting is one form of description, reflecting the "numbered nature of phenomena" (Sandelowski, 2001, p. 231). Counts effectively communicate the frequency of occurrence of some feature in the text (Miles & Huberman, 1994) and summarize patterns in data (Morgan, 1993). Counts are the most common form in which numbers are introduced into primarily qualitative studies (Niglas, 2004), with frequencies seen by some as indicative of the relative importance of emergent themes (Onwuegbuzie & Teddlie, 2003). The use of numbers can help to maintain analytical integrity (countering biased impressions), with benefit also for identifying relationships and hypothesis testing (Miles & Huberman, 1994).

Using software for counting carries a range of benefits, the most obvious of which are the ease of obtaining counts and the increased accuracy of the counts obtained (Chi, 1997). Qualitative software routinely provides frequencies with which particular codes or themes occur in terms of the number of sources and separate passages coded. Some qualitative programs also provide case counts (useful where cases comprise partial or multiple sources), word counts, character counts, and proportions for coded data (Figure 18.2a). In addition, both specialist word-counting programs and most qualitative programs will provide simple frequency counts of the incidence of all words within in a body of text, along with keyword in context (KWIC) information and the possibility of direct access to more detailed context (Figure 18.2b).

Figure 18.2 Software Counts for Codes and Words

a. Node (coding) summary report showing details of coding frequency (NVivo)

intellectual experience of research\creativity-originality — **Tree Node**

Created On	8/01/2008 4:07 PM	**By**	PB
Modified On	6/05/2009 12:35 PM	**By**	AM
Users	2		
Cases	22		

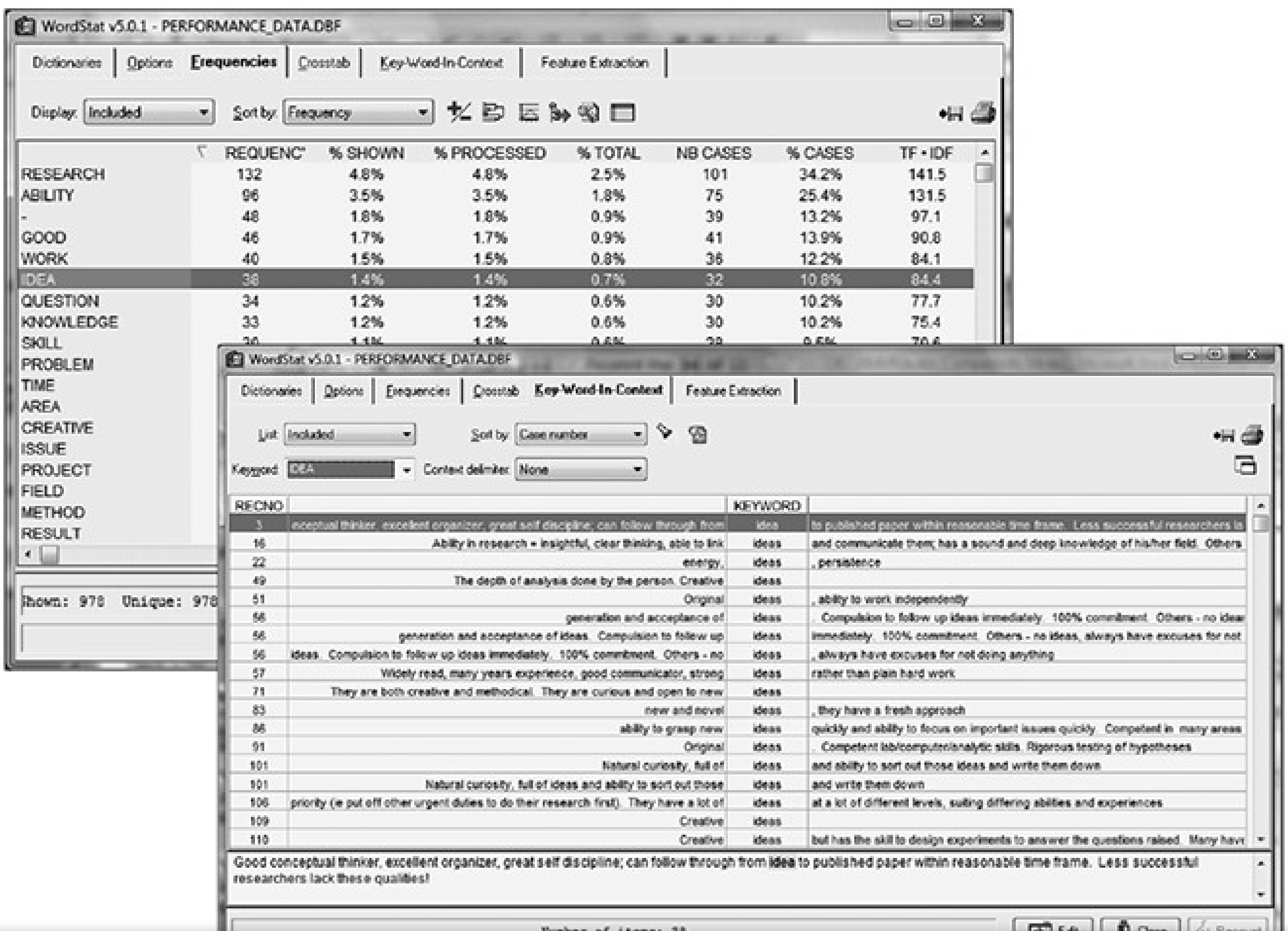
Type	Sources	References	Words	Paragraphs	Region	Duration	Rows
Document	11	31	2,084	78			
Memo	1	1	83	1			
Total	**12**	**32**	**2167**	**79**			**0**

intellectual experience of research\curiosity — **Tree Node**

Created On	6/04/2007 10:09 PM	**By**	PB
Modified On	19/06/2008 12:13 AM	**By**	PB
Users	1		
Cases	19		

Type	Sources	References	Words	Paragraphs	Region	Duration	Rows
Document	8	22	1,342	30			
Video	1	6	225			01:13:00	3
Total	**9**	**28**	**1567**	**30**		**01:13:00**	**3**

b. Word frequency counts and key-word-in-context display (WordStat)



Several theoretical and technical issues arise in using frequencies generated from qualitative coding that apply both when considering counts and when obtaining frequencies as a component of a more complex case- or matrix-based output:

- Whether one should base counts simply on the number of participants who mention something at all or on the overall frequency with which something is mentioned depends on the context in which counts are being obtained—did all cases have equal opportunity to mention the relevant item and so to be counted?—and the use to which they are being put—does volume signify relative importance? The possible meaning of a zero (0) count in those contexts is also relevant: 0 signifying something wasn't mentioned is meaningfully different from 0 signifying it didn't exist. Frequencies may be better regarded as ordinal rather than interval data, unless it can be ascertained that every instance is metrically comparable to every other instance. These issues are not exclusive to counts based on qualitative coding: There is no guarantee that every respondent in a survey, for instance, is interpreting and responding to the same categorical question in the same way.
- The specificity of what is being counted impacts on meaning and use of counts (Boyatzis, 1998). When a theme code is quantitized, its meaning tends to become fixed and single dimensional (Sivesind, 1999). Qualitative coding involving all occurrences, whether positive or negative, is a complication; even apparently factual descriptive codes are impacted by the reporting circumstances through which they are generated (Green et al., 2008; Sandelowski et al., 2009).
- The way in which (qualitative) texts are managed has implications for the generation of counts, particularly those reflecting volume. Say, for example, a passage of text is coded, and then the decision is made that the following text reflects the same code. Depending on whether the coding for the two passages is physically connected or not, that coding would be counted as one passage or as two. Similarly, when coding is removed from a passage, sometimes a blank character or line can be left behind, and so it is still counted for that code. Retrievals for all codes need to be checked before they are counted or exported.
- In using counts as part of the written report, issues arise through using percentages for small samples, relying on numbers to tell the whole story, and not providing sufficient context to allow the reader to properly interpret the numbers (Sandelowski, 2001).

Quantitizing Case Data

Quantitized data created as an export from qualitative software are transferred to a statistical package in the form of a regular case-by-variable matrix. Coding of text responses automatically embedded in the statistical database. Quantitized data can be analyzed statistically on their own, or the new variables can be merged with an existing statistical database, even if some respondents have not provided both sources of data, providing there is a field on which the different sources can be matched for each case. Issues that were raised above regarding counts generally apply also to quantitized case-based coding.

Exported coding, once transferred to a statistical package, allows for a different type of examination of regularities and complex relationships in the data from that carried out within the qualitative database. Relationships within the data can be tested using standard bivariate and multivariate statistics (Box 18.4), predictive models can be built using regression-based techniques, or data might be explored using principal components or factor analysis. Meeting assumptions for valid inferential statistics of random or representative selection of cases is often an issue for qualitative projects (but increasingly also for quantitative surveys). Use of nonparametric statistics, simple visual displays, and techniques such as cluster or correspondence analysis to examine associations in the data might therefore be more appropriate with exported coding than procedures that assume a large, probabilistic, normally distributed sample. In situations where conclusions may not be generalizable to a larger population, use of statistical analyses nevertheless may be useful in making comparisons and in suggesting leads for further analysis.

Matrix (Pattern) Data

Matrix data shows the pattern of relationship between two sets of items. In qualitative work, matrix displays can reduce information from complex field notes and interviews into a visual display that helps to make evident any patterns or regularities in the data. Cross-tabulations, or contingency tables, with their related statistical procedures, have always been a basic tool within statistical software, for use in quantitative survey analysis. Similarly, codes from *exported* qualitative case data can be cross-tabulated within a statistical program, but with the risk that they may produce spurious connections simply as a consequence of both codes being found somewhere in the text from the same person, rather than because they have a particular association. If a matrix is generated *within* qualitative software, however, it is

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present on the same segment(s) of data. Furthermore, the text associated with the count in each cell is available for checking, so that adjustments can be made, if necessary, and additional meaning ascertained.

Box 18.4: Using Qualitative and Converted Coding to Test an Experimental Hypothesis

Converted qualitative coding was combined with an existing quantitative database in an experimental test of the impact of training through classroom discussions involving collaborative reasoning on children's argumentation (Reznitskaya et al., 2001). Following training, children wrote individual persuasive essays based on a different problem from that discussed in training. The essays were coded (using NUD*IST) for presence of formal argument devices and use of textual evidence. ANOVA and ANCOVA were used to demonstrate that having an argumentation schema developed through training enabled students to consider and present more arguments, independently of socioeconomic status or vocabulary skills. Detailed text analyses were then conducted on a purposive sample of essays to examine and illustrate argumentation strategies used by the children, revealing that “collaborative reasoning students are generally more successful at generating and articulating an argument, considering alternative perspectives, marshalling text information, and effectively utilizing certain formal argument devices” (p. 171).

A range of matrix query options is available in NVivo, MAXQDA, and QDA Miner. The numeric results of the matrix query can be exported, usually as an Excel table or a tab-delimited text file that can then be imported (more or less directly) into a selected statistics program. Matrix queries generally take one of three forms:

- A comparative matrix using attribute (e.g., demographic) data, as described above. A matrix, or cross-tabulation, can be generated equally well using exported coding or within the qualitative software (because attributes apply to whole cases), but the supporting text is available only if it is generated in the QDA software (cf. Figure 18.1).
- A pattern analysis of the relationship between one set of codes and another. The counts within each cell of the matrix might be based on intersections in coding, for example, when data are coded for the nature of the problem being experienced and also for the coping strategies that are adopted in relation to the specific problem. Alternatively, they might be based on proximities within the data, for example, when

behavior (or attitudes to behavior) and the codes for these do not necessarily intersect but can be found within a specified proximity, or in a particular sequence. Numbers in the resulting exported matrix from either the intersection or proximity query could be based on either case counts within each cell or frequency counts of how often these associations were found overall.

- A similarity matrix based on the association between a set of codes and itself. That is, the same set of codes is entered in both rows and columns with a request to find either intersections or proximities (within a specified distance) between the codes. The result shares some similarity to the more familiar correlation matrix: Frequencies within each cell represent the number of times each code is found in association with another (counting either cases or separate instances) and show as a reflected matrix with the diagonal giving the total number of finds for each code (Figure 18.3).

Figure 18.3 Reflected (Similarity) Matrix

	commitment...	organised, ...	strategic	methodologi...	technical skill	substantive ...	analytic, thi...	creative, inn...
commitment, persist...	133	20	8	7	4	15	27	22
organised, disciplined	20	74	8	7	4	7	16	11
strategic	8	8	63	5	4	7	12	10
methodologically so...	7	7	5	96	12	19	37	27
technical skill	4	4	4	12	44	6	9	8
substantive knowled...	15	7	7	19	6	86	33	15
analytic, thinker	27	16	12	37	9	33	151	43
creative, innovative	22	11	10	27	8	15	43	138

NOTE: The cell entries on the diagonal show the total number of respondents using each concept; for example, *strategic* was used 63 times in total. Particular cells show the number of respondents who used that row-by-column combination when describing researchers who performed in particular ways; for example, *strategic* was used in the same context as *commitment* on eight occasions.

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Those using matrix data generated from qualitative coding need to be aware of the basis on which the matrix was created. For example, comparative tables are usually more akin to multiple response data than to a cross-tabulation suitable for bivariate chi-squared analysis of differences, as the categories being compared across groups (i.e., row codes) are rarely mutually exclusive. In any matrices based on intersections of coding, there is a need to ensure that accidental hits are not included, where the tail end of one code overlaps the beginning of another—perhaps just by the blank character between them—without there being any meaningful association. And for matrices based on proximities, care needs to be exercised in specifying how the counts are constructed, to avoid irregular overcounting

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where a single co-occurrence could involve either one intersecting or two separate passages for the pair of codes.

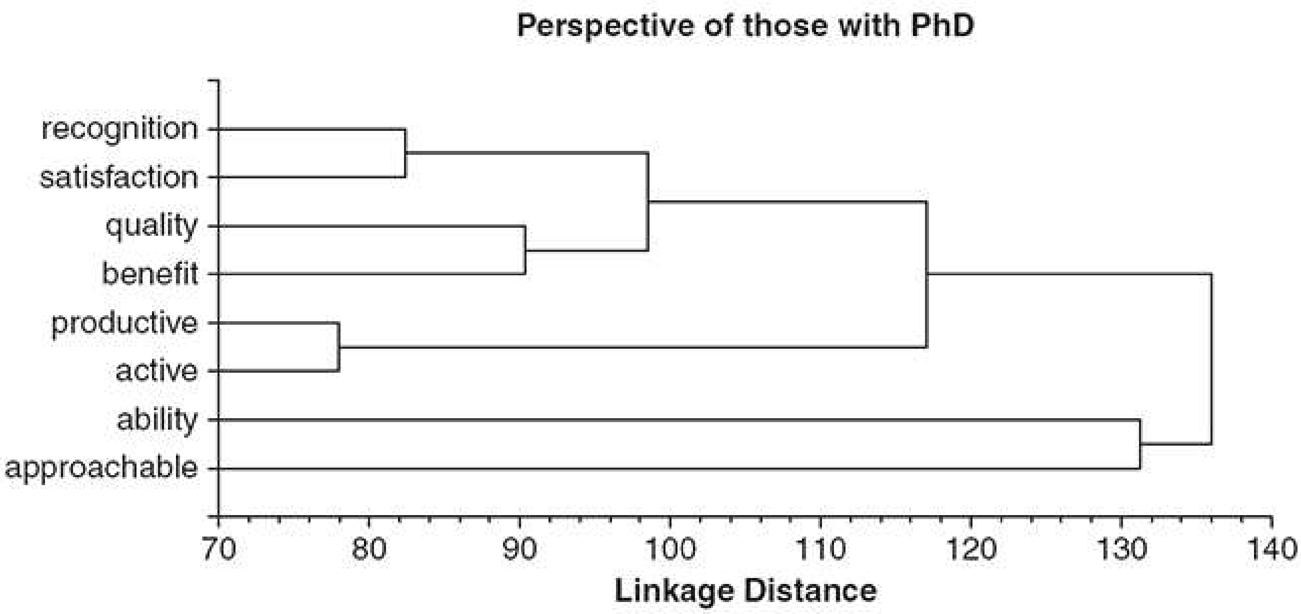
Exploratory Analyses and Visual Displays Using Quantitized Data

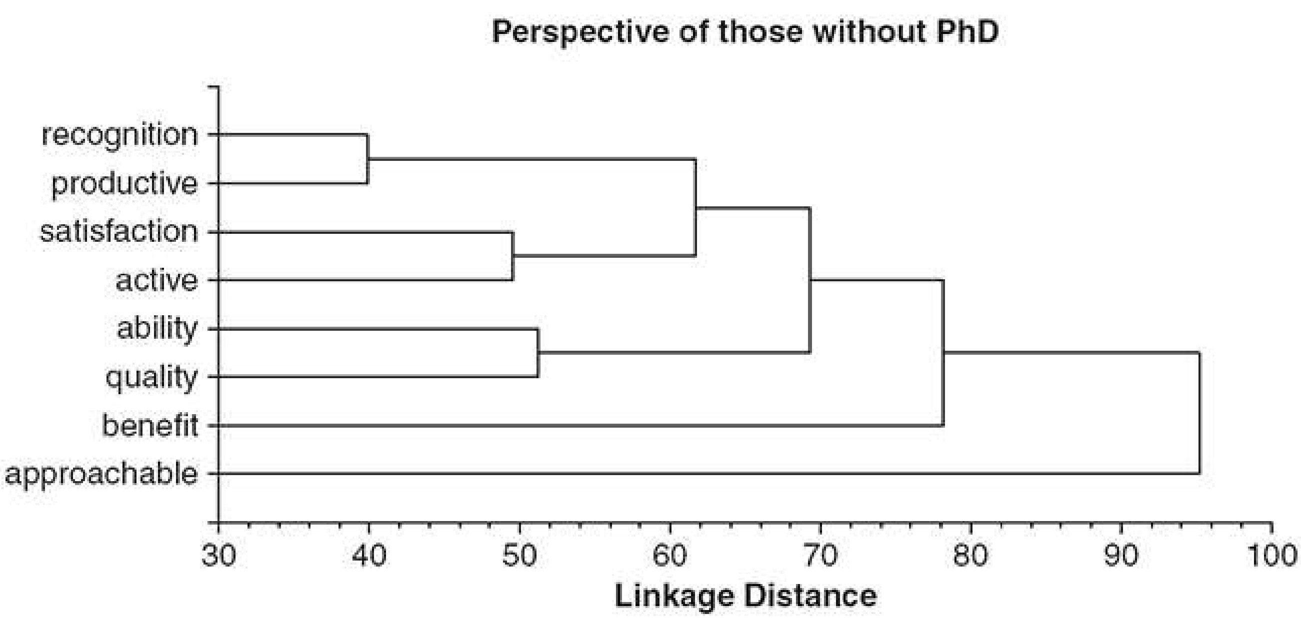
Exploratory statistical techniques with results presented as visual displays of relationships between codes (variables) are likely to be used to assist interpretive analysis of exported case and matrix data, rather than their being subject to statistical hypothesis testing. Multidimensional scaling, cluster analysis, and correspondence analysis are some of the exploratory techniques that have been applied to generate meta-themes, core dimensions, or comparative analyses—these techniques are particularly appropriate for data derived from qualitative coding as they do not assume that categories used are mutually exclusive or normally distributed. Specification of the type of distances to be calculated by the software for these types of analyses is impacted by the source and derivation of the data being used, however; that is, whether the data are binary, ordinal, or interval (Bartholomew, Steele, Moustaki, & Galbraith, 2002).

- Hierarchical cluster analysis is a classification technique based on case-by-variable data in which objects (cases or variables) are grouped on the basis of similarity in their pattern of distribution across the other axis. Clusters are progressively aggregated, with the results most commonly presented graphically as a dendrogram (Figure 18.4a).
- In multidimensional scaling (MDS), distances based on the similarity (or dissimilarity) of objects in a reflected matrix are used to generate dimensional plots of those objects. These plots and the associated dimensional statistics are used to reveal the structure of a set of data, where both the dimensions and any identifiable groupings of points in the plot are of interest (Figure 18.4b).
- Correspondence analysis generates a plot of data from cross-tabulated data, usually in two dimensions, providing an opportunity to see the relative ordering and spacing of categories across the rows and columns and the associations between row and column categories (Figure 18.4c).

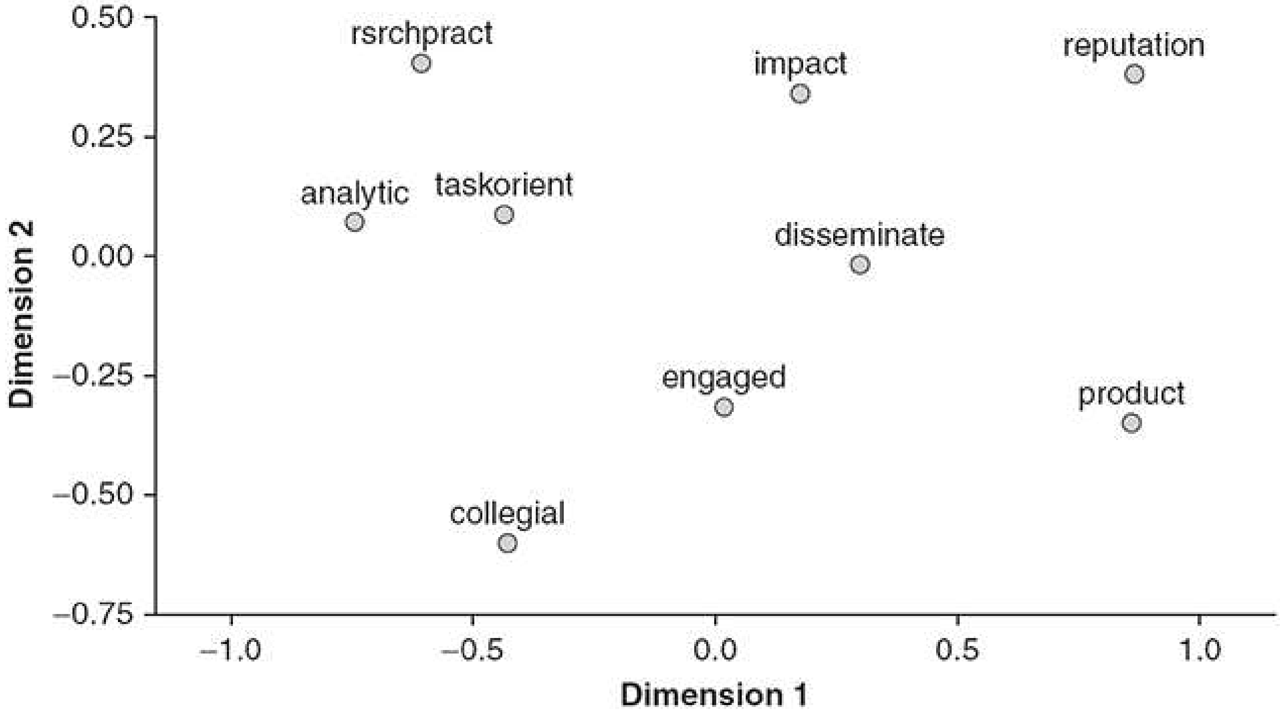
Figure 18.4 Visual Displays Built From Quantitized Data

a. **Cluster analysis:** Clustering of qualities of researchers based on similarities in descriptors used for each by samples of academics with and without a doctoral-level qualification. The differences in displays would send the inquiring researcher back to a qualitative data matrix to explore why some, for example, *recognition, quality,* and *ability,* are seen so differently by the two groups.

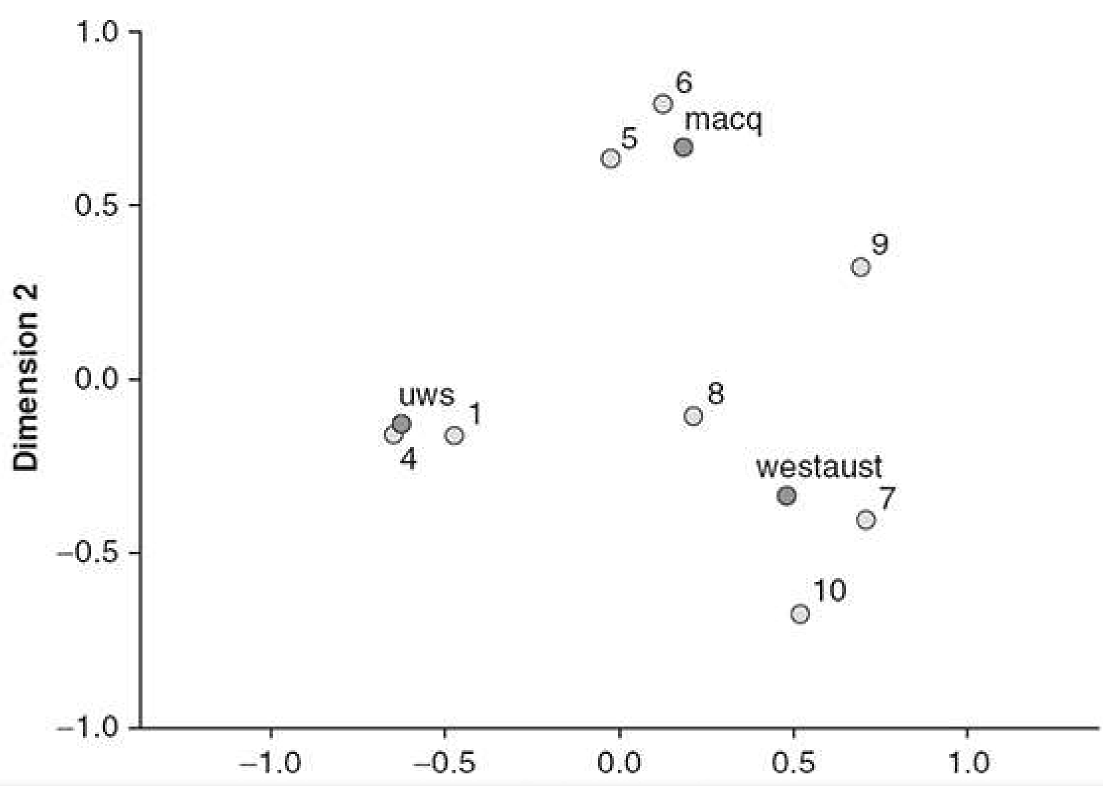




b. **Multidimensional scaling:** Two-dimensional plot of key elements in research performance.



c. **Correspondence analysis:** Association between university and decile measures of emphasis on analytic/thinking skills in describing high-performing researchers.



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Combination and Conversion Working Together

One of the difficulties of presenting a range of analysis strategies is that it can appear that each of these strategies is applied in relative isolation when, in fact, an integrative mixed methods project working with complex data is much messier than that and quite likely to involve a mix of strategies that defies easy classification. Studies often involve both conversion and combination of data. This may occur concurrently or iteratively, as alternate analytic strategies and the programs that support them are used in multiple, sequenced phases where the conduct of each phase arises out of or draws on the analysis of the preceding phase (Greene, 2007). Blending or fusing of diverse data sources to create new, composite variables to feed back into an analysis is another way in which combination and conversion work together (Bazeley, 2006).

In an early example by Louis (1982), rating scales covering all relevant aspects of an evaluation of an educational innovation were developed and completed for each site on the basis of a combination of documented sources, statistical data, and researchers' holistic knowledge of the sites. The combined set of data was then analyzed statistically. More recently, Kane and Trochim (2007) have proposed a method of concept analysis in which participants first develop a series of (qualitative) statements about the topic of interest and then group and rate a refined list of these for importance and feasibility. Cluster analysis and multidimensional scaling are applied to the paired and rated statements to create a concept map and a range of visual displays. These are then used to effectively communicate back to the participants the key areas that need to be developed or evaluated and the relative importance and feasibility of working in each of those areas, as a stimulus for discussion.

Interpreting Variable Data in Small to Medium N Samples

Inferential statistical procedures used for comparison, prediction, or explanation typically require large, normally distributed, probabilistically drawn samples. These are often not numeric sources or purposively selected samples for their data, and so they need to turn to other approaches.

Using Statistical Data to Examine Trends or Patterns

Mixed methods researchers' samples might not meet the requirements for traditional statistical analyses such as regression, but they nevertheless have potentially useful qualitatively or quantitatively derived variable data. Nonparametric statistics can assist in interpretation of characteristics and comparisons, or Q methodology might be employed (Newman & Ramlo, 2010 [this volume]), while visual displays such as boxplots, graphs, and charts can be useful also in suggesting trends or patterns in data (Dickinson, 2010 [this volume]; see also Box 18.5).

In her book on narrative methods, Elliott (2005) describes using quantitative sources to build a single life-history narrative. Others have used cluster analysis to generate comparative narrative profiles. These approaches are referred to by Teddlie and Tashakkori (2009) as qualitizing data.

Configurational Comparative Methods

Configurational comparative methods, perhaps still better known as qualitative comparative analysis (QCA), encompass a set of procedures developed initially by Charles Ragin (1987) that specifically seek to bridge the divide between small-*N* and large-*N* studies (Rihoux & Ragin, 2009). By combining case- and variable-oriented approaches and using both deductive and inductive processes, QCA straddles quantitative and qualitative approaches to research.

QCA methods rely on close case-level knowledge, combined with good theoretical understanding, to identify relevant cases and a limited set of variables (quantitatively or qualitatively derived) to analyze in relation to the presence or absence of an identified outcome. For crisp set data (csQCA), variables are dichotomized and a “truth table” is built listing all the found configurations of variables, along with their positive, negative, or is applied to the table to generate potential necessary and/or sufficient conditions. A minimum set of interrelated “prime implicants” of general significance for a given outcome from a small- or moderate-*N* database is then derived, usually with greater sensitivity and reliability than through using more traditional qualitative or quantitative techniques alone (Ragin, Shulman, Weinberg, & Gran, 2003). Unlike incremental additive statistical models, QCA may present multiple constellations of conjunctural factors that lead to the same result and, in so doing, rejects simplistic probabilistic models in favor of diversity that is more reflective of the complexity of the situation being studied (Berg-Schlosser, De Meur, Rihoux, & Ragin, 2009).

Table 18.1 Truth Table of Boolean Configurations with Five Conditions and One Outcome

CASEID	*GNPCAP*	*URBANIZA*	*LITERACY*	*INDLAB*	*GOVSTAB*	*SURVIVAL*
AUS	1	0	1	1	0	0
BEL, NET, UK	1	1	1	1	1	1
CZE	0	1	1	1	1	1
EST, FIN	0	0	1	0	1	C
FRA, SWE	1	0	1	1	1	1
GER	1	1	1	1	0	0
GRE,POR,SPA	0	0	0	0	0	0
HUN, POL	0	0	1	0	0	0
IRE	1	0	1	0	1	1
ITA, ROM	0	0	0	0	1	0

NOTE: Truth table from Rihoux and De Meur, 2009, p. 53, Table 3.7, based on conditions for the survival of democracy between the wars in Europe. The contradictory outcome for Estonia and Finland was resolved by adjusting the threshold for GNCAP, so that Finland and Czechoslovakia each changed value from 0 to 1 and consequently paired with other countries. (Used by permission, Sage Publications Ltd.)

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The basic method for QCA, which relied on dichotomizing all variables, has been extended to deal also with multivalue data (mvQCA) and fuzzy-set data (fsQCA). Analyses of crisp set (dichotomized) data are supported by TOSMANA and FSQCA; TOSMANA also supports mvQCA, and FSQCA supports fsQCA.

Strategies That Combine Visual, Numeric, and Text Data

Teddlie and Tashakkori (2009, p. 273) refer to social network analysis as "inherently mixed" in that, by default, it involves a mix of methods. The use of geographic information systems (GIS) in social research has those same characteristics of necessarily involving a mix of visual data with numeric or text data or both.

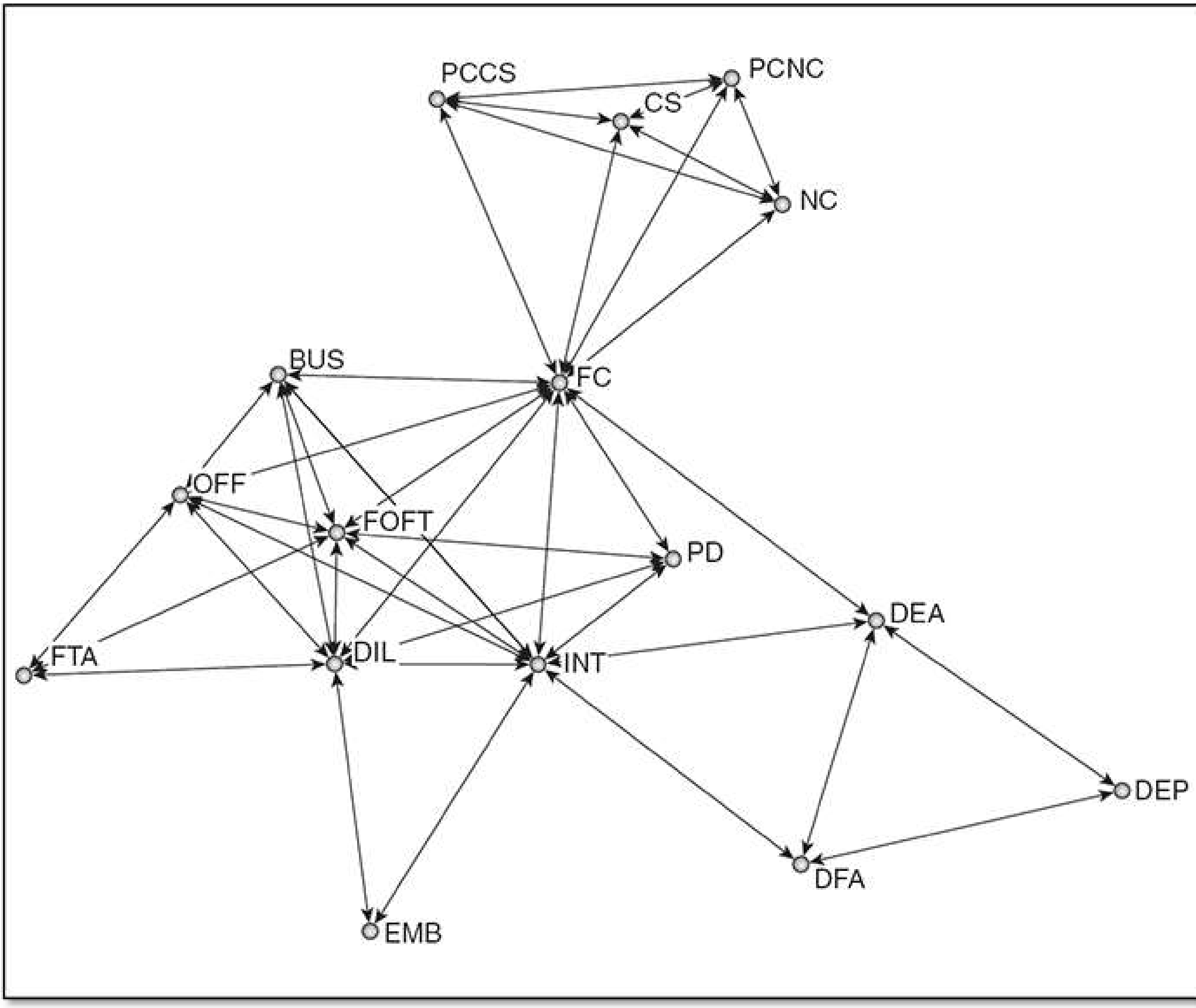
Social Network Analysis

The focus of social network analysis is on the ties that people (or other social objects) have, rather than on the attributes of the people in the networks. Either all of the ties within a defined population are considered or, when examining an egocentric network, ties for a specific person. Linkages between different organizations through their members might be examined at the level of the organization, for example, or the study might consider the way in which the structure of ties and an individual's place within that structure impacts on that individual and his or her relationships (Box 18.5).

In social network analysis, a visual display of network linkages is combined with mathematical and statistical analyses of the connections between nodes in the network (Scott, 2000). These analyses generate measures such as centrality, density, and connectivity of the network and of individual nodes within it. Cliques and bridges (a connecting node between two subnetworks) can be identified both visually and mathematically. Qualitative data relating to network connections and the way the network operates may be added to the mix, adding explanatory detail to the visual connections and measures provided by the network analysis software. Indeed, network relations are "embedded in particular social, cultural, temporal, and spatial contexts," and these are ignored at the peril of missing vital clues regarding the significance of the relationships (Clark, 2007, p. 20).

To systematically study the political decision-making process across a series of cases, using detailed narrative and documentary sources as a basis, Widmer, Hirschi, Serdült, and Vögeli (2008) first mapped actors by events, noting which actors were connected by an event, and how leadership in events progressed across actors over time. For each case, they then created a reflected matrix of participation by pairs of actors in the events (counting the number of events in which both had participated). A second matrix tabled process links between event leaders. These two matrices were multiplied (to give additional weight to the more sparse process matrix) to create a standard social network matrix reflecting connections between actors in the decision-making process, covering the range of decision-making events. This matrix could then be analyzed in UCINET, allowing visualization of the structure of actor networks (e.g., Figure 18.5) and providing scores for such things as network density, relative contact frequency, and actor degree centralization, for comparison with other decision-making cases.

Figure 18.5 Network Map of the Decision-Making Process for a Swiss International Treaty With Ghana



SOURCE: Widmer et al., 2008, p. 164, Figure 10.4 (b). This network demonstrated comparatively fewer actors than others, but that actor FC played a critical bridging role within it. The amount of contact between DIL and FOFT was also particularly heavy. (Used by permission, Thomas Widmer.)

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Geographic Information Systems (GIS)

GIS technology provides an effective tool for integrating qualitative, quantitative, and visual data where social factors are related to physical locations or environments. Different types of information, or changes over time, or for different participant groups, are linked by being compared or overlaid on a series of maps or on the same map. Originally developed to

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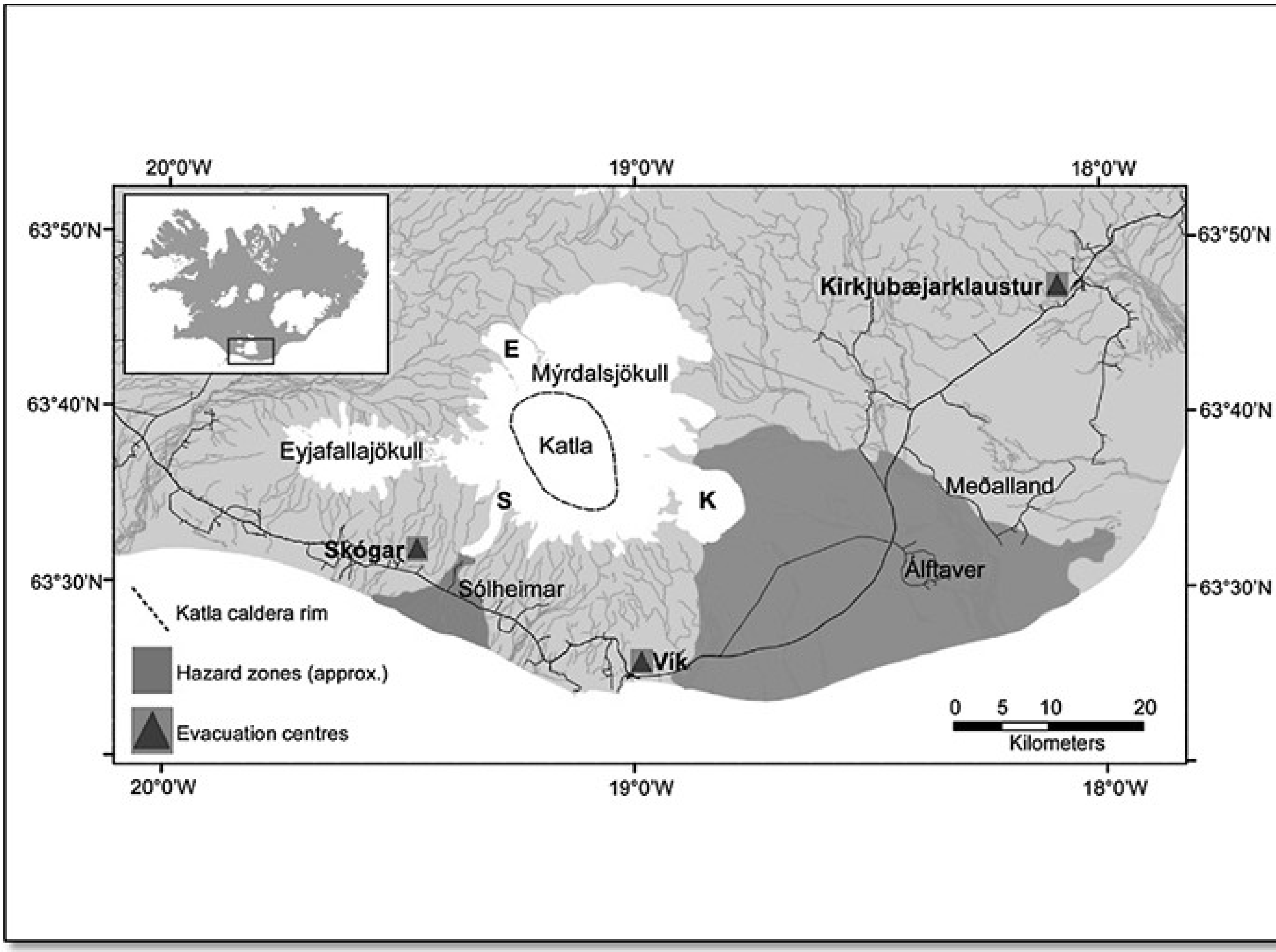
science project that involves references to location, travel, or distance. Combining geographical or spatial data with social data in an analysis ensures a better awareness of contextual factors and how these might influence patterns of behavior (Box 18.6).

Box 18.6: Combined Use of Mapping, Observation, Interviews, and Ratings Data to Evaluate Emergency Response to a Natural Hazard

To explore residents' preparedness to evacuate in the event of eruption of the Katla volcano in Iceland and consequent jökulhlaup (glacial outburst flooding) into the western hazard zone, Bird, Gisladottir, and Dominey-Howes (2009) used maps of the hazard zone, observed an evacuation trial, interviewed emergency workers, and survey-interviewed residents and tourists. Similar observation, mapping, interview, and survey methods were used also by Bird in the southern and eastern hazard zones (Figures 18.6 and 18.7). When these data are viewed in conjunction with each other and with resident comments, a clear picture emerges of some of the factors influencing residents' preparedness.

Figure 18.6 The Jökulhlaup (Glacial Meltwater) Hazard Zone to the South and East of Mýrdalsjökull Following Eruption of the Katla Volcano in Iceland



SOURCE: Deanne Bird, Department of Environment and Geography, Macquarie University, and Department of Geography and Tourism, University of Iceland, 2009. (Used with permission.)

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Figure 18.7 Resident Ratings of Preparedness to Evacuate in the Event of Jökulhlaup

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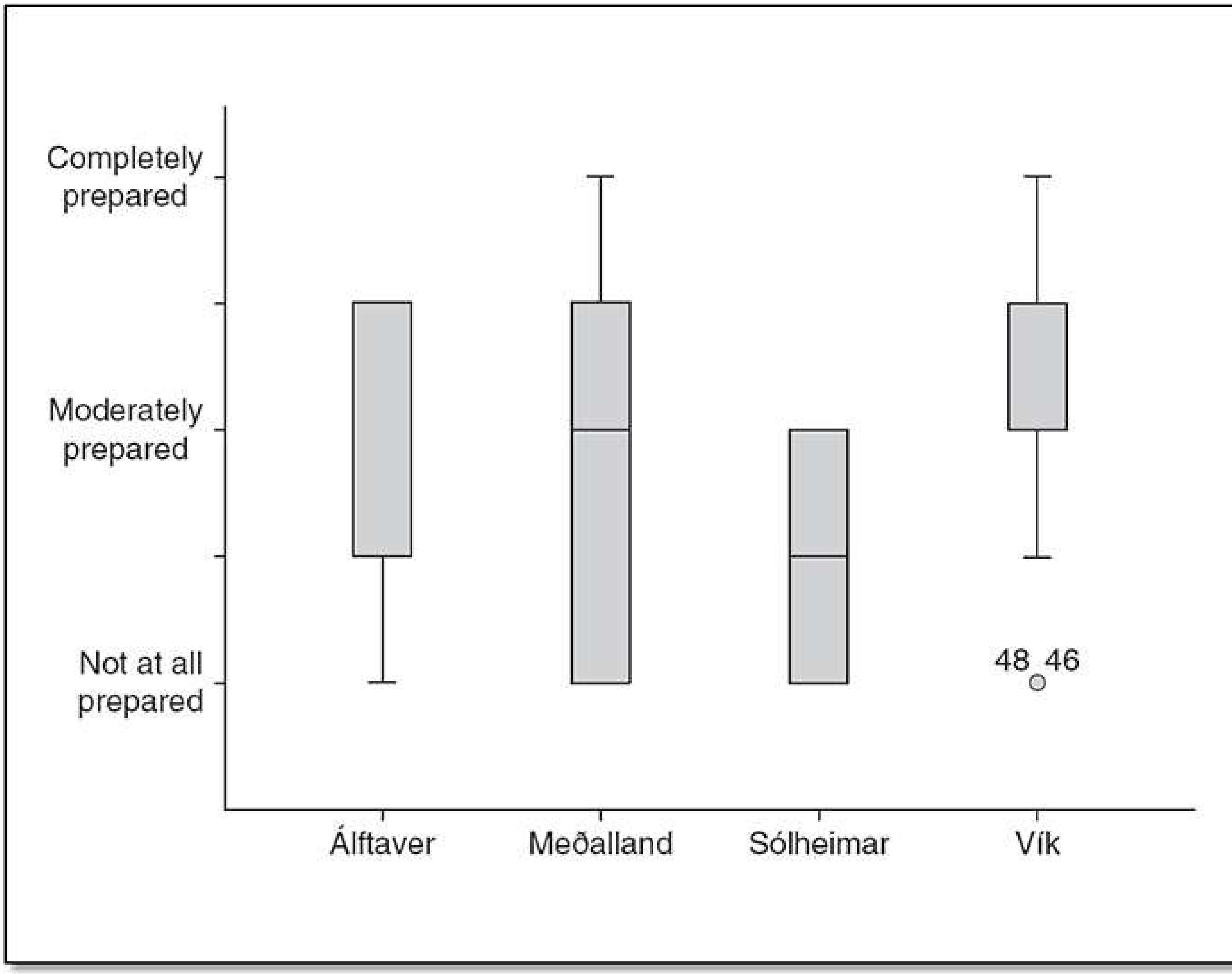

SOURCE: Deanne Bird, Department of Environment and Geography, Macquarie University, and Department of Geography and Tourism, University of Iceland, 2009. (Used with permission.)

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Residents in the farming communities of Sólheimar, Álftaver, and Meðalland are to be evacuated due to the risk of jökulhlaup, while houses in the low-lying coastal area of Vík are to be evacuated due to tsunami risk. Evacuation for the three farming communities is a more complex process involving disconnecting electric fencing and releasing livestock.

Very few residents across the region feel completely prepared for an evacuation. Residents in all areas other than Sólheimar will be given 30 minutes warning to complete preparations and evacuate; Sólheimar residents, who have to evacuate to the Vík centre, will be given only 15 minutes because if the flood flows from the southern catchment, they are located directly adjacent to the southern outlet glacier; hence, they feel less confident than others about

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have to travel only 5 minutes to reach the evacuation center, hence their generally higher level of preparedness. Residents in Álftaver are generally better prepared because they have worked on developing an alternative plan to the official one; the latter requires that they leave their higher homes and cross a low-lying area in the direct path of the flood to get to their evacuation center in Kirkjubæjarklaustur.

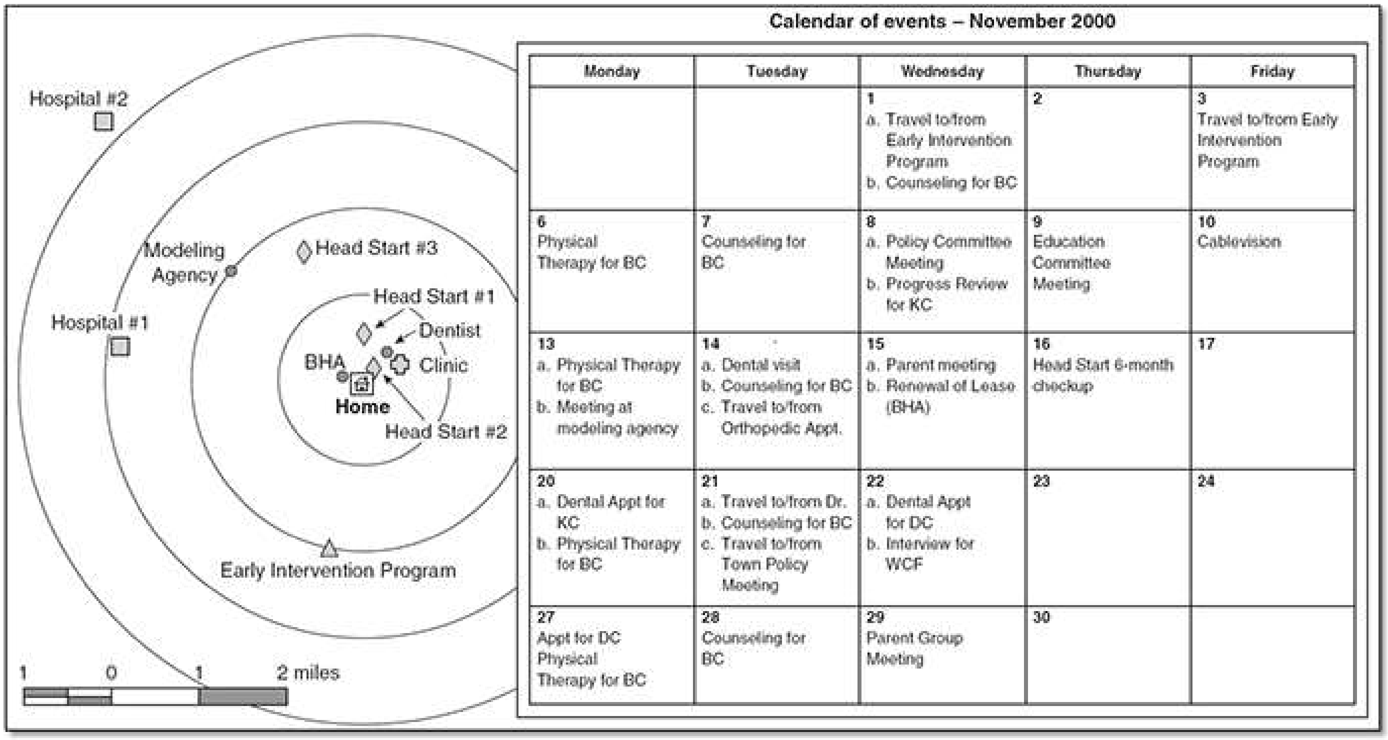
Social factors overriding geographic influences explain the marked exceptions within each area: The two unprepared people in Vík are recently arrived residents, and the completely prepared person in Meðalland keeps in constant touch with events and has actively sought information on previous eruptions from Katla and risk mitigation procedures.

Locational references within interviews or news stories or other qualitative sources might be mapped (Box 18.7), or alternatively, a large variety of factors related to a specific location might be gathered and managed in a database linked to GIS software in the process of undertaking a case study. The visual presentation of the data makes GIS a particularly powerful analytic and communication tool: Visual analysis can usefully precede more formal statistical analysis; GIS can bring previously ignored geographic variables into an analysis; and, by including many different contextual variables within the single integrated analysis, it provides a more holistic view of what is being considered (Jung, 2007; Steinberg & Steinberg, 2006).

Box 18.7: Adding a Spatial Component to Ethnography with GIS

To understand how caregivers of children with disabilities navigate services, Skinner, Matthews, and Burton (2005) combined ethnographic data with GIS technology to create visual displays of when and where carers went (Figure 18.8):

Figure 18.8 GIS Mapping of Daily Activities



NOTE: Skinner et al., 2005, p. 231, Map 7.1. The location of the meetings and appointments attended by the primary caregiver (November 2000). GIS is used to organize and map the data points. (Map produced by Stephen A. Matthews, December 2000.) (Used with permission, University of Chicago Press.)

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> We use existing data sets, augment them with new and refined measures of spatial context and structure, integrate these geographic data sets with an array of ethnographic data products (i.e., field notes, recoded notes, family profiles, photographs, etc.), and then analyze the result with data visualization/mapping techniques and spatial statistical analysis. (p. 230)

They found the combination of methods helped them to better understand the contextual factors impacting on parents and carers as they attempted to access and use services for their children. As noted by one of the mothers: "You tell them that I don't just sit on my butt all day watching TV. I'm out there working for my children" (p. 235).

Synthesis and Metasynthesis

It is quite common in mixed methods research to need to bring together varied sources and forms of data to be synthesized in the process of analysis. In a study of recovery from lung transplantation, Happ, DeVito Dabbs, Tate, Hricik, and Erlen (2006) used Excel to record

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interview data, which they then analyzed graphically and statistically. In another analysis, also using Excel, Happ et al. took an alternative approach to synthesizing their data: They qualitized scaled data to combine it with information on key dimensions derived from qualitative analysis, and then again used Excel to sort the data.

The data entry, sorting, and filtering capacity of a spreadsheet makes it a useful tool to extend the researcher's capacity to build the kind of data matrices advocated and popularized by Miles and Huberman (1994). Although these strategies can be comparatively reductionist, they are also capable of delivering an overview of patterns in the data more rapidly than methods relying on working with full verbatim transcripts of data—and different types of data can be synthesized within the one matrix, with or without conversion of data from one type to another (Box 18.8). Spreadsheet matrices are particularly useful where time for analysis is limited, data is of varied types, or the data lacks "richness" and where relevant issues largely have been identified before analysis.

Box 18.8: Research Opportunities for New Academic Staff

A spreadsheet was used with brief notes and key comments derived from semistructured interviews with 56 heads of academic departments, in six discipline areas across 12 Australian universities, regarding the research career opportunities afforded new academic staff in their departments (Bazeley et al., 1996; see Figure 18.9).

Figure 18.9 Data Synthesis in Excel

	A	B	O	P	Q	R	S	T
1	*University Type*	*Department*	*Department-Infrastructure*	*Department-Finances*	*New Staff-Load*	*New Staff-Financial help*	*New Staff-Other help*	*New Staff-Mentoring*
32	1	PHYSICS	Very good	No problems	Considerably reduced	Generous	Provided eg courses	Formal scheme
33	3	PHYSICS	very good	good	lightened by casuals	plenty	study leave	attached to group
34	2	PHYSICS	good, but no maintenance money, computers outdated	"existing on small ARC"	lighter in first year	can shuffle extra money into new areas	Equipment provided by groups	responsibility of the groups
35	1	PSYCHOLOGY	Some dept money for unfunded projects. Space problems but equipment fine.	Money for equip., not staff	Heavy teaching -"a weakness"	Mech A money for grant applicants	Help with applics.(advice, pay for RA). Teaching relief first year.	Recently formalised for junior staff
36	1	PSYCHOLOGY	"Always tight" but hire only those they can support		"Overloaded", heavy load	Can access senior staff res.funds		Nothing formal. Many work with senior staff anyway
37	3	PSYCHOLOGY	More facilities than equipment	Problematic	Heavy teaching	Available	Encouragement and advice	Keeping a fairly close eye on postgrads and junior staff (informally)
	2	SOCIAL WORK	not needed		lot of indiv.	no dept	stats and	faculty

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Data were sorted using categorical variables. Sorting of responses based on discipline revealed that at that time,

- New academic staff in physics had extensive opportunities given them—"honeymoon periods" from teaching, computer facilities, financial support–and that research activity was "expected."
- In nursing, the majority of new academic staff were still undergoing research training; support for research was more patchy and teaching demands were high.
- Staff in psychology had research qualifications, research was "supported," and necessary equipment was usually available, but teaching loads were a problem.

Interestingly, patterns were much more clearly defined by discipline than by the status of the university, and in general, the “pure” disciplines of physics and history had more in common than was shared with other disciplines; similarly, the practitioner-oriented disciplines of nursing and social work had much in common but differed from others.

Strategies for data synthesis can be applied not only to multiple sources of data within a study but also to results and conclusions drawn from multiple studies. The synthesis of results from differently conducted studies extends the more established concept of meta-analysis, a statistical technique developed to amalgamate and compare the results of a series of quantitative studies. When that technique was introduced, it was seen as beneficial where each individual study was not sufficiently strong in itself to establish a general conclusion. Meta-analyses and/or meta-syntheses are often called for in the context of evidence-based practice or when funding bodies expect a systematic review of previous research (Harden & Thomas, 2005; Pawson, 2006). As with single multimethod studies, meta-synthesis might involve separate, sequential, or integrated analyses, the latter avoiding the issue of having to classify component studies as quantitative or qualitative in the first place (Sandelowski, Voils, & Barroso, 2006).

Meta-analysis requires use of a common framework for measurement, such as an effect size, in order to be able to compare and combine the study results. Similarly, synthesis of components within a study, or meta-synthesis of results from multiple studies involving a variety of methodological approaches, requires application of a common conceptual framework (Box 18.9) to build a coherent analysis.

Integration of results from different studies often requires transformation of data in order to be able to effectively combine diverse sources. Coded data might be converted to variable data to allow synthesis using statistical techniques or, as with the Harden and Thomas example, the results of quantitative studies qualitized, for textual analysis in combination with the conclusions from qualitative studies. In a metasynthesis, the pooled data might then be analyzed using effect sizes or through identifying common themes.

Excel is a useful basic tool for synthesis and metasynthesis, where results of studies are

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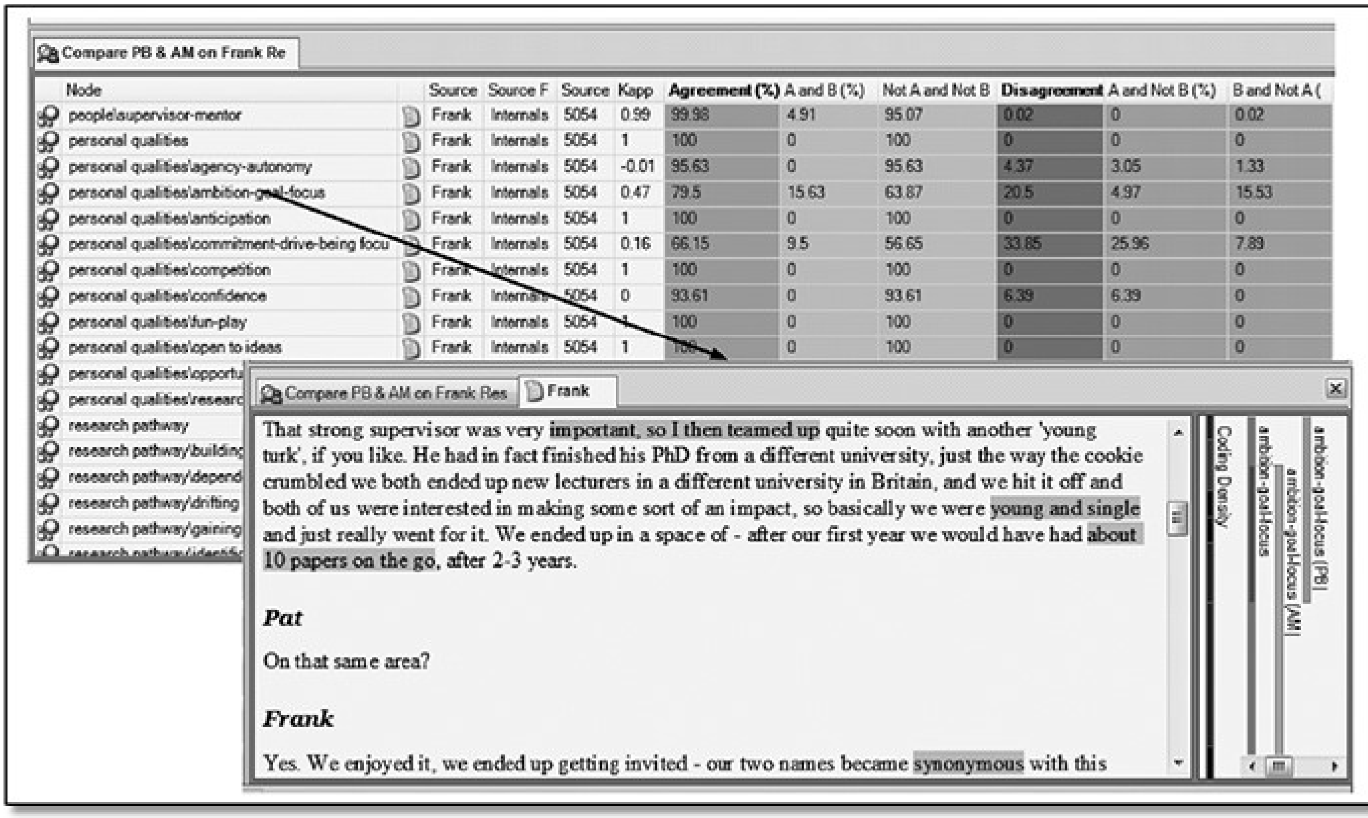
the basis of selected study components. Excel has the advantage of simplicity of use and of being able to handle mixed forms of data within the one display. For more complex analyses, specialized statistical or qualitative software will be needed, depending on how the data are being treated.

Improving Rigor

While there is general agreement that use of a computer improves (although never guarantees) rigor of coding and analysis, there is significant debate about what constitutes reliability and when it matters, especially in relation to qualitative coding and analysis. There are at least two situations, however, where transparency and consistency of coding is critical with relevance to mixed methods analysis: where multiple coders are working on the same set of data sources for the same purpose, and where qualitative data are being coded to facilitate conversion for statistical analysis (Boyatzis, 1998). Several programs, including EthnoNotes, Atlas.ti, and NVivo 8, now offer ways of carefully tracking the work of different coders (or the same coder at different times), providing both data for team discussion about coding strategies and, in EthnoNotes and NVivo, Cohen's Kappa indices of level of agreement in coding (Figure 18.10). A key advantage of this type of display is the opportunity for team researchers to see exactly how their coding agrees or disagrees, as a basis for discussion and refinement of practice.

Figure 18.10 Coding Comparison Query (NVivo)



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Box 18.9: Applying a Common Framework Based on Qualitative Data

A common framework is typically based on variable within trials data or quantitative studies, but when Harden and Thomas (2005) conducted a systematic review of studies on barriers to and facilitators of fruit and vegetable intake among children aged 4 to 10 years, they drew on the qualitative reports to create a framework. An initial meta-analysis of effect sizes from trials data on this topic had not shown any clear results relating interventions to outcomes. They then used NVivo to aggregate findings across qualitative “views” studies, from which they generated 13 themes. Six of these themes contributed to understanding the children's perspectives on what helped or hindered them from eating fruit and vegetables. These six themes were then used as the mechanism for combining the findings of the trials data with the qualitative data: A matrix was used to facilitate a constant comparative analysis that moved between the views data and narrative descriptions of interventions described in the trial reports. The authors noted that “the use of children's views to structure the final synthesis challenges traditional notions of who experts are and what constitutes expert opinion" (p. 264). They have since successfully applied this approach of using views data to structure a meta-synthesis in a number of other studies.

Concluding Comments

When those involved in the practical tasks of research work together with software specialists to resolve analysis problems, advances in methods result. Methodologists observing these developments become excited about new possibilities, yet sadly the "researcher in the street" often continues to struggle with pencil, scissors, and paper methods of analysis, largely oblivious to the increasing range of opportunities to improve extent, depth, and quality of integration in mixed methods analyses. As the mixed methods community moves on from debates about paradigms and typologies to practical strategies for working with mixed data, perhaps more attention will be given to methods of integrating data analyses and the technology that can support both separate and integrated analyses.

That is not to say that the solution to advancing mixed methods analyses is purely technical. As noted by Rihoux, Ragin, Yamasaki, and Bol (2009),

> Just because a computing operation is *technically feasible doesn't mean that it is useful or even desirable.* Once again: the [software] should never be used in a "pushbutton" manner but rather in a reflexive way. Needless to say, the same should apply to any formal tool—statistical tools as well—in social science research. (p. 173, italics in original)

Software ever remains the tool and not the method, and fitness for purpose is a primary criterion in determining what to use of software's offerings and when to use it. Appropriate use of technology can increase the capacity of researchers to more rigorously examine the detail and consistency of the findings they present and so contribute to inference quality (Tashakkori & Teddlie, 2008), but perhaps more critically, it can help researchers to see data in new ways and so contribute to building understanding and refining theory.

Research Questions and Exercises

Questions to Ask When You Are Planning an Analysis

1. Looking at qualitative data you are going to be working with, ask:
    - Are there ways in which I could combine quantitative variable data with this *during the analysis process* to facilitate comparisons?
    - Are there locational components that could be helpfully mapped?
    - Would it help to map the network of relationships between people (or other objects)?
    - Would using numbers help to clarify comparisons or reporting from the qualitative data?
    - Would there be any benefit in converting qualitative codes to variable data, for graphing, for statistical analyses, or perhaps, as input for QCA or social network analysis?
2. Looking at quantitative (variable, statistical) data you are working with, ask:
    - Are there ways in which these data tell a story, even if they are unable to be tested using inferential statistics? Would diagrams help to tell the story? Do the data together follow a common pattern, even though any one element is not significant?
    - Do I have any qualitative data that would help to explain the patterns revealed through the statistical analyses?

Exercises

1. Most software is available in free or 30-day trial versions, available for download from the Web sites indicated. Most also provide sample data or projects, and some provide tutorials and extensive electronic help files. Choose those that appear interesting to you and experiment with the sample data, or try importing some of your own (start with a small amount). Don't be disappointed if you don't become an instant expert, however, especially for mixed methods applications!
2. Identify an issue of interest to you in the domain you are studying or researching, for which you have a number of articles (say, 10 or more, preferably involving a range of analysis types). Create a spreadsheet in Excel, and list the articles in the first column (avoiding the first row). Now list various aspects of concern and some descriptor variables, related to the issue, across the tops of the columns. In the cells, type in or categorize each article with reference to the aspect for that column. (You might want to format the cells so that the text wraps and is top and left aligned, so that you can see it all. Also, use Freeze Panes or Split Panes to keep the header row and identification column visible as you work down and across.) Now select the whole sheet (click on the top left corner), and choose to Sort (Data menu) based on data in one of the categorized columns. Review the text to see if any pattern in another column has become evident.

outcomes derived using QCA methods compared with logistic regression modeling. Consider these differences in light of your understanding of the cases/participants you are investigating.

4. If you have some data that have been thematically coded, create a case-by-variable spreadsheet or statistical database from the coding and explore relationships in it using pivot tables (Excel), multiple-response cross-tabulations, nonparametric comparisons, or exploratory multivariate statistical analyses, or match with a continuous outcome variable and apply *t* tests or other predictive statistical analyses. Have you discovered any new associations or patterns in your data from these exercises? What issues are raised by the conversions? Return to the qualitative data to assist in understanding particular associations.
5. Take a set of variable data (or converted qualitative coding), and in a statistical database or Excel, explore the range of visual displays (charts and graphs) that might be created using it. Does this help to make trends or patterns any clearer?
6. Explore the possibilities for combining social network analysis with GIS principles by thinking about your own network of friends: With whom have you had contact over the past month? What form did that contact take (e.g., face-to-face, phone, text, Internet)? How frequent was the contact with each one? Where is the other person located? Who, among your network, is likely to be in contact with each other? Now, try plotting the various ties, but including as much as you can of the spatial and contact information through where you place your contacts and how you depict the links. How might such an ego-net look different for someone who is at a different stage in the life cycle?

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