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Describing and Illustrating Data Analysis in Mixed Research

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Abstract

In this methodological paper, the authors propose a tool that brings together various quantitative and qualitative data analysis (i.e., mixed analysis) techniques into one meta-framework to assist mixed researchers (who use qualitative and quantitative approaches within the same study) in the data analysis phase of mixed research studies. A meta-framework for mixed analysis techniques is described, which incorporates 13 criteria that methodologists have used to create their mixed analysis typologies. In particular, a heuristic example is used with the aid of screenshots to illustrate how one can utilize several of these data analysis techniques to conduct mixed analyses.

Keywords: Mixed research, Mixed methods research, Quantitative research, Qualitative research, Mixed analysis, Analysis screenshots

1. Mixed Research

Mixed research, the third methodological paradigm—alongside qualitative and quantitative research—involves "mix[ing] or combin[ing] quantitative and qualitative research techniques, methods, approaches, concepts or language into a single study" (Johnson & Onwuegbuzie, 2004, p. 17). Because of its complexity relative to qualitative and quantitative research, one of the more challenging steps in the mixed research process is that of analyzing data. Mixed researchers have to be competent in utilizing quantitative *and* qualitative data analysis techniques or employ team members (i.e., co-researchers) who can conduct several types of analyses. To assist mixed researchers, Onwuegbuzie and Combs (2010) developed an inclusive framework for mixed analyses. In the first section of this article, we describe their inclusive framework. In the second part, we provide a heuristic example to illustrate, using screenshots, how one can utilize this framework to conduct mixed analyses.

2. Meta-Framework for Mixed Analysis Techniques

Since Greene, Caracelli, and Graham's (1989) seminal article a little more than 20 years ago, several mixed analysis techniques have emerged. In particular, there have been numerous articles (e.g., Bazeley, 1999, 2003, 2006, Caracelli & Greene, 1993; Chi, 1997; Datta, 2001; Greene, 2008; Happ, DeVito Dabbs, Tate, Hricik, & Erlen, 2006; Jang, McDougall, Pollon, & Russell, 2008; Lee & Greene, 2007; Li, Marquart, & Zercher, 2000; Onwuegbuzie, 2003; Onwuegbuzie & Collins, 2009; Onwuegbuzie & Combs, 2009a; Onwuegbuzie & Dickinson, 2008; Onwuegbuzie & Leech, 2004, 2006; Onwuegbuzie, Slate, Leech, & Collins, 2007, 2009; Onwuegbuzie & Teddlie, 2003; Sandelowski, 2000, 2001; Teddlie, Tashakkori, & Johnson, 2008; West & Tulloch, 2001) and chapters in seminal mixed research books (e.g., Bazeley, 2009, Creswell & Plano Clark, 2007, 2010; Greene, 2007; Johnson & Christensen, 2008; Rao & Wolcock, 2003; Tashakkori & Teddlie, 1998; Teddlie & Tashakkori, 2009; Todd, Nerlich, McKeown, & Clarke, 2004). These articles and book chapters have been instrumental in providing mixed analysis strategies for mixed researchers. However, these strategies typically have been presented in an isolated manner as standalone techniques with little or no interaction with other mixed analysis techniques. Indeed, as surmised by Greene (2008), to date, despite the extensiveness of the field of mixed analysis, "this work has not yet cohered into a widely accepted framework or set of ideas" (p. 14). As such, it is clear that an integrated, interactive framework is needed that provides mixed researchers with a map of the mixed- analytical landscape.

In developing their inclusive and interactive framework, Onwuegbuzie and Combs (2010) used classical content analysis (Berelson, 1952) to review mixed research articles in which authors developed typologies for mixed analysis strategies (e.g., Bazeley, 1999, 2003, 2006, 2009; Caracelli & Greene, 1993; Chi, 1997; Creswell & Plano Clark, 2007, 2010; Datta, 2001; Greene, 2007, 2008; Greene et al., 1989; Happ et al., 2006; Li et al., 2000; Onwuegbuzie, 2003; Onwuegbuzie, Collins, & Leech, in press; Onwuegbuzie & Dickinson, 2008; Onwuegbuzie & Leech, 2004, Onwuegbuzie et al., 2007, 2009; Onwuegbuzie & Teddlie, 2003; Sandelowski, 2000, 2001; Tashakkori & Teddlie, 1998; Teddlie & Tashakkori, 2009; Teddlie et al., 2008; West & Tulloch, 2001). Their analysis revealed the following 13 criteria that the aforementioned authors have used to create their mixed analysis typologies:

1. rationale/purpose for conducting the mixed analysis
2. philosophy underpinning the mixed analysis
3. number of data types that will be analyzed
4. number of data analysis types that will be used
5. time sequence of the mixed analysis
6. level of interaction between quantitative and qualitative analyses
7. priority of analytical components
8. number of analytical phases
9. link to other design components
10. phase of the research process when all analysis decisions are made
11. type of generalization
12. analysis orientation
13. cross-over nature of analysis

2.1 Criterion 1: Rationale/Purpose for Conducting the Mixed Analysis

Greene et al. (1989) conceptualized a typology for mixed methods purposes/designs that involves the following five purposes: triangulation, complementarity, development, initiation, and expansion. Applying these to mixed analysis decisions, when *triangulation* is the rationale for conducting the mixed analysis, the researcher would compare findings from the qualitative data with the quantitative results. If *complementarity* is noted as the purpose for the mixed analysis, then the researcher would seek elaboration, illustration, enhancement, and clarification of the findings from one analytical strand (e.g., qualitative) with results from the other analytical strand (e.g., quantitative). When *development* is identified as the purpose, then the researcher would use the results from one analytical strand to help inform the other analytical strand. With *initiation* as a rationale for performing a mixed analysis, the researcher would look for paradoxes and contradictions that emerge when findings from the two analytical strands are compared. Such contradictions might lead to new research questions. Finally, with expansion as a purpose, the researcher would attempt to expand the breadth and range of a study by using multiple analytical strands for different study phases.

2.2 Criterion 2: Philosophy Underpinning the Mixed Analysis

In mixed research, researchers from all paradigmatic traditions potentially can utilize both quantitative and qualitative analyses (Bazeley, 2009), depending on their research questions. As such, philosophical assumptions and stances can play a role in the analytical decisions made. Onwuegbuzie et al. (in press) identified the following 12 philosophical belief systems that characterize mixed research: pragmatism-of-the-middle philosophy (Johnson & Onwuegbuzie, 2004), pragmatism-of-the-right philosophy (Rescher, 2000), pragmatism-of-the-left philosophy (Maxcy, 2003), the anti-conflationist philosophy (Roberts, 2002), critical realist orientation (McEvoy & Richards, 2006), the dialectical stance (Greene, 2008; Greene & Caracelli, 1997), complementary strengths stance (Morse 2003), transformative-emancipatory stance (Mertens, 2003), a-paradigmatic stance (Reichardt & Cook 1979), substantive theory stance (Chen 2006), communities of practice stance (Denscombe, 2008), and, most recently, dialectal pragmatism (Johnson, 2009). Philosophical belief systems influence the mixed analysis strategies used. (For additional information about mixed methods paradigms/worldviews, see Onwuegbuzie et al., in press; Onwuegbuzie, Johnson, & Collins, 2009.)

2.3 Criterion 3: Number of Data Types That Will Be Analyzed

Mixed data analysis can involve both qualitative and quantitative data (Creswell & Plano Clark, 2007, 2010). Conversely, mixed analysis can occur with just one data type (Onwuegbuzie et al., 2007). For example, according to Onwuegbuzie et al., if the data type is qualitative then the first phase of the mixed analysis would be qualitative and in the second phase, data would be converted into a quantitative form or quantitized (i.e., transformed into numerical codes that can be analyzed statistically; Miles & Huberman, 1994; Tashakkori & Teddlie, 1998). Conversely, quantitative data, after being subjected to a quantitative analysis, can then be qualitized (i.e., transformed into narrative data that can be analyzed qualitatively; Tashakkori & Teddlie, 1998).

2.4 Criterion 4: Number of Data Analysis Types That will be Analyzed

When conducting a mixed analysis, at least one qualitative analysis and at least one quantitative analysis are needed to conduct a mixed analysis (Creswell & Tashakkori, 2007). Therefore, an additional question for mixed methods researchers to consider would be the number of qualitative analyses and quantitative analyses needed in the study.

2.5 Criterion 5: Time Sequence of the Mixed Analysis

The qualitative and quantitative analyses can be conducted in chronological order, or sequentially (i.e., sequential mixed analysis) or they can be conducted in no chronological order, or concurrently (i.e., concurrent mixed analysis). When concurrent mixed analyses are used, the analytical strands do not occur in any chronological order (Tashakkori & Teddlie, 1998). Rather, either analytical type can occur first because the two sets of analyses are functionally independent. Several options are presented for sequential mixed analyses (Teddlie & Tashakkori, 2009). The qualitative analysis phase can be conducted first and then used to inform the subsequent quantitative analysis phase (i.e., sequential qualitative-quantitative analysis) or the quantitative analysis phase is conducted first, which then informs the subsequent qualitative analysis phase (i.e., sequential quantitative-qualitative analysis). In addition, the qualitative and quantitative analyses can occur sequentially in more than two phases (i.e., iterative sequential mixed analysis, Teddlie & Tashakkori, 2009).

2.6 Criterion 6: Level of Interaction between Quantitative and Qualitative Analyses

Another component in mixed analyses decisions involves the point at which the various analysis strands interact. Parallel mixed analysis is likely the most common mixed analysis technique (Teddlie & Tashakkori, 2009), which involves two separate processes, for example, a quantitative analysis of quantitative data and a qualitative analysis of qualitative data. According to Teddlie and Tashakkori (2009), “Although the two sets of analyses are independent, each provides an understanding of the phenomenon under investigation. These understandings are linked, combined, or integrated into meta-inferences” (p. 266).

2.7 Criterion 7: Priority of Analytical Components

Another dimension to consider when conducting a mixed analysis is the priority or emphasis given to the analytical strands. Specifically, the qualitative and quantitative strands can have equal priority (i.e., equal status) with respect to addressing the research question(s), or one analytical strand can have a higher priority than the other strand (i.e., dominant status) (cf. Morse, 2003).

2.8 Criterion 8: Number of Analytical Phases

Mixed analyses can be phase-based in nature. For example, Greene (2007, p. 155) identified the following four phases of analysis: (a) data transformation, (b) data correlation and comparison, (c) analysis for inquiry conclusions and inferences, and (d) utilization of one methodological tradition within the analysis of data from another tradition. Another phase-based typology presented by Onwuegbuzie and Teddlie (2003) is a seven-step process for mixed data analysis: (a) data reduction, (b) data display, (c) data transformation, (d) data correlation, (e) data consolidation (f) data comparison, and (g) data integration. Thus, whether or not to use a phase-based analytical approach is another consideration for mixed researchers.

2.9 Criterion 9: Link to Other Design Components

Mixed analyses can be design-based, wherein the analyses are linked directly to the mixed research designs for the study. Teddlie and Tashakkori (2009) developed a typology that contains the following six techniques: (a) parallel mixed data analysis that are linked to parallel mixed designs, (b) conversion mixed data analysis that are linked to conversion mixed designs, (c) sequential mixed analysis that are linked to sequential mixed designs, (d) multilevel mixed data analysis, (e) fully integrated mixed data analysis that are linked to fully integrated designs, and (f) application of analytical techniques of one tradition to the other. According to Creswell and Plano Clark (2007), "The type of data analysis will vary depending on the type of mixed design used" (p. 135). These authors link four analysis techniques to their four major mixed methods designs (for more information, see Creswell & Plano Clark, 2010).

2.10 Criterion 10: Phase of the Research Process When All Analysis Decisions are Made

Decisions about the mixed analysis of a study can be made a priori, a posteriori, or iteratively. A priori decisions are more likely to occur in *quantitative-dominant* mixed analyses; whereas, a posteriori are more likely to occur in *qualitative-dominant* mixed analyses (cf. Johnson, Onwuegbuzie, & Turner, 2007). Decisions regarding the mixed analyses that are made iteratively means that some analytic decisions are made a priori, whereas the remaining analytic decisions are emergent. Iterative-analytic decisions represent the most common decisions in mixed research.

2.11 Criterion 11: Type of Generalization

The type of generalizations pertinent to the study can inform the mixed analysis design. Onwuegbuzie, Slate, et al. (2009) have identified five major types of generalizations that

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researchers can make, as follows: (a) external (statistical) generalizations (i.e., making generalizations, inferences, or predictions on data obtained from a representative statistical (i.e., optimally random) sample to the *population* from which the sample was drawn), (b) internal (statistical) generalizations (i.e., making generalizations, inferences, or predictions on data obtained from one or more representative or elite participants [e.g., key informants, politically important cases, sub-sample members]), (c) analytic generalizations (i.e., "applied to wider theory on the basis of how selected cases 'fit' with general constructs"; Curtis, Gesler, Smith, & Washburn, 2000, p. 1002), (d) case-to-case transfer (i.e., making generalizations or inferences from one case to another (similar) case (Firestone, 1993; Kennedy, 1979; Miles & Huberman, 1994), and (e) naturalistic generalization (i.e., the readers of the article make generalizations entirely, or at least in part, from their personal or vicarious experiences [Stake, 2005], such that meanings arise from personal experience, and are adapted and reified by repeated encounter [Stake, 1980; Stake & Trumbull, 1982]). These researchers assert that mixed analysis involves data analysis that yields one or more of these five types of generalizations, and have named this as the *fundamental principle of data analysis*.

2.12 Criterion 12: Analysis Orientation

Analysis orientation, conceptualized by Onwuegbuzie, Slate, et al. (2009) and extending the work of Ragin (1989), is a typology for classifying mixed analysis techniques. The qualitative and quantitative analyses can be any combination of the following: case-oriented, variable-oriented analyses, and process/experience-oriented analyses. Case-oriented analyses focus on the selected case(s) to analyze and to interpret the meanings, experiences, perceptions, or beliefs of one or more individuals. Because case-oriented analyses aid in understanding phenomena pertaining to one or relatively few cases, they are more often used in qualitative analyses; however, case-oriented analyses can be used for any number of cases in quantitative research with techniques such as single-subject analyses and descriptive analyses. Variable-oriented analyses are used to identify relationships among constructs (i.e., variables) and tend to yield external generalizations. Thus, variable-oriented analyses tend to be applied to quantitative analyses—although small samples also can be used to explore relationships among variables via qualitative analyses. Finally, process/experience-oriented analyses are used to evaluate processes or experiences relating to one or more cases over time, with processes tending to be associated with variables and experiences tending to be associated with cases.

2.13 Criterion 13: Cross-Over Nature of Analysis

Another criterion to consider when making decisions about mixed analyses is the degree to which a cross-over analysis will be used. *Cross-over mixed analysis* (Onwuegbuzie & Combs, 2010) is an extension of Greene's (2007) "broad analytic concept" (p. 153) of "using aspects of the analytic framework of one methodological tradition in the analysis of data from another tradition" (p. 155). Cross-over mixed analysis involves using one or more analysis types associated with one tradition to analyze data associated with a different tradition (Onwuegbuzie & Combs, 2010). For example, using visual displays to analyze qualitative data (Greene, 2007) and using effect sizes in qualitative analyses (cf. Onwuegbuzie & Teddlie, 2003) are both types of cross-over mixed analyses.

3. Heuristic Example: A Step-by-Step Guide to the Mixed Analysis Process

The following mixed research study (Onwuegbuzie & Combs, 2009b) provides an example of how one can utilize the Onwuegbuzie and Combs' (2010) 13-criteria meta-framework for mixed analysis techniques to guide the mixed analysis process.

3.1 Research Questions and Context of the Study

The study was conducted to examine the role that coping strategies play in the context of graduate students' learning of statistics. Specifically, the following research questions were addressed: (a) What is the relationship between statistics anxiety and coping strategies? (Quantitative Research Question) and (b) To what extent does the relationship between statistics anxiety and coping strategies manifest itself in statistics classrooms (Mixed Research Question)? Two phases of the study involved a quantitative phase (i.e., Phase 1) and an embedded qualitative phase (i.e., sequential mixing of qualitative and quantitative data, Phase 2). Because the participants in the quantitative and qualitative phases represented master's and doctoral students from two different institutions, and the quantitative Phase 1 informed the qualitative Phase 2, the mixed research sampling design used was a Sequential Design using Parallel Samples (Onwuegbuzie & Collins, 2007).

In the initial quantitative phase of the study (Phase 1: Survey Sample), 115 graduate students enrolled in an introductory-level, quantitative-based educational research course were administered the Statistics Anxiety Rating Scale (STARS; Cruise & Wilkins, 1980) and the Coping Strategies Inventory for Statistics (CSIS; Jarrell & Burry, 1989). In the embedded qualitative phase (Phase 2: Focus Group Sample), 17 doctoral students were interviewed and asked about the role that coping strategies played in both the formation and alleviation of statistics anxiety. In addition, these students during Phase 2 completed the STARS and CSIS. In Phase 1 of the study, the major analytical procedure involved canonical correlation analysis, which is a multivariate analysis technique used to examine the relationship between two sets of measures when each set contains two or more variables or subscales. As such, the canonical correlation analysis was utilized to identify a combination of coping strategy dimensions that might predict a combination of statistics anxiety dimensions.

In Phase 2, quantitative analyses were used to compare participants' scores from each of the two phases of the study. In addition, focus group interviews were conducted to explore students' experiences with the statistics course. The qualitative data were used to identify themes pertaining to anxiety and coping strategies, and then were compared to the STARS and CSIS using both a cross-case and within-case analysis.

3.2 Mixed Analysis Design

A two-level embedded mixed research design was utilized in the current study, which was designed to examine the role that statistics anxiety and coping strategies play in the context of graduate students' learning of statistics. The study represented a fully mixed sequential design. This design, which incorporated dialectical pragmatist assumptions and stances (i.e., Criterion 2, philosophical underpinning), involved mixing qualitative and quantitative approaches at several stages including the data analysis stages. Both phases were given approximately equal weight (i.e., Criterion 7, priority of analytical components). Phase 1 generated quantitative data and Phase 2 generated both quantitative and qualitative data (i.e., Criterion 3, number of data types), and the analysis of data at Phase 1 informed the analysis of data at Phase 2 (i.e., Criterion 6, level of interaction). In addition, within Phase 2 (embedded qualitative phase), the analysis of the quantitative data (i.e., STARS, CSIS) had lower priority than the analysis of qualitative data (i.e., Criterion 7, priority of analytical components) and informed the analysis of qualitative data (i.e., interviews, Criterion 6, level of interaction). Phase 2 of the study was embedded because it contained the collection and analysis of both qualitative and quantitative data (i.e., Criterion 4, number of data analysis types). The analyses in Phases 1 and 2 were conducted sequentially (i.e., Criterion 5, time sequence of mixed analysis). Phase 2 utilized cross-over mixed analysis techniques in which quantitative data (i.e., STARS, CSIS) were qualitized (i.e., narrative profile formation) and qualitative data were quantitized (e.g., effect sizes), and the quantitative and qualitative data were correlated (i.e., Criterion 13, cross-over nature of analysis). The mixed analysis framework was neither design-based nor phase-based (i.e., Criteria 8, number of analytical phases; Criterion 9, link to other design components). The rationale for conducting the mixed analysis based on Greene et al.'s (1989) framework was that of complementarity, initiation, triangulation, development, and expansion (i.e., Criterion 1, purpose for conducting the mixed analysis). Mixed analysis decisions occurred iteratively (i.e., Criterion 10, phases of research process where analysis decisions are made).

Because Phase 1 involved investigation of the relationship between statistics anxiety and coping strategies using a large sample, it yielded a variable-oriented analysis (i.e., Criterion 12, analysis orientation) that led to external statistical generalizations (i.e., Criterion 11, type of generalization). In contrast, Phase 2 yielded both a variable- and case-oriented analysis because Phase 2 involved the assessment of the relationship between statistics anxiety and coping strategies using a relatively small sample (i.e., Criterion 12, analysis orientation) that led to analytic generalizations (i.e., Criterion 11, type of generalizations).

3.3 Mixed Analysis: Step-by-Step

In Onwuegbuzie and Combs' (2009b) study, several levels of mixed analysis can be found. Phase 1 involved a quantitative analysis of quantitative data (i.e., descriptive and inferential statistics) and Phase 2 involved a qualitative analysis of qualitative data (constant comparison analysis of focus group interview data). The researchers could have conducted the mixed analysis with these two steps: (a) quantitative analysis of quantitative data (Phase 1), and (b) qualitative analysis of qualitative data (Phase 2). However, they conducted additional mixed analyses in Phase 2 that yielded the embedded qualitative phase. Within this phase, in addition to a quantitative analysis of quantitative data (i.e., STARS, CSIS), and a qualitative analysis of qualitative data (i.e., focus group interview data), they conducted a qualitative analysis of quantitative data (i.e., used STARS and CSIS to compare with interview data) and a quantitative analysis of qualitative data (e.g., within each focus group they conducted a micro-interlocutor analysis in which they documented the number of times each person spoke, who talked first, frequency counts for themes; Onwuegbuzie, Dickinson, Leech, & Zoran, 2009). Thus, this study demonstrates various combinations of quantitative and qualitative analysis. In the following sections, each step of the mixed analyses will be explained.

3.4 Study Phase 1: Survey Sample

3.4.1 Step 1: Quantitative analysis of quantitative data, descriptive statistics

Students' scores (n = 115) on the STARS and CSIS were entered into SPSS. Descriptive statistics (i.e., mean, standard deviation) were computed for the six subscales of the STARS and the two subscales of the CSIS. In addition, median percentile rank equivalent scores (MPRES) were calculated, as developed by Onwuegbuzie (2004), by comparing the median anxiety scores obtained in the study to the percentile rank norms reported by the developers of the STARS (i.e., Cruise, Cash, & Bolton, 1985). Thus, a MPRES of 81 for the subscale, *worth of statistics*, indicates that at least 50% of the present sample scored higher than did 81% of the norm group on this dimension (Onwuegbuzie, 2004). The finding that the MPRES ranged from 62 to 81 indicated that the participants in the quantitative phase represented a moderate-to-high statistics-anxious group.

3.4.2 Step 2: Quantitative analysis of quantitative data, inferential statistics

A canonical analysis was conducted to determine the relationships between the six STARS subscales and the two CSIS subscales. Onwuegbuzie and Combs (2009b) determined that the first canonical function was both statistically significant and practically significant, with the first canonical correlation (R_{c1} = .60) contributing 35.9% (i.e., R_{c1}^2) to the shared variance. The standardized canonical function coefficients were examined and conclusions were drawn about the contributions of the statistics anxiety variable cluster and the coping strategies cluster. Thus, there was a multivariate relationship between statistics anxiety and coping strategies, wherein examination-taking coping strategies represented a much more important predictor of statistics anxiety than did study coping strategies, and interpretation anxiety made the most substantial contribution to the multivariate relationship among the six anxiety dimensions.

3.5 Study Phase 2: Focus Group Sample

3.5.1 Step 3: Quantitative analysis of quantitative data, descriptive statistics

Data from the STARS and CSIS were entered into SPSS. In this step, descriptive statistics (i.e., mean, standard deviation, MPRES) were used to analyze the scores of the 17 participants on the STARS and CSIS.

3.5.2 Step 4: Quantitative analysis of quantitative data: inferential statistics.

Additional quantitative analyses were conducted to compare the students in Phase 1 of the study to those in Phase 2 of the study. For example, t tests were conducted to compare the levels of statistics anxiety and coping strategies of participants in Phase 1 (i.e., Survey Sample) and Phase 2 (i.e., Focus Group Sample).

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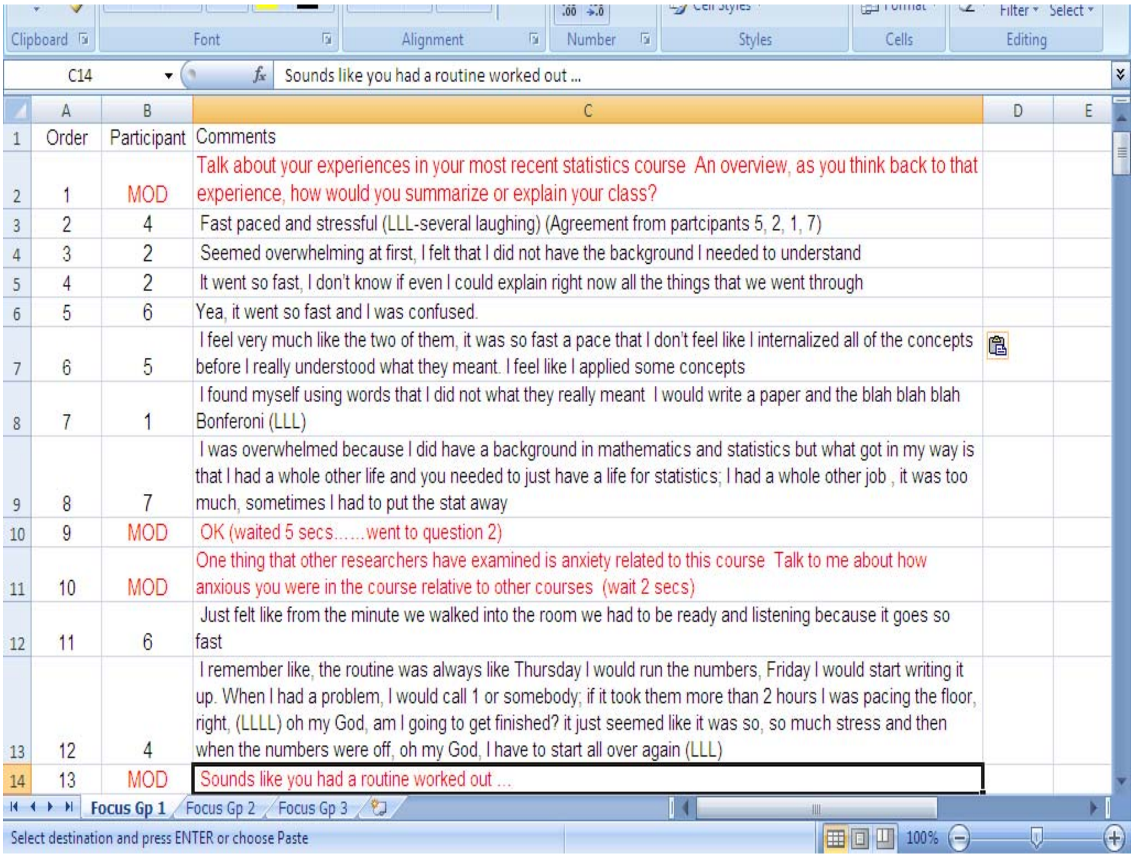
3.5.3 Step 5: Qualitative analysis of qualitative data, method of constant comparison and quantitative analysis of qualitative data.



	A	B	C
1	Order	Participant	Comments
2	1	MOD	Talk about your experiences in your most recent statistics course An overview, as you think back to that experience, how would you summarize or explain your class?
3	2	4	Fast paced and stressful (LLL-several laughing) (Agreement from partcipants 5, 2, 1, 7)
4	3	2	Seemed overwhelming at first, I felt that I did not have the background I needed to understand
5	4	2	It went so fast, I don't know if even I could explain right now all the things that we went through
6	5	6	Yea, it went so fast and I was confused.
7	6	5	I feel very much like the two of them, it was so fast a pace that I don't feel like I internalized all of the concepts before I really understood what they meant. I feel like I applied some concepts
8	7	1	I found myself using words that I did not what they really meant I would write a paper and the blah blah blah Bonferoni (LLL)
9	8	7	I was overwhelmed because I did have a background in mathematics and statistics but what got in my way is that I had a whole other life and you needed to just have a life for statistics; I had a whole other job , it was too much, sometimes I had to put the stat away
10	9	MOD	OK (waited 5 secs......went to question 2)
11	10	MOD	One thing that other researchers have examined is anxiety related to this course Talk to me about how anxious you were in the course relative to other courses (wait 2 secs)
12	11	6	Just felt like from the minute we walked into the room we had to be ready and listening because it goes so fast
13	12	4	I remember like, the routine was always like Thursday I would run the numbers, Friday I would start writing it up. When I had a problem, I would call 1 or somebody; if it took them more than 2 hours I was pacing the floor, right, (LLLL) oh my God, am I going to get finished? it just seemed like it was so, so much stress and then when the numbers were off, oh my God, I have to start all over again (LLL)
14	13	MOD	Sounds like you had a routine worked out ...

Figure 1. Excel spreadsheet of focus group interviews. The number in the order column represents the order of the comments during the interview (e.g., the moderator spoke first). The participant column was used to identify the focus group participant. The comments column represents the words that were spoken, audible sounds (e.g., laughter), silence, and nonverbal behaviors (nodding).

The focus group interviews were transcribed and typed into a Word document. Then, the transcript was imported into an Excel spreadsheet. As shown in Figure 1, each row of the spreadsheet contained the order of the comments in the overall interview (e.g., who spoke first, second), the participants' identification number, and the participants' comments. Nonverbal behaviors, which were noted by the interview moderator and assistant moderator, were described in parenthesis following the comments.

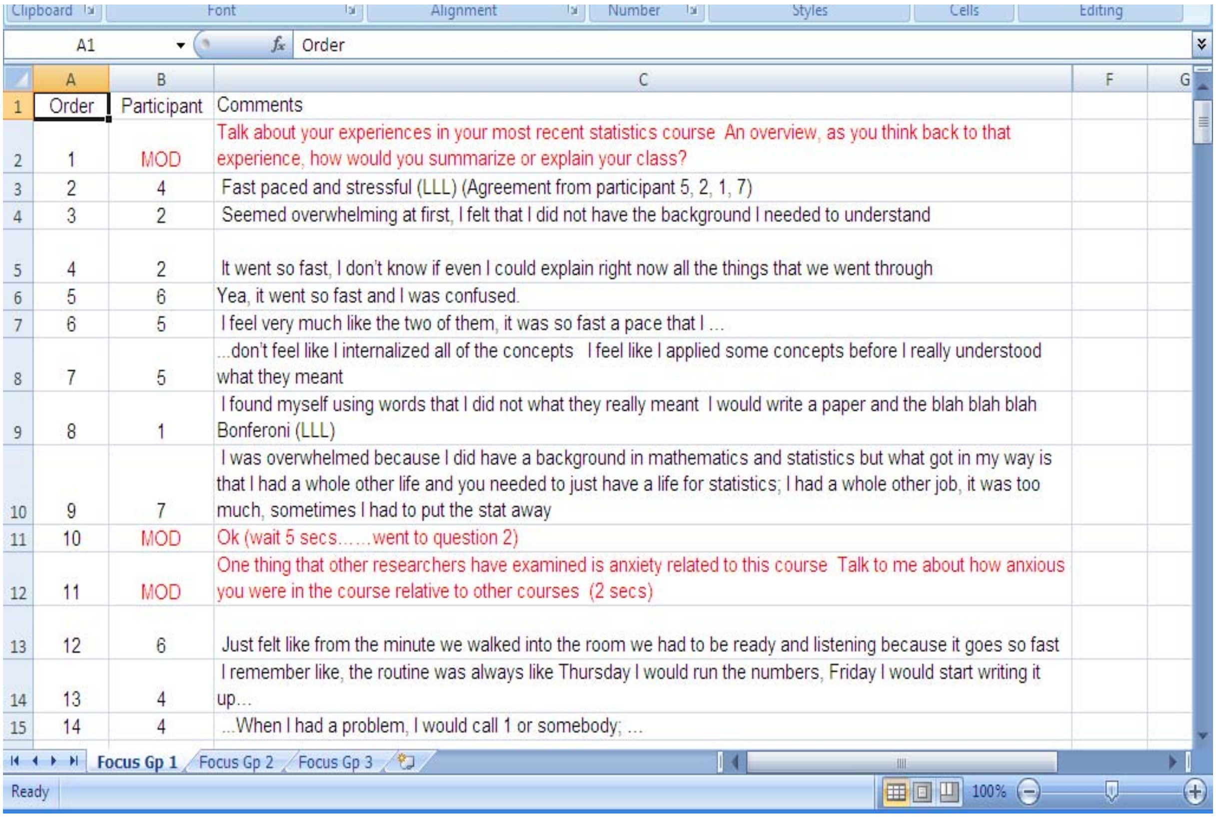
Next, statements were unitized and each unit represented a significant statement (Glaser & Strauss, 1967), with each statement providing evidence of anxiety related to the statistics course or evidence of coping strategies used in the statistics course. When participants' comments contained multiple units, new rows were added in the spreadsheet and the divided comments were indicated by use of ellipses, as shown in Figure 2. Using the method of constant comparison (Glaser & Strauss, 1967), Onwuegbuzie and Combs (2009b) compared statements to each other and labeled similar clusters with the same code. Initially, statements were coded as either "anxiety" or "coping", using a "1" to indicate the presence of the code and a "0" to indicate that the comment was not related to the code (i.e., quantitized). Next, using the sort function in Excel, statements related to the code of anxiety were sorted and grouped together, as shown in Figure 3. Then, anxiety statements were read and codes were developed based on similar comments. Using the method of constant comparison, codes were collapsed and refined. The same process was used with the statements related to coping strategies. More specifically, each significant statement was linked to a formulated meaning and to a theme. The six resulting themes related to the students' anxieties in the statistics course were lack of understanding, class anxiety, multiple responsibilities, performance expectations, prior experiences, and writing anxiety, as shown in Table 1.

Table 1. Description of Emerging Themes for Anxiety from Statistics Course

Theme	Description	Significant Statement Examples
Lack of understanding	Anxious from a lack of understanding about statistics	"I found myself using words that I did not know what they really meant."
Class anxiety	Anxious while participating in the statistics class	"Just felt like from the minute we walked into the room we had to be ready and listening because it goes so fast."
Multiple responsibilities	Anxious from balancing multiple responsibilities in and out of the class	"What got in my way is that I had a whole other life and you needed to just have a life for statistics; I had a whole other job, it was too much."
Performance expectations	Anxious about performance, assessment, and expectations from self or others	"I must be an idiot since I don't know how to do this, so trying to balance what we should be as a graduate students and maybe what is asking too much of us."
Prior experiences	Anxious due to prior experiences or lack of experiences with statistics	"I'd never taken a statistics class before and I knew it was one of my weak areas."
Writing Anxiety	Anxious about writing	"For me, it was the writing. SPSS was not hard. Writing was hard."

Table 2. Description of Emerging Themes for Coping Strategies Used in Statistics Course

Theme	Description	Significant Statement Examples
Peer support	Asks for and receives help from other peers and collaborates with others	"For me, one of the biggest advantages I saw right then was being in the cohort because you really utilized that cohort, I could call Aretha, and another student, [we] emailed all the time."
Professor support	Asks for and receives help from the professor	"He was very accessible I thought outside of class which was helpful because as those questions come up, you'd shoot him an email and within hours or a day you'd have a response."
Personal management	Manages self with organizational tools, routines, and self-care	"Taking notes, that was very stressful. I was so worried that I wasn't going to get everything and when I got the digital recorder, I didn't panic if I missed something."
Class structure	Utilizes the resources provided in the course	"The way the course was presented is we had an example paper, we had a step by step routine in how to do it, and um an assignment page."
Study skills	Applies skills such as listening, correcting errors, and seeking additional resources	"I would try to go back and see the errors I had made on the papers, what were those words that weren't supposed to be used."



Order	Participant	Comments
1	MOD	Talk about your experiences in your most recent statistics course An overview, as you think back to that experience, how would you summarize or explain your class?
2	4	Fast paced and stressful (LLL) (Agreement from participant 5, 2, 1, 7)
3	2	Seemed overwhelming at first, I felt that I did not have the background I needed to understand
4	2	It went so fast, I don't know if even I could explain right now all the things that we went through
5	6	Yea, it went so fast and I was confused.
6	5	I feel very much like the two of them, it was so fast a pace that I ...
7	5	...don't feel like I internalized all of the concepts I feel like I applied some concepts before I really understood what they meant
8	1	I found myself using words that I did not what they really meant I would write a paper and the blah blah blah Bonferoni (LLL)
9	7	I was overwhelmed because I did have a background in mathematics and statistics but what got in my way is that I had a whole other life and you needed to just have a life for statistics; I had a whole other job, it was too much, sometimes I had to put the stat away
10	MOD	Ok (wait 5 secs......went to question 2)
11	MOD	One thing that other researchers have examined is anxiety related to this course Talk to me about how anxious you were in the course relative to other courses (2 secs)
12	6	Just felt like from the minute we walked into the room we had to be ready and listening because it goes so fast
13	4	I remember like, the routine was always like Thursday I would run the numbers, Friday I would start writing it up...
14	4	...When I had a problem, I would call 1 or somebody; ...

Figure 2. Excel spreadsheet of focus group interview, showing how comments were unitized into significant statements (Glaser & Strauss, 1967), with each statement providing evidence of anxiety related to the statistic course or evidence of coping strategies used in the statistics course. When participants' comments contained multiple units, new rows were added in the spreadsheet and the divided comments were indicated by use of ellipses. For example, note the sixth comment, made by Participant 5. This comment was divided into two units. A row was added and the order was renumbered to indicate this addition, which was necessary to return to the original order after subsequent sorting processes.

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Order	Participant	Comments	Anxiety	Coping
1	MOD	Talk about your experiences in your most recent statistics course An overview, as you think back to that experience, how would you summarize or explain your class?		
2	4	Fast paced and stressful (LLL) (Agreement from participant 5, 2, 1, 7)	1	0
3	2	Seemed overwhelming at first, I felt that I did not have the background I needed to understand	1	0
4	2	It went so fast, I don't know if even I could explain right now all the things that we went through	1	0
5	6	Yea, it went so fast and I was confused.	1	0
6	5	I feel very much like the two of them, it was so fast a pace that I …	1	0
7	5	…don't feel like I internalized all of the concepts I feel like I applied some concepts before I really understood what they meant	1	0
8	1	I found myself using words that I did not what they really meant I would write a paper and the blah blah blah Bonferoni (LLL)	1	0
9	7	I was overwhelmed because I did have a background in mathematics and statistics but what got in my way is that I had a whole other life and you needed to just have a life for statistics; I had a whole other job, it was too much, sometimes I had to put the stat away	1	0
10	MOD	Ok (wait 5 secs……went to question 2)		
11	MOD	One thing that other researchers have examined is anxiety related to this course Talk to me about how anxious you were in the course relative to other courses (2 secs)		
12	6	Just felt like from the minute we walked into the room we had to be ready and listening because it goes so fast	1	0
13	4	I remember like, the routine was always like Thursday I would run the numbers, Friday I would start writing it up…	1	0
14	4	…When I had a problem, I would call 1 or somebody; …	0	1

Figure 3. Excel spreadsheet of focus group interview, showing how comments were coded as anxiety or coping. The moderator comments were not coded

3.6 Within-Case Analysis

3.6.1 Step 6: Qualitative analysis of quantitative data

To conduct the within-case analysis, Phase 2 participants' scores on the STARS and CSIS were ranked from highest to lowest. Two students were selected who had high statistics anxiety scores and low coping strategy scores. In addition, the students were selected based on the number of significant statements shared during the interview. In addition, two students were selected who displayed lower levels of statistic anxiety and higher levels of coping strategies. After these four key informants were identified, their scores and resulting percentiles on the STARS and CSIS were subjected to a narrative profile analysis. Specifically, the STARS and CSIS scores were qualitized by comparing them to normative data (i.e., normative profiles; Tashakkori & Teddlie, 1998) and these normative profiles provided more richness to the qualitative data (i.e., complementarity, development, expansion; Greene et al., 1989).

3.6.2 Step 7. Quantitative analysis of quantitative data, descriptive statistics

STARS and CSIS scores of the four key informants were compared to those participants representing Phase 1 using MPRES.

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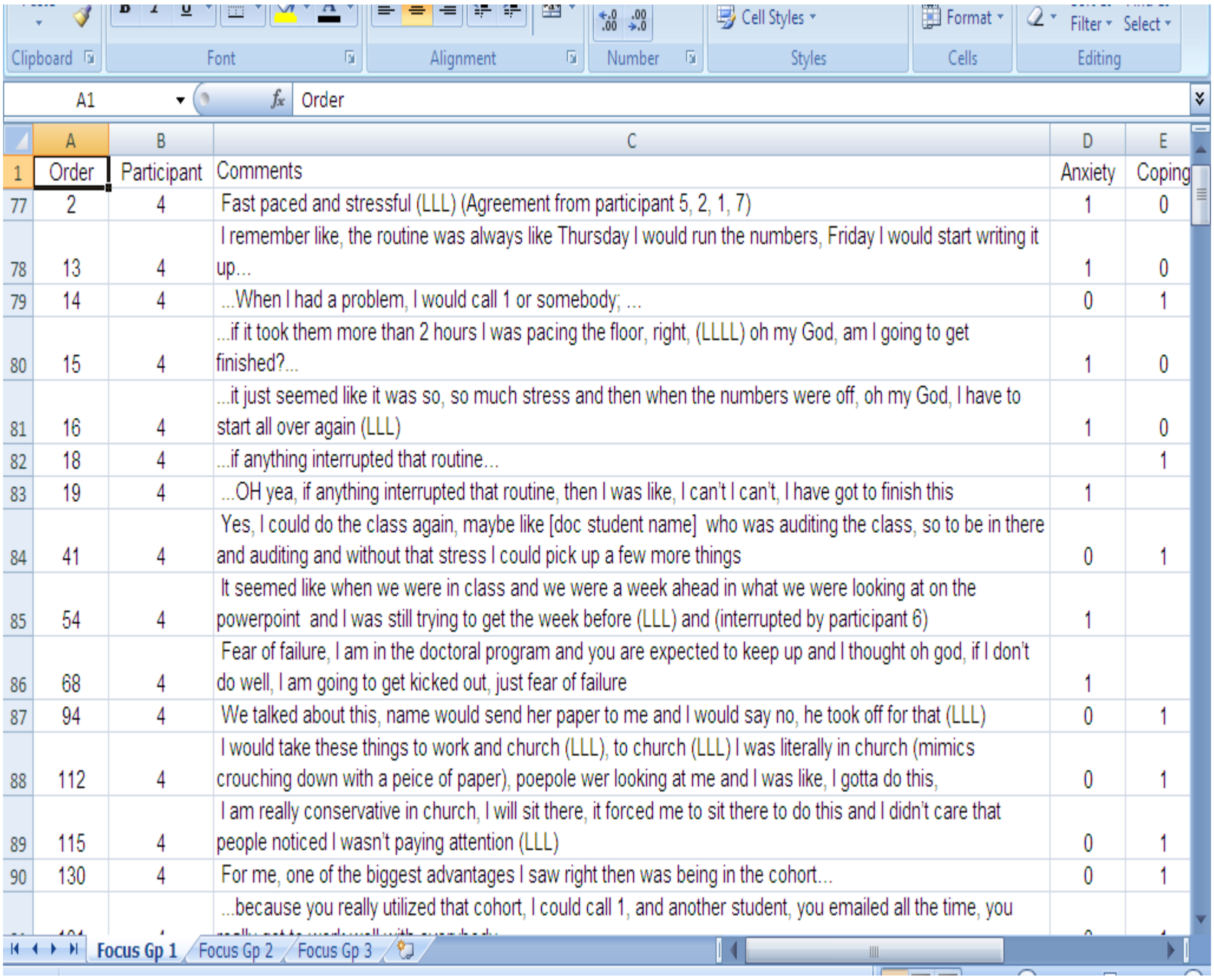
3.6.3 Step 8. Comparing qualitative analysis of qualitative data with quantitative analysis of quantitative data

These four participants' comments were sorted in Excel by participant, as shown in Figure 4. The participant comments were compared (i.e., data comparison) to the STARS and CSIS scores to see if their comments supported (i.e., triangulation; Greene et al., 1989) or refuted (i.e., initiation; Greene et al., 1989) their measures on the STARS and CSIS.



	A	B	C	D	E
1	Order	Participant	Comments	Anxiety	Coping
77	2	4	Fast paced and stressful (LLL) (Agreement from participant 5, 2, 1, 7)	1	0
78	13	4	I remember like, the routine was always like Thursday I would run the numbers, Friday I would start writing it up…	1	0
79	14	4	…When I had a problem, I would call 1 or somebody; …	0	1
80	15	4	…if it took them more than 2 hours I was pacing the floor, right, (LLLL) oh my God, am I going to get finished?...	1	0
81	16	4	…it just seemed like it was so, so much stress and then when the numbers were off, oh my God, I have to start all over again (LLL)	1	0
82	18	4	…if anything interrupted that routine…		1
83	19	4	…OH yea, if anything interrupted that routine, then I was like, I can't I can't, I have got to finish this	1	
84	41	4	Yes, I could do the class again, maybe like [doc student name] who was auditing the class, so to be in there and auditing and without that stress I could pick up a few more things	0	1
85	54	4	It seemed like when we were in class and we were a week ahead in what we were looking at on the powerpoint and I was still trying to get the week before (LLL) and (interrupted by participant 6)	1	
86	68	4	Fear of failure, I am in the doctoral program and you are expected to keep up and I thought oh god, if I don't do well, I am going to get kicked out, just fear of failure	1	
87	94	4	We talked about this, name would send her paper to me and I would say no, he took off for that (LLL)	0	1
88	112	4	I would take these things to work and church (LLL), to church (LLL) I was literally in church (mimics crouching down with a peice of paper), poepole wer looking at me and I was like, I gotta do this,	0	1
89	115	4	I am really conservative in church, I will sit there, it forced me to sit there to do this and I didn't care that people noticed I wasn't paying attention (LLL)	0	1
90	130	4	For me, one of the biggest advantages I saw right then was being in the cohort…	0	1
			…because you really utilized that cohort, I could call 1, and another student, you emailed all the time, you		

Figure 4. Excel spreadsheet of focus group interview, showing how comments were sorted by participant for use with the within case analysis

3.7 Cross-Case Analysis

3.7.1 Step 9: Combining qualitative and quantitative data

To conduct the cross-case analysis, several of Miles and Huberman's (1994) visual displays were utilized. For example, a case-ordered descriptive meta-matrix was used in which the participants were ordered by both the STARS and the CSIS and this ordering was compared to their qualitative statements stemming from the focus group interviews. Each of the six anxiety themes were quantitized; that is, for each focus group participant, a theme was coded as a "1" to indicate if a statement made by the participant was classified as representing the theme, and was coded as a "0" otherwise. Each person's ranking of the STARS and the profile of "1"s and "0"s pertaining to the anxiety themes were compared to his/her statements pertaining to anxiety and patterns were noted. This procedure was repeated for the coping themes.

In addition, an antecedents matrix was used in which the outcome variables (i.e., STARS, all anxiety statements and themes) were displayed alongside the potential antecedents (i.e., CSIS and coping statements and themes) to determine the role that coping strategies played in moderating levels of statistics anxiety across all the participants and as a function of demographic variables. This display revealed several links among the sets of variables.

4. Interpretation of Findings

Based on the nine steps outlining the mixed analysis for the study, Onwuegbuzie and Combs (2009b) surmised that the six statistics anxiety themes and five coping strategy themes support the contention that both statistics anxiety and coping strategies represent multidimensional constructs. Further, according to these authors, the findings from the within-case analyses and cross-case analyses provided support for the quantitative results, helping to confirm a multivariate relationship between levels of statistics anxiety and coping strategies (triangulation), as well as providing information about the nature of this relationship (i.e., complementarity, development, and expansion) and about participants for whom the multivariate relationship was weak or unclear (i.e., initiation). Also, the within-case analyses and cross-case analyses helped the researchers identify specific coping strategies that reduced statistics anxiety levels. Thus, the authors concluded that taken together, the quantitative and qualitative findings suggest that interventions aimed at increasing coping strategies might help to reduce levels of statistics anxiety.

5. Summary and Conclusions

In this article, we presented an inclusive, interactive framework for mixed analyses using the 13 criteria that were identified by Onwuegbuzie and Combs (2010) after they reviewed the extant literature of mixed analysis strategies. A heuristic example was used to highlight the various decisions made by Onwuegbuzie and Combs (2009b) in their mixed research study concerning statistics anxiety and coping strategies of graduate students enrolled in a statistics course. This heuristic example showed the utility of Onwuegbuzie and Combs' (2010) 13-Criteria Meta-Framework for Mixed Analysis Techniques, which is summarized in Table 3. By using this framework, Onwuegbuzie and Combs (2009b) were able to design and undertake a more comprehensive, coherent, and interactive analysis than otherwise would have been the case, thereby yielding a more rigorous mixed research study. As such, Onwuegbuzie and Combs' (2009b) study adds incremental validity to the mixed analysis meta-framework, consistent with the call of Greene (2008) for "a widely accepted framework or set of ideas" (p. 14). We hope that other mixed researchers will use this meta-framework to design their mixed analyses, and assess the utility and limitations of the meta-framework for themselves. By documenting their use of this meta-framework, as we have accomplished in the present article, a body of evidence can be built that either provides support for the meta-framework or offers direction for improvement.

Table 3. Summary of Onwuegbuzie and Combs' (2010) 13-Criteria Meta-Framework for Mixed Analysis Techniques Used by Onwuegbuzie and Combs (2009b)

Criteria	How Criteria were Manifested in Onwuegbuzie and Combs' (2009b) Study
Rationale/purpose for conducting the mixed analysis	Involved complementarity, initiation, triangulation, development, and expansion (Greene, Caracelli, & Graham, 1989)
Philosophy underpinning the mixed analysis	Involved dialectical pragmatist assumptions and stances (Johnson, 2009)
Number of data types that will be analyzed	Collected both quantitative and qualitative data (Creswell & Plano Clark, 2007, 2010)
Number of data analysis types that will be used	Utilized both qualitative analysis and quantitative analysis (Creswell & Tashakkori, 2007; Onwuegbuzie, Slate, Leech, & Collins, 2007, 2009; Onwuegbuzie & Teddlie, 2003)
Time sequence of the mixed analysis	Involved sequential analysis (Tashakkori & Teddlie, 1998; Teddlie & Tashakkori, 2009)
Level of interaction between quantitative and qualitative analyses	Analyzed data at Phase 1 that informed the analysis of data at Phase 2 (Teddlie & Tashakkori, 2009)
Priority of analytical components	Conducted qualitative and quantitative analyses at approximately equal weight (Johnson, Onwuegbuzie, Turner, 2007; Morse, 2003)
Number of analytical phases	Not linked directly to any phases of the mixed analysis (Greene, 2007; Onwuegbuzie & Teddlie, 2003)
Link to other design components	Not linked directly to any mixed research designs (Creswell & Plano Clark, 2010; Teddlie & Tashakkori, 2009)
Phase of the research process when all analysis decisions are made	Made mixed analysis decisions iteratively (Johnson, Onwuegbuzie, & Turner, 2007)
Type of generalization	Made external statistical generalizations based on Phase 1 analyses and analytic generalizations based on Phase 2 analyses (Onwuegbuzie, Slate, Leech, & Collins, 2009)
Analysis orientation	Involved variable-oriented analysis at Phase 1 and a variable- and case-oriented analysis at Phase 2 (Onwuegbuzie, Slate, Leech, & Collins, 2009)
Cross-over nature of analysis	Qualitized (i.e., narrative profile formation; Tashakkori & Teddlie, 1998) quantitative data (i.e., STARS, CSIS) and quantitized qualitative data (e.g., effect sizes; Onwuegbuzie, 2003; Onwuegbuzie & Teddlie, 2003); and correlated the quantitative and qualitative data (Onwuegbuzie & Combs, 2010)

References

Bazeley, P. (1999). The *bricoleur* with a computer: Piecing together qualitative and quantitative data. *Qualitative Health Research, 9,* 279-287. doi:10.1177/104973299129121749.

Bazeley, P. (2003). Computerized data analysis for mixed methods research. In A. Tashakkori & C. Teddlie (Eds.), *Handbook of mixed methods in social and behavioral research* (pp. 385-422). Thousand Oaks, CA: Sage.

Bazeley, P. (2006). The contribution of computer software to integrating qualitative and quantitative data and analyses. *Research in the Schools, 13*(1), 64-74.

Bazeley, P. (2009). Mixed methods data analysis. In S. Andrew & E. J. Halcomb (Eds.), *Mixed methods research for nursing and the health sciences* (pp. 84-118). Chichester, UK: Wiley-Blackwell.

Berelson, B. (1952). *Content analysis in communicative research.* New York, NY: Free Press.

Caracelli, V. W., & Greene, J. C. (1993). Data analysis strategies for mixed-method evaluation designs. *Educational Evaluation and Policy Analysis, 15*, 195-207. doi:10.2307/1164421.

Chen, H. T. (2006). A theory-driven evaluation perspective on mixed methods research. *Research in the Schools, 13*(1), 75-83.

Chi, M. T. H. (1997). Quantifying qualitative analyses of verbal data: A practical guide. *The Journal of the Learning Sciences, 6,* 271-315. doi:10.1207/s15327809jls0603_1

Creswell, J. W., & Plano Clark V. L. (2007). *Designing and conducting mixed methods research.*

Creswell, J. W., & Plano Clark V. L. (2010). *Designing and conducting mixed methods research* (2nd ed.). Thousand Oaks, CA: Sage.

Creswell, J. W., & Tashakkori, A. (2007). Developing publishable mixed methods manuscripts. *Journal of Mixed Methods Research, 1,* 107-111. doi:10.1177/1558689806298644.

Cruise, R. J., & Wilkins, E. M. (1980). *STARS: Statistical Anxiety Rating Scale*. Unpublished manuscript, Andrews University, Berrien Springs, MI.

Cruise, R. J., Cash, R. W., & Bolton, D. L. (1985, August). *Development and validation of an instrument to measure statistical anxiety.* Paper presented at the annual meeting of the Statistical Education Section. Proceedings of the American Statistical Association, Las Vegas, NV.

Curtis, S., Gesler, W., Smith, G., & Washburn, S. (2000). Approaches to sampling and case selection in qualitative research: Examples in the geography of health. *Social Science and Medicine, 50,* 1001-1014. doi:10.1016/j.jas.2007.02.013.

Datta, L. (2001). The wheelbarrow, the mosaic, and the double helix: Challenges and strategies for successfully carrying out mixed methods evaluation. *Evaluation Journal of Australia*, *1*(2), 33-40.

Denscombe, M. (2008). Communities of practice: A research paradigm for the mixed methods approach. *Journal of Mixed Methods Research, 2,* 270-283. doi:10.1177/1558689808316807

Firestone, W. A. (1993). Alternative arguments for generalizing from data, as applied to qualitative research. *Educational Researcher, 22*(4), 16-23. doi:10.3102/0013189X022004016.

Glaser, B. G., & Strauss, A. L. (1967). *The discovery of grounded theory: Strategies for qualitative research.* Chicago, IL: Aldine.

Greene, J. C. (2007). *Mixed methods in social inquiry*. San Francisco, CA: Jossey-Bass.

Greene, J. C. (2008). Is mixed methods social inquiry a distinctive methodology? *Journal of Mixed Methods Research*, *2*, 7-22. doi:10.1177/1558689807309969

Greene, J. C., & Caracelli, V. J. (1997). Defining and describing the paradigm issue in mixed-method evaluation. In J. C. Greene & V. J. Caracelli (Eds.), *Advances in mixed-method evaluation: The challenges and benefits of integrating diverse paradigms* (New Directions for Evaluation, No. 74, pp. 5-17). San Francisco, CA: Jossey-Bass.

Greene, J. C., Caracelli, V. J., & Graham, W. F. (1989). Toward a conceptual framework for mixed-method evaluation designs. *Educational Evaluation and Policy Analysis, 11*, 255-274. doi:10.2307/1163620

Happ, M. B., DeVito Dabbs, D. A., Tate, J., Hricik, A., & Erlen, J. (2006). Exemplars of mixed methods data combination and analysis. *Nursing Research, 55*(2, Supplement 1), S43-S49. doi:10.1097/00006199-200603001-00008

Jang, E. E., McDougall, D. E., Pollon, D., & Russell, M. (2008). Integrative mixed methods data analytic strategies in research on school success in challenging environments. *Journal of Mixed Methods Research*, *2*, 221-247. doi:10.1177/1558689808315323

Jarrell, M. G., & Burry, J. A. (1989, November). *Coping Strategies Inventory for Statistics*. Paper presented at the annual meeting of the Mid-South Educational Research Association, Little Rock, AR.

Johnson, R. B. (2009). Toward a more inclusive "Scientific Research in Education." *Educational Researcher*, *38*, 449-457. doi:10.3102/0013189X09344429

Johnson, R. B., & Christensen, L. B. (2008). *Educational research: Quantitative, qualitative, and mixed approaches* (3rd ed.). Thousand Oaks, CA: Sage.

Johnson, R. B., & Onwuegbuzie, A. J. (2004). Mixed methods research: A research paradigm whose time has come. *Educational Researcher*, *33*(7), 14-26.

Johnson, R. B., Onwuegbuzie, A. J., & Turner, L. A. (2007). Toward a definition of mixed methods research. *Journal of Mixed Methods Research, 1,* 112-133. doi:10.1177/1558689806298224

Kennedy, M. (1979). Generalizing from single case studies. *Evaluation Quarterly, 3,* 661-678.

Lee, Y-j., & Greene, J. C. (2007). The predictive validity of an ESL placement test: A mixed methods approach. *Journal of Mixed Methods Research, 1*, 366-389. doi:10.1177/1558689807306148

Li, S., Marquart, J. M., & Zercher, C. (2000). Conceptual issues and analytical strategies in mixed-method studies of preschool inclusion. *Journal of Early Intervention, 23*, 116-132. doi:10.1177/105381510002300206

Maxcy, S. J. (2003). Pragmatic threads in mixed methods research in the social sciences: The search for multiple modes of inquiry and the end of the philosophy of formalism. In A. Tashakkori & C. Teddlie (Eds.), *Handbook of mixed methods in social and behavioral research* (pp. 51-89). Thousand Oaks, CA: Sage.

Maxwell, J. A. (2004, April). *Realism as a stance for mixed methods research*. Paper presented at the annual meeting of the American Educational Research Association, San Diego, CA.

McEvoy, P., & Richards, D. (2006). A critical realist rationale for using a combination of quantitative and qualitative methods. *Journal of Research in Nursing*, *11*, 66-78.

Mertens, D. (2003). Mixed methods and the politics of human research: The transformative-emancipatory perspective. In A. Tashakkori & C. Teddlie (Eds.), *Handbook of mixed methods in social and behavioral research* (pp. 135-164). Thousand Oaks, CA: Sage.

Miles, M. B., & Huberman, A. M. (1994). *Qualitative data analysis: An expanded sourcebook* (2nd ed.). Thousand Oaks, CA: Sage.

Morse, J. M. (2003). Principles of mixed methods and multimethod research design. In A. Tashakkori & C. Teddlie (Eds.), *Handbook of mixed methods in social and behavioral research* (pp. 189-208). Thousand Oaks, CA: Sage.

Onwuegbuzie, A. J. (2003). Effect sizes in qualitative research: A prolegomenon. *Quality & Quantity: International Journal of Methodology*, *37*, 393-409.

Onwuegbuzie, A. J. (2004). Academic procrastination and statistics anxiety. *Assessment & Evaluation in Higher Education*, *29*, 3-18.

Onwuegbuzie, A. J., & Collins, K. M. T. (2007). A typology of mixed methods sampling designs in social science research. *The Qualitative Report*, *12*, 281-316. Retrieved from http://www.nova.edu/ssss/QR/QR12-2/onwuegbuzie2.pdf

Onwuegbuzie, A. J., & Collins, K. M. T. (2009, March). *An innovative method for analyzing themes in mixed research: Introducing chi-square automatic interaction detection (CHAID).*

Paper presented at the annual meeting of the American Educational Research Association, San Diego, CA.

Onwuegbuzie, A. J., & Combs, J. P. (2009a). *An innovative method for analyzing themes in mixed research: Introducing mixed thematic-exploratory factor analyses*. Manuscript submitted for publication.

Onwuegbuzie, A. J., & Combs, J. P. (2009b, April). *The relationship between statistics anxiety and coping strategies among graduate students: A mixed research study*. Paper presented at the annual meeting of the American Educational Research Association, San Diego, CA.

Onwuegbuzie, A. J., & Combs, J. P. (2010). Emergent data analysis techniques in mixed methods research: A synthesis. In A. Tashakkori & C. Teddlie (Eds.), *Handbook of mixed methods in social and behavioral research* (3rd ed., pp. 397-430). Thousand Oaks, CA: Sage.

Onwuegbuzie, A. J., & Dickinson, W. B. (2008). Mixed methods analysis and information visualization: Graphical display for effective communication of research results. *The Qualitative Report*, *13*, 204-225. [Online] Available: http://www.nova.edu/ssss/QR/QR13-2/onwuegbuzie.pdf

Onwuegbuzie, A. J., & Leech, N. L. (2004). Enhancing the interpretation of "significant" findings: The role of mixed methods research. *The Qualitative Report*, *9*, 770-792. [Online] Available: http://www.nova.edu/ssss/QR/QR9-4/ onwuegbuzie.pdf

Onwuegbuzie, A. J., & Leech, N. L. (2006). Linking research questions to mixed methods data analysis procedures. *The Qualitative Report*, *11*, 474-498. [Online] Available: http://www.nova.edu/ssss/QR/QR11-3/onwuegbuzie.pdf

Onwuegbuzie, A. J., & Teddlie, C. (2003). A framework for analyzing data in mixed methods research. In A. Tashakkori & C. Teddlie (Eds.), *Handbook of mixed methods in social and behavioral research* (pp. 351-383). Thousand Oaks, CA: Sage.

Onwuegbuzie, A. J., Collins, K. M. T., & Leech, N. L. (in press). *Mixed research: A step-by-step guide*. New York, NY: Taylor & Francis.

Onwuegbuzie, A. J., Dickinson, W. B., Leech, N. L., & Zoran, A. G. (2009). Toward more rigor in focus group research: A new framework for collecting and analyzing focus group data. *International Journal of Qualitative Methods*, *8*(3), 1-21.

Onwuegbuzie, A. J., Johnson, R. B., & Collins, K. M. T. (2009). A call for mixed analysis: A philosophical framework for combining qualitative and quantitative. *International Journal of Multiple Research Approaches*, *3*, 114-139.

Onwuegbuzie, A. J., Slate, J. R., Leech, N. L., & Collins, K. M. T. (2007). Conducting mixed analyses: A general typology. *International Journal of Multiple Research Approaches*, *1*, 4-17.

Onwuegbuzie, A. J., Slate, J. R., Leech, N. L., & Collins, K. M. T. (2009). Mixed data analysis: Advanced integration techniques. *International Journal of Multiple Research Approaches, 3,* 13-33.

Ragin, C. C. (1989). *The comparative method: Moving beyond qualitative and quantitative strategies*. Berkeley, CA: University of California Press.

Rao, V., & Wolcock, M. (2003). Integrating qualitative and quantitative approaches in program evaluation. In F. J. Bourguignon & L. Pereira de Silva (Eds.), *Evaluating the poverty and distribution impact of economic policies* (pp. 165-190). New York, NY: The World Bank.

Reichardt, C. S., & Cook, T. D. (1979). Beyond qualitative versus quantitative methods. In T. D. Cook & C. S. Reichardt (Eds.), *Qualitative and quantitative methods in evaluation research* (pp. 7-32). Thousand Oaks, CA: Sage.

Rescher, N. (2000). *Realistic pragmatism: An introduction to pragmatic philosophy*. Albany, NY: State University of New York Press.

Roberts, A. (2002). A principled complementarity of method: In defence of methodological eclecticism and the qualitative–qualitative debate. *The Qualitative Report*, 7(3). [Online] Available: www.nova.edu/ssss/QR/QR7–3/roberts.html

Sandelowski, M. (2000). Combining qualitative and quantitative sampling, data collection, and analysis techniques in mixed-method studies. *Research in Nursing Health, 23*, 246-255. doi:10.1002/1098-240X(200006)23:3<246::AID-NUR9>3.3.CO;2-8

Sandelowski, M. (2001). Real qualitative researchers don't count: The use of numbers in qualitative research. *Research in Nursing and Health, 24*, 230-240.

Stake, R. E. (1980). The case study method in social enquiry. In H. Simons (Ed.), *Towards a science of the singular* (pp. 62-75). CARE Occasional Publications No. 10. Norwich, UK: Center for Applied Research in Education, University of East Anglia.

Stake, R. E. (2005). Qualitative case studies. In N. K. Denzin & Y. S. Lincoln (Eds.), *The Sage handbook of qualitative research* (3rd ed., pp. 443-466). Thousand Oaks, CA: Sage.

Stake, R. E., & Trumbull, D. J. (1982). Naturalistic generalizations. *Review Journal of Philosophy and Social Science, 7,* 3-12.

Tashakkori, A., & Teddlie, C. (1998). *Mixed methodology: Combining qualitative and quantitative approaches.* Applied Social Research Methods Series (Vol. 46). Thousand Oaks, CA: Sage.

Teddlie, C., & Tashakkori, A. (2009). *Foundations of mixed methods research: Integrating quantitative and qualitative techniques in the social and behavioral sciences.* Thousand Oaks, CA: Sage.

International Journal of Education
ISSN 1948-5476
2010, Vol. 2, No. 2: E13

Teddlie, C., Tashakkori, A., & Johnson, R. B. (2008). Emergent techniques in the gathering and analysis of mixed methods data. In S. N. Hesse-Biber & P. Leavy (Eds.), *Handbook of emergent methods* (pp. 389-414). New York, NY: The Guilford Press.

Todd, Z., Nerlich, B., McKeown, S., & Clarke, D. D. (2004). *Mixing methods in psychology: The integration of qualitative and quantitative methods in theory and practice*. New York, NY: Psychology Press.

West, E., & Tulloch, M. (2001, May). *Qualitising quantitative data: Should we do it, and if so, how*? Paper presented at the annual meeting of the Association for Social Research, Wollongong, New South Wales, Australia.