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The Contribution of Computer Software to Integrating Qualitative and Quantitative Data and Analyses

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In published mixed methods studies, qualitative and quantitative approaches have typically been combined by using them side-by-side or sequentially, until the point when the separately generated results are interpreted and conclusions drawn. Integration of different forms of data during analysis, or of different approaches within a single analysis, is much less commonly reported. In this paper, integration of these types is shown to be facilitated by use of computer software. Such integration is seen as occurring: (a) when text and numeric data are combined in an analysis; (b) when data are converted from one form to another during analysis; or (c) when combination and conversion occur together iteratively or in generating blended data for further analyses. Examples are provided to illustrate these various, computer-facilitated approaches to mixing methods.

It has been argued that "multiple research methods and tools of inquiry—qualitative, non-experimental, and experimental—are essential arsenal for researchers who attempt studies on 'what works' in education. Without effective use of a variety of research methods at appropriate times, the quality of evidence on a program suffers, and interpretations of causality are limited" (Chatterji, 2004, p.9). The combination of multiple methods[1] "has a long standing history" in evaluation research where both formative and summative aspects of programs are considered (Rallis & Rossman, 2003; Weiss, 1972). Indeed, "most real-world evaluations pose multiple and diverse questions that cross paradigmatic boundaries, so evaluators tend to be pragmatic in drawing on methods" (Rallis & Rossman, 2003, p.493). Mixing of methods, particularly at the stage of data analysis, has a lesser history, however, perhaps in part because of lack of tools to undertake all but the simplest forms of it.

There is no single approach to undertaking a mixed method study. Those who have attempted typologies have variously arrived at 4, 5, 6 or 8 types of study in which elements of quantitative and qualitative approaches are combined into a unique design (e.g., Creswell, 2003; Greene, Caracelli, & Graham, 1989; Morgan, 1998; Niglas, 2004; Tashakkori & Teddlie, 1998). Johnson and Onwuegbuzie (2004) outline the basis for even more elaborate typologies, but conclude by noting that the design possibilities for combination cannot be thus limited: choices are guided necessarily by the pragmatic demands of the research question, with studies therefore fitting an almost unlimited number of possible designs. These authors then focus (I think more usefully) on the stages one might go through in the process of designing, conducting, and analyzing the data from a mixed methods study. Bryman (2006) critiques the typology approach more generally from the point of view that they are largely built on theoretical modeling, rather than a review of research in practice (the exceptions being those by himself, Greene et al., 1989, and Niglas, 2004).

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Integration in Mixed Methods Research

One of the critical decision points, and a way in which mixed methods studies might be differentiated, is the point at which elements of quantitative and qualitative approaches are brought together (i.e., integrated), whether that be in the design of the question, at data collection, data analysis, at the point of interpretation, or some combination of these (Caracelli & Greene, 1993; Creswell, 2003). Most commonly, integration of approaches occurs only, or primarily, at the point of final interpretation for the study (Bryman, 2006; Greene et al., 1989); that is, results from quantitative and qualitative components of a study are considered in relation to each other primarily as conclusions are being drawn.

Bryman (2006) found the majority (57%) of the 232 social science articles he reviewed used a combination of a separately administered survey instrument and qualitative interviewing (mostly in a cross-sectional design), whereas in approximately 27% both quantitative and qualitative data were derived from a single data source (the majority of these being a survey which included open ended questions). Indeed, some have argued for total separation of the qualitative and quantitative components of a multimethod study, with integration considered legitimate *only* at the point of final interpretation (e.g., Morse, 2003; Sale, Lohfield, & Brazil, 2002). The purpose of using multiple methods in studies where quantitative and qualitative data are treated separately is generally to attempt to validate the findings by having corroborative evidence derived from different methods (classically referred to as methodological triangulation), or more often, to explain or complement findings from one method by using another (Bryman, 2006; Greene et al., 1989). Thus, for example, the findings of a quantitative study might be 'fleshed out' with qualitative data, or the different sources might contribute different aspects to build a more complete picture. These approaches do not pose a particular or new challenge with regard to analytic procedures as the researcher employs standard statistical and text analysis procedures as appropriate to each separate set of data.

Relatively few studies, even among those using mixed methods, report integration at the stage of data analysis: Greene et al. (1989) found 5 only in their sample of 57 evaluation studies and Bryman also noted, when presenting a preliminary report of his 2006 paper,[2] that just 7 of the 232 studies reviewed used an approach involving transformed data. Niglas (2004), in contrast, reported a much higher proportion, classifying more than 50% of the 145 mixed methods studies she identified within her sample of 1,156 educational articles as having integrated data analysis. The difference lies in the definition of what makes for integrated data analysis: Niglas included any study in this category that made a numeric report from qualitative data, such as indicating the number or proportion of people interviewed who mentioned a particular theme or issue. She notes that "real integration of qualitative and quantitative approaches" before the discussion was "very rare" (personal communication, February 1, 2006).

Strategies for Integration

Caracelli and Greene (1993) identified four integrative strategies for mixed methods analysis: (a) data transformation, in which one form of data are transformed into another for further analysis; (b) typology development, in which a classification of concepts or categories developed from one set of data is applied to another; (c) extreme case analysis, in which the outliers or residuals revealed by one analysis are explored using alternative data or methods; and (d) data consolidation/merging to create new variables for use in further analysis. Iterative application of different analysis strategies was seen to have value in further explicating the initial analyses of either or both sources. Indeed, integration of mixed-form analyses was most evident when data from one type was used in analyses of the other type, with the intent of reapplying the results to further the analysis of either data type.

The mixed methods research purpose most frequently served by integration of analyses is initiation, that is, to be provocative and bring fresh perspectives through contradiction and (intended or unintended) discovery of paradox (Caracelli & Greene, 1993; Greene et al., 1989; Rossman & Wilson, 1985). Caracelli and Greene note, however, that particular strategies for integration might be used fruitfully also in the context of expansion, development, and complementarity, but that integration is inconsistent with triangulation (defined as corroboration or validation), given the latter requires independence of methods.

Given the potential for enriched understanding that an integrative strategy holds, Caracelli and Greene (1993) ask why integration before interpretation and discussion is so uncommon. Salient suggestions included the impact of the paradigm debates coupled with an acceptance of diversity of approaches (i.e., that they should be used independently); the popular association of mixed methods with triangulation and consequent lack of consideration of integrative strategies; and the view that integration or synthesis of results is an intellectual or ideologically driven activity (which, therefore, occurs independently of data handling). I would argue four further practical reasons why it has not been popular: to achieve integration of data analyses requires a breadth of skills that has not been commonly available in a single researcher, or alternatively a close-knit multi-skilled team; it requires the capacity to imagine and envision what might be possible—to tread new paths—along with the logic (and skills) required to bring that about; students (and others) are frequently encouraged to write results from different components of their studies separately (integration in a dissertation is in the 'too hard' basket, or is seen as 'risky'); and, finally, integration is greatly benefited by data handling technology (computer software) to facilitate the process, which, until relatively recently, has not been readily available. Integrative software is still very much in development, and indeed, software for qualitative analysis, from which much of it is derived, is only now beginning to gain wide acceptance in the academic community.

Two Major Routes to Integration in Analysis

In asking how does (or might) the use of computer software and processing power facilitate or extend integration of analyses, the key question for this paper relates to this issue of data handling technology. The paper will focus on the more 'everyday' possibilities for computer assisted analysis of mixed methods data using spreadsheets or databases, and commonly available qualitative and quantitative analysis software. There is a large and growing range of other analysis techniques and specialist software available to the enthusiastic user, often requiring programming for specific purposes: it is beyond the scope of this paper to review their use here.

I propose that *in terms of data handling*, two major routes to integration underlie the various strategies one might adopt when using software:

1. *Combination* of data types within an analysis, such as when categorical or continuous variables are used both for statistical analysis and as a basis for comparison of coded narrative (qualitative) material. This could occur through using both text and numeric data gathered at the same time, for example through a survey instrument; or using sequentially gathered data, most commonly (as identified by Bryman, 2006) a combination of survey and interview.
2. *Conversion* of data from one type to another for analysis, typically the conversion of qualitative codes to codes used in a statistical analysis, but also, alternatively, through the contribution of quantitative data to a narrative analysis of events, circumstances, or perhaps a life history (Elliott, 2005; Tashakkori & Teddlie, 1998).[3]

Strategies such as data consolidation, blending or merging are likely to involve both conversion and combination.

Using Software to <u>Combine</u> Numeric and Text Data for Analysis

The first challenge faced by the researcher seeking to combine mixed forms of data and procedures for working with them is one of data management—how to link observational or interview text or open-ended survey responses (i.e., textual data) to demographics, responses to fixed-alternative questions, or other measurements (data in numeric form). Traditionally, brief explanatory comments provided in surveys have simply been 'eyeballed' by the researchers looking for illustrative comments; responses to open-ended questions might have been category coded to allow for frequency counts and interrelationship with other variables; and unstructured text has simply been marked with the demographic characteristics of the interviewee, as additional information to be noted by the researcher working with that text.

The advent of text-handling spreadsheets and databases and, in particular, of text analysis software, has heralded solutions to these data management problems, and opened up new possibilities for more rigorous and/or deeper analysis of this type of data. They have not necessarily solved the theoretical issues which could arise when different forms of data are combined, however.

Using a General-Purpose Spreadsheet or Database

In its most elementary form, integration of data through combination occurs in structured surveys where a pre-categorized (closed) response to a question is followed up with a request to respondents to provide comment, explanation or illustration of their answer. Comments might be sorted by the categorized responses to provide illustrative material to assist in interpreting what each response really meant to the survey respondents. Such sorting is a simple task in any spreadsheet or database, through which all open responses from any given subgroup (demographic, or based on categorical responses to a parallel question) can be brought together and compared with those from a different subgroup. Analysis in such cases rarely extends beyond identification of patterns in the text in relation to respondent groups, although it is also possible to consider patterns of which respondents gave what kinds of answers and to investigate anomalies in the responses, for example, when people who chose contrasting categories of closed response provided the same kind of elaboration of their answers.

Unstructured data can be similarly organized in a spreadsheet by defining a set of issues to explore, and entering brief summaries of what was said by each respondent under each issue (issues in columns, respondents in rows). Data which categorizes respondents are also entered as one or more columns, and are used to sort the textual comments, revealing any patterns in responses which may be present. This is quite a reductionist approach to qualitative analysis (Miles & Huberman, 1994), but is useful where time for analysis is limited or the data lack 'richness' and where relevant issues are largely identified before analysis. 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. This method was used with data derived from interviews with heads of academic departments, in six discipline areas across twelve Australian universities, regarding the research career opportunities afforded new academic staff in their departments (Bazeley et al., 1996). Sorting of responses revealed that new staff in physics had much greater opportunities given them ("honeymoon periods" from teaching, computer facilities, financial support) and that research activity was "expected," in comparison with those in nursing where the majority of new academic staff were still undergoing research training, support for research was more patchy and teaching demands were high, while for those in psychology, staff 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.

Using Qualitative Data Analysis Software

Using qualitative data analysis software (QDAS), when the textual comments warrant more detailed analysis, allows the researcher to take analysis of mixed, structured survey data a step further than is possible using a spreadsheet or database. Assuming appropriate formatting, a number of QDAS programs now have a facility for autocoding text for the question to which it was a response, as well as for importing individual matching statistical data (such as demographics or categories of response to closed questions). This allows the kind of sorting (of text response by value of pre-categorized response variable) any database can do, as outlined above. But, unlike spreadsheets or regular databases, the greater flexibility of coding systems in QDAS means that the text material can also be readily coded into new emergent concepts or categories.[4] Text stored in these new coding categories, also, can be viewed comparatively across demographic subgroups, or in relation to responses to parallel (or other) categorically coded questions. This technique was used to combine analysis of responses to both closed and open-ended questions covering knowledge of and attitude to organ donation, given by those who had been faced with this issue in a personal way (Pearson, Bazeley, Plane, Chapman & Robertson, 1995). Answers to a question on reasons why one might personally choose to donate were coded to create three categories reflecting altruism, pragmatism, and anxiety about the integrity of the body. These then could be considered in relation to grief resolution (and other variables). The patterning of responses was clear for those expressing a pragmatic viewpoint (who were resolved or resigned) or a concern with body integrity (unresolved, or at best, resigned), but those expressing altruism were equally likely to be resolved or unresolved in their grief. Further examination of the sorted text revealed a fresh perspective on the data: all of those unresolved in their grief who expressed altruism did so in life-or-death terms, for example: "If other people can live, why not?" In contrast, all of those who were resolved in their grief and who expressed altruism did so in quality-of-life terms, for example: "A man would be very selfish if he died with healthy organs and didn't give someone else a chance to lead *a normal life*" (emphasis added).

More generally, using QDAS, the capacity to combine unstructured text (or similar) data with demographic, categorical, or scaled information opens up a range of possible analytic strategies that would be much more difficult to achieve without software. Variable data are combined with coded text by using the values of the variables (which apply to whole cases) to sort the intersecting text for a particular coding category, or a set of categories. This facilitates comparison of how different demographic subgroups might refer to an experience, concept, belief or issue; it allows the researcher to compare experiences or expressed attitudes as they arise in different contexts; it opens the possibility to corroborate or confirm the meaning of scaled scores by matching scale points with text in which participants describe relevant experience. For example, patients recovering from day surgery completed a 10 point visual analogue scale to record the level of pain they were experiencing, and were interviewed also about their experience of surgery and pain (Coll, nd). Their descriptions of their experience of pain could be sorted by the rating they had given for the level of pain experienced. In this way, it could be determined what each point on a pain scale of this type meant for people experiencing it, thus making use of the scale more meaningful for further research.

The interaction of multiple variables in relation to a particular coding category or concept can be achieved through refining the query in a way that is somewhat analogous to use of a two-factor analysis of variance, for example, to examine the interaction of gender and discipline with respect to an element of academic experience. Alternatively multiple interactions can be examined through repeated querying of the data for different subgroups, as in a multi-layered contingency table. The matrix function in NVivo facilitates this kind of comparative querying by allowing multiple comparisons at one time, with or without restrictions on what data are considered within each query, but the end result also can be achieved, albeit a little more tediously, with most QDAS. NVivo was used, for example, to compare expressions of satisfaction (personal pleasure) gained from doing research for male and female social scientists and scientists (Bazeley & Richards, 2000). The sorted text suggested that those in each discipline group gained satisfaction from different sources, while differences were not apparent for gender. Approximately half of the members in each discipline group reported satisfaction (gaining personal pleasure from engaging in research), but those in the sciences who did so were likely to refer to the sense of agency they experienced in doing research, while most of those in the social sciences made reference to achieving a goal or a task when expressing satisfaction.

Benefits from Combining Numeric and Text Data for Analysis

Multi-method approaches typically bring quantitative and qualitative sources together by using qualitative comments, interviews, or documentary sources to corroborate, illustrate, or elaborate on the meaning of categorized responses to survey questions and quantified instruments; to provide a basis using one type of data for sampling or instrumentation using the other; or to provoke new thinking. As noted earlier, in most published research this has meant only that the qualitative data are placed alongside the quantitative data for analysis, rather than being integrated with it. Use of a computer program in the process of mixing methods can not only assist in, but greatly extend the use of data gathered for complementary or expansion purposes because such use facilitates matching of different data sources for individual respondents; comments, expressions of attitude, or observations made by a particular person can be matched with their particular rating of their own experience, or their demographic details. The comparison process is therefore refined, providing the basis for comparative pattern analysis, illustrative understanding, and potential also to reveal new (or previously unobserved) dimensions in the data (such as source of satisfaction, in the example above). This strengthening of the comparative process may well be one of the more exciting outcomes of using these techniques for the researchers involved, particularly for those employing grounded theory methodology (Strauss, 1987).

Furthermore, when data are matched in the way described, instances where individuals go against a trend can be readily identified and explored in detail. These cases might be outliers on a statistical measure, deviant cases in qualitative terms, or cases where there is an apparent contradiction in the data from the different sources (Caracelli & Greene, 1993; Miles & Huberman, 1994). For example, from the examination of gender and discipline differences in satisfaction referred to earlier, two social scientists (one male, one female) also expressed agency, while one scientist did not. These cases could be identified, revealing that the two social scientists both worked in experimental psychology (which has more in common, perhaps, with science than social science), and the one scientist's current work was all to do with recording the history and biography of science and scientists (which has more in common with social science than science). It could be argued, then, that rather than contradicting the observed trend, these apparently discrepant cases added confirmation.

When contradictions or other anomalies arise from an exercise in combining data sources, then like subgroup comparisons, this also has the potential to stimulate analytical thinking beyond simple illustration (serving an initiation purpose for mixing methods). The cause of the contradiction or anomaly might be explained methodologically (an important insight in itself), new substantive understanding could result, or, as with triangulation, it could create the need for further data collection in order to resolve emergent discrepancies (Erzberger & Kelle, 2003; Jick, 1979).

Using Software to <u>Convert</u> Coding from Qualitative Data for Statistical Analysis

For as long as any of us can remember, open ended responses to survey questions have been category coded for inclusion in a statistical database (Bazeley, 1999). In my early consulting experience when survey techniques were dominant in social research, I would typically make an initial classification of (several hundred) responses into 40-50 categories, which were then recoded into 6-8 broader categories for analysis. The kinds of issues raised in the examples and responses given would then be related to other quantitative responses in the survey. Recent text-analysis modules for some statistical programs now attempt to automate this process by categorizing the open ended responses based on the co-occurrence of words (e.g., SPSS, Wordstat). Some freedom for manipulation of categories is usually available to the researcher. The categorized responses then can be considered along with other statistical data. Disadvantages in these methods include the 'cost' of coding time for the manual method and the potential for generation of meaningless categories using the automated method. While these processes work satisfactorily for short answer responses which generally deal very briefly with just one or two concerns, they 'fall down' for more complex data. The principal disadvantage in these processes of direct conversion for statistical use, however, is that one loses ready access to the original text as one progresses through the analysis process and, consequently, to nuances in the way people express their concerns.

Relatively recent developments (primarily since 1997) in QDAS have changed this situation somewhat. The frequency with which concepts, categories, or themes have been identified in unstructured data by the researcher-analyst is now readily provided, and a number of programs export individual coding information which, either directly or indirectly, is read as a case by variable matrix in a statistical program, hence allowing further statistical analysis. Additionally, in some programs, more complex associations between variables can be exported as a quantified matrix (e.g., as a similarity matrix). The defining characteristic of what is happening, in these instances, is that data are being converted (morphed, transformed) for reporting or for further analysis—a process generally referred to as quantitizing the qualitative data (Tashakkori & Teddlie, 1998). Critically, however, ready access to the text which supports the exported numeric information is retained.

Counting in Qualitative Analysis

Counting themes, or instances of a category in a qualitative database, constitutes a very simple form of conversion of data from textual to numeric form. For the majority of studies that develop quantitative reports from qualitative data, the quantitative data generated are just descriptive statistics reporting numbers of themes or categories found (Creswell, 2003; Niglas, 2004). Use of counts communicates more effectively and reliably than does use of vague terms to indicate more or less frequent occurrence of some feature in the text (Miles & Huberman, 1994; Sandelowski 2001). Counts can be seen as reflecting the importance of various emergent themes (Onwuegbuzie & Teddlie, 2003), although it can be argued that frequency and importance are not necessarily synonymous.

Qualitative software programs can readily provide various kinds of counts, including the number of text segments coded at a particular category, the number of cases with coding, or volume measures which might include the total number of characters or words coded, the proportion of text coded, and so on. These might be used as simple counts or proportions and descriptively reported as part of a qualitative write-up. While researchers have often used counts of qualitatively derived themes in their work, measures of volume have typically necessitated having the text broken into predetermined segments for coding to facilitate counting and assessment as a proportion of the total (Chi, 1997). When software is used to facilitate such counting of occurrences, however, it becomes less necessary to break the text into predetermined segments in order to code and count, and the whole measurement process is considerably simplified.

Volume counts (in this case, lines of text) were used, for example, by Holbrook and Bourke (2004) in a study of Ph.D. examiner's reports, to determine the relative emphasis given to major components of the dissertation (e.g., literature, methods, analysis, discussion), as well as the relative amounts that comprised summative versus formative evaluation of the work, as a first step in their analysis of the Ph.D. examination process. This was then followed up with qualitative analyses of the types of comments made (e.g., Holbrook, Bourke, Lovat, & Dally, 2004). Similarly, a decreasing number of lines of text between occurrences was used by Anderson et al. (2001) to verify the snowballing spread of argument strategies between children working in problem-solving groups.

When subgroups are compared (as described earlier), the resulting analyses provide not only an assessment of the qualitative differences in the coded text between the groups, but also a count of the frequency with which that coded concept was used by members of each group. Each alternative component of the information provided (numbers, text) adds to the analytic picture: how many report and how they report might each be conditioned by (or associated with) the subgroup to which each person (or source) belongs; each type of analysis provides different but complementary information.

Converting Qualitative Coding to a Case by Variable Matrix for Statistical Analysis

When conversion is taken a step further, and codes derived from qualitative data are recorded separately for each case in the data (either as presence/absence of each code or as frequency of occurrence), then one has a case by variable matrix. Such case-coding matrices might be based on the presence or absence of *a priori* categories, or on interpretive coding categories generated during the process of analysis. Assuming satisfaction of necessary statistical assumptions for the processes chosen, this type of matrix provides the basic form of data for most statistical analyses, including hypothesis testing, predictive modeling, and exploratory analyses. It can be used either on its own, or it can be amalgamated with an existing quantitative database for the same cases. 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 for presence of formal argument devices and use of textual evidence. ANOVA and ANCOVA were used to demonstrate that having an argument 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).

Conversion of coding for statistical analysis raises a number of issues to be addressed by the researcher: (a) there needs to be sufficient cases (preferably probabilistically rather than purposefully selected) to provide statistically sound samples for the procedures selected; (b) a decision has to be made about whether it is more appropriate to export information reflecting volume of text coded, or simply the presence or absence of a code, and (c) if the qualitative category codes data which are non-directional (e.g., that the issue of the character of a witness was raised, without identifying the conclusion reached), then, depending on the purpose, further coding of the data within that category (to more specific codes, e.g., reflecting a positive or negative assessment) could be necessary before export (Bazeley, 2003).

Exploratory Statistical Analysis of Patterns of Association in Qualitatively Assigned Codes

Statistical techniques which include cluster analysis, correspondence analysis, and multidimensional scaling have been fruitfully applied to quantitized qualitative data, to develop or clarify concepts or themes, or to test hypotheses (Ryan & Bernard, 2000, 2003). Sometimes the resulting statistical analyses are, in turn, qualitized as more holistic descriptions are built from the statistical evidence, demonstrating the recursiveness often present in mixed methods analysis. For example, Excel and SPSS were used by Niglas (2004) in a primarily quantitative content analysis of mixed methods studies. She used scales to record variation across 145 mixed methods studies on a range of design characteristics. K-means cluster analysis of the quantitative content analysis variables classified the studies into eight distinctive groups, and the characteristics which best differentiated the groups were calculated. Findings based on the statistical analysis were compared with memo-style notes taken during the initial reading of the studies to generate brief descriptions for each of the eight groups—thus qualitizing the quantitized data which, in turn, had been derived from interpretive (qualitative) reading of text. These eight groups were then used to organize the articles for further statistical analyses and conceptual mapping.

A range of statistical techniques, including several based on patterns of association, are being used in an ongoing concept analysis of research performance (Bazeley, unpublished data). The primary data comprise descriptions given by 295 academics for eight different aspects ('brands') of research performance—descriptions of researchers who are productive, active, recognized, satisfied, approachable, and/or who demonstrate quality, ability, benefit. These have been coded using NVivo to create a set of descriptors. Additionally, basic demographic data are available, along with each academic respondent's weighting of the importance (or value) of each of these eight aspects of performance for doing research and for assessing research (as interval scales). These additional numeric data have been imported into the NVivo database for use in combination with text responses, and coding based on the descriptions given has been exported from NVivo in a number of forms, each contributing to a different type of analysis. For example:

1. A table showing which respondents used which descriptors overall (a case by variable matrix) when combined with the additional quantitative data is allowing a comparison to determine whether research performance is thought about differently depending on gender, discipline, educational status or level of interest or involvement in research.
2. Descriptors used by each academic respondent for researchers displaying each particular aspect of performance, weighted by the value they assign to that aspect of performance, are being exported in order to contribute to a general model of research performance based on both frequency and weighting of responses. For example, if a description of 'good communicator' is given for a productive researcher, it is likely to be given a higher weighting than if it is given as a description for being approachable, when the total picture provided by the descriptors is being developed.
3. A matrix of the frequencies with which each descriptor was used for each aspect of performance has provided the basis for cluster analysis of performance types, confirming a classic quality-quantity divide in understanding performance, but also revealing that social factors and approachability in particular are seen as being quite outside the general domain of research performance, a conclusion supported also by the importance ratings given to approachability. The form of expression used for each descriptor, according to the type being described, is also being reviewed within the NVivo database. For example, although quality and ability 'hang together' statistically, the text suggested differences in emphasis underlying the way that descriptors, such as having substantive knowledge, displaying originality, or theoretical understanding, are expressed in the context of each of ability or quality (Bazeley, 2001).
4. Multidimensional scaling is being applied to a descriptor-by-descriptor similarity matrix, based on the frequency of co-occurrence of

descriptors given for each performance type (i.e., the number of times respondents used any pair of descriptors in the same context of describing a researcher of a particular type). This process will identify broader dimensions underlying the concept of research performance held by academics and should lead to a simplified conceptual model of research performance, to feed back into further qualitative and quantitative analyses.

5. Scaled weighting data imported into the NVivo database are being used to compare the form of expression of a description given for each performance type, in relation to the value assigned to that type by the same individual. For example, do respondents use different terms or expressions for, say, methodological understanding in the context of ability, depending on whether they rate ability high or low in importance?

These techniques are all being used in an exploratory way, appropriate to the purpose of exploring and elucidating a concept. Extensions to this work are likely to involve confirmatory strategies.

Benefits from Using QDAS in Converting Data for Statistical Analysis

Integration of analyses using conversion of data is useful in initiating fresh perspectives through exploratory studies, particularly those involving concept analysis; for creation or validation of scaled measures; development of typologies; and for studies attempting to identify predictors of an outcome. Such analyses bring the power of statistical analysis to an inductive project, particularly in exploring the structure of data, while retaining the freedom and power of the qualitative techniques to provide situated meaning. Integration involving conversion of data is useful also in studies designed to test hypotheses (such as those on children's argumentation, described above), or to build predictive models where the foundational data are text (for example, from legal judgments, or case histories).

One of the primary benefits of using qualitative coding as the basis for statistical analysis is that the researcher does not have to pre-determine the categories which will be used for analysis. At the same time, there is no guarantee that all participants in the research process will be equally comprehensive in their discussion of the topic, raising the issue, for example, of whether absence of mention of a topic represents lack of importance, deliberate omission, or a temporary lapse in attention.

Richards (2005) drew a distinction between quantitative coding as data reduction, and qualitative coding as data retention, in particular, the retention of the links between ideas and the data that generate those ideas. The reduction of text to numbers, as in quantitative content analysis, carries the associated problem "that researchers cannot be sure that the meanings they attach to words on a survey and to the resulting statistical summaries are similar to those held by the respondents; the data have become decontextualized" (Rossman & Wilson, 1994, p. 321). In contrast, the use of QDAS in the generation of codes for statistical analysis carries with it the key advantage that text associated with the codes used is retained in a readily accessible way, thus assisting 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.

Blending Analytic Strategies: Combination and Conversion Working Together

Integration of data and analyses through an amalgamation of both combination and conversion may be necessary to reconcile "divergent findings, paradox, and contradiction" that can result from mixed methods studies, or indeed, to initiate creative insights through resolution of "dissonance, doubt, and ambiguity" (Rossman & Wilson, 1994, p. 323). Iterative use of alternate analytic strategies and the programs which support them within a single analysis is one form of this type of integration of data. Blending or merging of diverse data sources to create new composite variables which are then fed back into the analysis is another.

This latter strategy was used by Kemp (1999) in her study of the community service needs of spinal injured people. She found dissonance between quantitative data indicating that there was a desperate shortage of community service provision, and qualitative data that suggested ambivalence in the spinal injured population about whether they would access services they had most complained about not having, should they become available. Qualitative coding regarding attitude to use of services was combined with a quantitative variable reflecting current use of services to create a new composite variable. Further quantitative analyses using this variable pointed to a perception of arbitrariness in distribution of community services for the spinal injured population. The computed variable, imported back into the qualitative database, was then used in association with both service satisfaction scales and respondents' qualitative responses about the beneficial and detrimental effects of services to reveal that the quantitative arbitrariness of service provision was, in fact, not so arbitrary, but rather, that services were allocated on the proviso that persons with spinal injuries adopt life plans which met the expectations of service providers (i.e., to be different rather than ordinary).

In reflecting on this experience, Kemp (2001) saw this process of integration as paralleling the iterative process of protein transfer between the sense and anti-sense strands comprising the double helix of DNA. The image of the unwinding and rebuilding of DNA molecules evokes dissonance and ambiguity, and a transformative, interpretive method that can juxtapose numbers and words to achieve a cohesive, integrated explanation. The use of QDAS in association with statistical software facilitates such juxtaposition of numbers and words to create new variables and new understanding.

Conclusion

Published reports of studies that truly integrate qualitative and quantitative data sources in analysis are rare, as are those which apply both textual and statistical interpretive techniques to a single data source. Studies that use computers to do so are even rarer.

In this paper, I have not attempted to survey the whole field of integration of data and/or analyses in mixed methods research, nor the full range of computer-based strategies available for such integration. Rather I have concentrated on explaining and illustrating the use of 'off-the-shelf' computer software to achieve a combination of qualitative and quantitative data or analyses, or conversion from qualitative to quantitative coding and analysis, as common strategies for integration. To date, it is developments in software programs for analysis of qualitative data that have contributed most noticeably to researchers' capacity for integrating methods in the ways described in this paper. Indeed, Lyn Richards (2002) has argued that the most radical *methodological* changes that came about with qualitative computing were not in what the computer could do (such as coding), so much as the uses to which it could be put in driving a complex and iterative data interrogation process. Just some of what is currently possible, and the rewards from learning to use software tools, have been illustrated above. Tools are still being developed, a process which is both responsive to and which can lead to new techniques in data analysis. The future is open to imagination, and need.

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Notes

[1] I prefer to use the term *multimethod* to refer to studies in which two or more methods (of any type) are being used such that each retains its distinctive quality, and *mixed method* to refer to studies where the activities associated with each of two or more methods are intertwined or blended prior to final interpretation. In line with common practice, however, I sometimes use the term *mixed method* also in a more generic sense to refer to the general class of studies in which methods are combined in some way or another.

[2] Presented at Sixth International Conference on Logic and Methodology, Amsterdam, August, 2004.

[3] Because the computer plays a lesser role in this type of conversion, and with space limitations, it will not be a focus of discussion in this paper.

[4] Programs differ in whether such coding has to be done directly on the data sources in their original imported form (usually a document for each person), or whether already coded material (e.g., sorted by question asked) can be coded on to new categories. Where both options are available (as in NVivo), choice depends on whether it is more useful to understand all of a person's responses when coding a particular comment, or whether it is more helpful to simply focus on the issue being investigated in that question.