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A Call for Conducting Multivariate Mixed Analyses

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Abstract

Several authors have written methodological works that provide an introductory- and/or intermediate-level guide to conducting mixed analyses. Although these works have been useful for beginning and emergent mixed researchers, with very few exceptions, works are lacking that describe and illustrate advanced-level mixed analysis approaches. Thus, the purpose of this article is to introduce the concept of *multivariate mixed analyses*, which represents a complex form of advanced mixed analyses. These analyses characterize a class of mixed analyses wherein at least one of the quantitative analyses and at least one of the qualitative analyses *both* involve the simultaneous analysis of multiple variables. The notion of multivariate mixed analyses previously has not been discussed in the literature, illustrating the significance and innovation of the article.

Keywords: Mixed methods data analysis, Mixed analysis, Mixed analyses, Advanced mixed analyses, Multivariate mixed analyses

1. Crossover Nature of Mixed Analyses

At least 13 decision criteria are available to researchers during the data analysis stage of mixed research studies (Onwuegbuzie & Combs, 2010). Of these criteria, the criterion that is the most underdeveloped is the crossover nature of mixed analyses. Yet, this form of mixed analysis represents a pivotal decision because it determines the level of integration and complexity of quantitative and qualitative analyses in mixed research studies. Broadly speaking, the crossover nature of mixed analyses is represented by an interactive continuum whereby non-crossover mixed analyses and crossover mixed analyses lie at the opposite ends of the continuum.

1.1 Non-Crossover Mixed Analyses

As described by Onwuegbuzie and Combs (2010), non-crossover mixed analyses, representing the least integrated way of mixing and combining qualitative and quantitative analyses, involve (a) the collection of both qualitative and quantitative data and (b) the qualitative analysis of qualitative data *and* quantitative analysis of quantitative data (i.e., *within-tradition analysis*). Although non-crossover mixed analyses are not as complex as are crossover mixed analyses, they are much more complex to conduct than are analyses conducted in monomethod studies (i.e., qualitative analysis of qualitative data only *OR* quantitative analysis of quantitative data only). Indeed, a mixed research study wherein a non-crossover mixed analysis is conducted might involve any one of the 58 classes of quantitative data analysis approaches identified by Onwuegbuzie, Leech, and Collins (2011) (cf. Figure 1) combined with any of the identified 34 qualitative data analysis approaches identified by Onwuegbuzie and Denham (2014) (cf. Table 1), any of Miles and Huberman's (1994) 19 within-case analysis methods (cf. Table 2), any of Miles and Huberman's (1994) 18 cross-case analysis methods (cf. Table 3), any of Saldaňa's (2012) 32 coding techniques (cf. Table 4), or the like.

Measurement Techniques	
Name of Analytical Technique	**Description**
Classical Test Theory	Analyzes the relationship among observed scores, true scores, and error in an attempt to predict outcomes of psychological and behavioral measurement
Item Response Theory (Latent Trait Theory, Strong True Score Theory, Modern Mental Test Theory)	Analyzes the probabilistic relationship between the response that a person provides (e.g.. examinee) on a quantitative item(s) and item parameters (e.g., item difficulty, item discrimination, guessing parameter) and person parameters/latent traits (e.g., ability, personality trait)
Multilevel Item Response Theory	Estimates latent traits of the respondent at different levels and examines the relationships between predictor variables and latent traits at different levels
Exploratory Factor Analysis	Explores the underlying structure of correlations among observed variables in an attempt to reduce dimensionality of data, wherein a small(er) number of factors significantly account for the correlations among the set of measured variables; utilizes estimates of common variance or reliability on the main diagonal of the correlation matrix that is factor analyzed
Principal Component Analysis	Explores the underlying structure of correlations among observed variables in an attempt to reduce dimensionality of data, wherein a small(er) number of factors significantly account for the correlations among the set of measured variables; utilizes the total variance of each variable to assess the shared variation among the variables. That is, it uses "ones" on the diagonal of the correlation matrix that is factor analyzed. Principal component analysis typically is conducted for variable reduction because it can be used to develop

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	scores that are combinations of observed variables, whereas exploratory factor analysis is more appropriate for exploring latent constructs and allows for error in estimation models.
Confirmatory Factor Analysis	Verifies the factor structure of a set of observed variables; it allows testing of the hypothesis that a relationship between observed variables and their underlying latent constructs exists
Multiple Factor Analysis (optimal scaling, dual scaling, homogeneity analysis, scalogram analysis)	Analyzes observations described by two or more sets of variables, and examines the common structures present in some or all of these set
Hierarchical Factor Analysis	Differentiates higher-order factors from a set of correlated lower-order factors
Assessing One Variable/Participant at a Time	
Descriptive Analyses (i.e., measures of central tendency, variation/dispersion, position/relative standing, and distributional shape)	Summarizes and describes a set of data one variable at a time in quantitative terms
Single-Subject Analysis	Analyzes observations from one or more individuals in which each individual serves as her/his own control (i.e., individual participant is the unit of analysis, although a group such as a classroom also can be the analytic unit); note that it is possible to include several variables at once in a design but analyses typically focus on one variable at a time
Assessing Differences through Variance Analysis	
Independent samples *t* test	Examines the difference between the means of two independent groups
Dependent samples *t* test (paired samples *t* test)	Examines the difference between the means of two groups, wherein the scores in one group is paired or dependent on the scores in the other group
Analysis of Variance (ANOVA)	Partitions the observed variance into components based on different sources of variation; one-way ANOVA examines the equality of several independent groups based on one dependent/outcome variable; factorial ANOVA examines the effects of two or more independent/explanatory/predictor variables and their interactions
Analysis of Covariance (ANCOVA)	Examines whether one or more factors (and their interactions) have an effect or are related to the outcome variable after removing the variance associated with which quantitative predictors (covariates)
Multivariate Analysis of Variance (MANOVA)	Examines whether one or more factors have an effect or are related to two or more outcome variables
Multivariate Analysis of Covariance (MANCOVA)	Examines whether one or more factors (and their interactions) have an effect or are related to two or more outcome variables after removing the variance associated with quantitative predictors (covariates)

Hierarchical Linear Modeling (HLM) (multilevel modeling, mixed effects modeling, covariance components modeling, random-coefficient regression modeling)	Analyzes variance in an outcome variable when data are in nested categories (e.g., students in a class, classes within a school, schools in one school district)
Multivariate Hierarchical Linear Modeling	Analyzes variance in multivariate dependent variables when the covariance structure of the independent variables is of interest
Repeated Measures Analysis of Variance (RMANOVA)	Involves an analysis of variance conducted on any design wherein the independent/predictor variable(s) have all been measured on the same participants under multiple conditions
Mixed Analysis of Variance (Mixed ANOVA)	Examines differences between two or more independent groups whereby repeated measures have been taken on all participants such that one factor represents a between-subjects variable and the other factor represents a within-subjects variable. Observations also may be nested by a unit (e.g., person) where units are generally treated as a between-subject variable.
Repeated Measures Analysis of Covariance (RMANCOVA)	Examines whether one or more factors (and their interactions) have an effect or are related to the outcome variables (i.e., repeated measures) after removing the variance associated with quantitative predictors (covariates)
Assessing Group Membership/Relationships	
Cluster Analysis	Assigns a set of observations, usually people, into groups or clusters wherein members of the group are maximally similar
Q Methodology	Involves finding relationships between participants across a sample of variables
Profile Analysis	Classifies empirically individual observations based on common characteristics or attributes measured by an observed variable(s)
Multivariate Profile Analysis	Classifies empirically individual observations based on common characteristics or attributes (i.e., multiple dependent variables) measured by observed variables (i.e., multiple independent variables)
Chi-Square Analysis	Involves any test statistic that has a chi-square distribution but generally analyzes the independence of two categorical variables via a contingency table
Chi-Square Automatic Interaction Detection (CHAID)	Examines the relationships between a categorical dependent measure (dichotomous, polytomous, ordinal) and a large set of selected predictor variables that may interact themselves; it involves a series of chi-square analyses (i.e., iterative, chi-square tests of independence) being conducted between the dependent and predictor variables
Multivariate Chi-Square Automatic Interaction Detection (CHAID)	Examines the relationships between two or more categorical dependent measure (dichotomous, polytomous, ordinal) and a large set of selected predictor variables that may interact themselves; it involves a series of

	chi-square analyses (i.e., iterative, chi-square tests of independence) being conducted between the multiple dependent and predictor variables
Descriptive Discriminant Analysis	Explains group separation (i.e., categorical dependent/outcome variable) as a function of one or more continuous or binary independent variables
Predictive Discriminant Analysis	Predicts a group membership (i.e., categorical dependent/outcome variable) by one or more continuous or binary independent variables
Assessing Time and/or Space	
Time Series Analysis	Involves analyzing, using frequency-domain methods or time-domain methods, an ordered sequence of observations over time, taking into account the serial dependence of the observations for the purpose of modeling and forecasting.
Survival Analysis	Analyzes time-to-event data (i.e., failure time data)
Geostatistics	Analyzes spatiotemporal (i.e., existing in both space and time) datasets
Panel Data Analysis	Analyzes a particular participant or group of participants within multiple sites, periodically observed over a defined time frame (i.e., longitudinal analysis).
Correspondence Analysis	Converts data organized in a two-way table into graphical displays, with the categories of the two variables serving as points; this graphical display presents the relationship between the two categorical variables
Canonical correspondence analysis (CCA)	Relates specific variables (e.g., types of species) to variables of interest (e.g., types of environments)
Fuzzy correspondence analysis	Similar to Correspondence Analysis, except uses “fuzzy data”—data that are coded with multiple categories instead of the common “0” or “1”
Multiple Correspondence Analysis	Analyzes the pattern of relationships of several categorical dependent variables
Discriminant Correspondence Analysis	Categorizes observations in predefined groups using nominal variables
Proportional Hazard Model	Estimates the effects of different covariates influencing the times-to-failure of a system (i.e., hazard rate)
Explaining or Predicting Relationships Between Variables	
Linear Regression	Examines the linear correlations between one (simple regression) or more (multiple regression) binary or continuous explanatory variables and a single continuous dependent variable
Non-Linear Regression	Examines the non-linear correlations between one or more binary or continuous explanatory variables and a single continuous dependent variable
Probit regression	Examines the non-linear correlations between one or more binary or continuous explanatory variables and a binomial response variable

Regression Discontinuity Analysis	Examines causal effects of interventions, wherein assignment to a treatment condition is determined, at least partly, by the value of an observed covariate that lies on either side of a fixed threshold/cut-score
Logistic Regression (logit regression)	Examines the relationship between one (simple logistic regression model) or more (multiple logistic regression model) binary or continuous explanatory variables and a single categorical dependent variable
Multivariate Logistic Regression	Examines the relationship between one or more explanatory variables and two or more categorical dependent variable(s)
Descriptive Discriminant Analysis	Explains group separation (i.e., categorical dependent/outcome variable) as a function of one or more continuous or binary independent variables
Predictive Discriminant Analysis	Predicts a group membership (i.e., categorical dependent/outcome variable) by one or more continuous or binary independent variables.
Log-Linear Analysis (multi-way frequency analysis)	Determines which of a set of three or more variables (and/or interactions) best explains the observed frequencies with no variable serving as the dependent/outcome variable
Canonical Correlation Analysis	Examines the multivariate relationships between two or more binary or continuous predictor variables and two or more binary or continuous outcome variables
Path Analysis	Describes and quantifies the relationship of a dependent/outcome variable to a set of other variables, with each variable being hypothesized as having a direct effect or indirect effect (via other variables) on the dependent variable
Structural Equation Modeling (causal modeling, covariance structure analysis)	Involves building and testing statistical models; it encompasses aspects of confirmatory factor analysis, path analysis, and regression analysis
Multilevel Structural Equation Modeling	Used when the units of observation form a hierarchy of nested clusters and some variables of interest are measured by a set of items or fallible instruments
Multilevel latent class modeling	Analyzes data with a multilevel structure such that model parameters are allowed to differ across groups, clusters, or level-2 units; the dependent variable is not directly observed but represents a latent variable with two or more observed indicators
Correlation coefficient	Measures the association between two variables
Multidimensional Scaling	Explores similarities or dissimilarities in data; it displays the structure of a set of objects from data that approximate the distances between pairs of the objects
Social Network Analysis	Involves the identification and mapping of relationships and flows among people, groups, institutions, web sites, and other information- and knowledge-producing units of different sizes; it provides both a visual and a

	mathematical analysis of complex human systems; the unit of analysis is not the individual, but an element consisting of a collection of two or more individuals and the linkages among them
Propensity Score Analysis	Replaces multiple covariates such that just one score is applied as a predictor rather than multiple individual covariates, thereby greatly simplifying the model; balances the treatment and control groups on the covariates when participants are grouped into strata or subclassified based on the propensity score; it adjusts for differences via study design (matching) or during estimation of treatment effect (stratification/regression)

Figure 1. Established classes of quantitative data analysis techniques and descriptions

Note. [a] For many of these analyses, nonparametric versions and Bayesian versions exist.

Adapted from "Toward a new era for conducting mixed analyses: The role of quantitative dominant and qualitative dominant crossover mixed analyses," by A. J. Onwuegbuzie, N. L. Leech, and K. M. T. Collins, 2011, in M. Williams & W. P. Vogt (Eds.), *The Sage handbook of innovation in social research methods*, pp. 354-356. Copyright 2011 by Sage Publications.

Table 1. List of formal qualitative analysis techniques identified by Onwuegbuzie and Denham (2014)

Type of Analysis	Short Description of Analysis
1. Word Count	Counting the total number of words used or the number of times a particular word is used
2. Semiotics	Using talk and text as systems of signs under the assumption that no meaning can be attached to a single term
3. Text Mining	Analyzing naturally occurring *text* in order to discover and capture semantic information
4. Discourse Analysis	Selecting representative or unique segments of language use, such as several lines of an interview transcript, and then examining the selected lines in detail for rhetorical organization, variability, accountability, and positioning
5. Classical Content Analysis	Counting the number of codes
6. Schema Analysis	Searching for cultural schemata (i.e., scripts) in texts, which include identifying semantic relationships between elements of component schemas
7. Latent Content Analysis	Uncovering underlying meaning of text
8. Manifest Content Analysis	Describing observed (i.e., manifest) aspects of communication via objective, systematic, and empirical means
9. Keywords-In-Context	Identifying keywords and utilizing the surrounding words to

	understand the underlying meaning of the keyword
10. Constant Comparison Analysis	Systematically reducing data to codes, then developing themes from the codes
11. Membership Categorization Analysis	Utilizing the role that interpretations play in making descriptions and the consequences of selecting a particular category (e.g., baby, sister, brother, mother, father = family)
12. Narrative Analysis	Considering the potential of stories to give meaning to individual's lives, and treating data as stories, enabling researchers to take account of research participants' own evaluations
13.Conversation Analysis	Utilizing the behavior of speakers to describe people's methods for producing orderly social interaction
14. Ethnographic Decision Models (EDM)	Building a model of the decision process for a behavior of interest, resulting in a display of data, via decision trees, decision tables, or sets of rules that take the form of *if-then* statements
15. Critical Discourse Analysis	Focusing on the ways that social and political power are reproduced in language; showing how power differences (e.g., gender differences) are conceived, perpetuated, bolstered, and resisted
16. Frame/Framing Analysis	Analyzing how people understand situations and activities
17. Social Semiotic Analysis	Undertakes analysis of sign and text as conditioned by social organization of participants involved and by the immediate conditions of their interaction emphasizing the plane of production
18.Domain Analysis	Utilizing the relationships between symbols and referents to identify domains
19. Taxonomic Analysis	Creating a system of classification that inventories the domains into a flowchart or diagram to help the researcher understand the relationships among the domains
20. Componential Analysis	Using matrices and/or tables to discover the differences among the subcomponents of domains
21. Theme Analysis	Involving identifying cognitive principles that reoccur, and uncovering relationships among domains and relationships of all the various components of the cultural milieu
22. Dialogical Narrative Analysis	Assessment of the communicative act embedded within a precise historical realization and based on the premise that every individual dialogic interaction is an interaction between two specific ideological horizons of which the individuals are representatives (i.e., frame of historical consciousness)
23. Qualitative Comparative Analysis	Systematically analyzing similarities and differences across cases, typically being used as a theory-building approach, allowing the analyst to make connections among previously built categories, as well as to test and to develop the categories further
24. Multimodal Discourse Analysis	Analysis of integration of language in combination with other semiotic

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(MDA)	resources *or modes* such as images, scientific symbolism, gesture, architecture, music, or sound integrated across *sensory modalities* (e.g., visual, auditory, tactile, olfactory, gustatory, kinesthetic) into multimodal phenomena such as print materials, videos, websites, or three-dimensional objects
25. Dimensional Analysis	Natural analysis assigning general dimensions to all analyzed parts of a phenomenon or situation based on the question "*What all is involved here*" (i.e., provisional coding). Designation of all dimensions observed in data builds an analytic dictionary. Further analysis leads to discovery of "critical mass" of dimensions that represent emergent pathways based on conditions, processes and consequences with perspective controlling designation and salience for all dimensions
26. Framework Analysis	Analyzing inductively to provide systematic and visible stages to the analysis process, allowing for the inclusion of a priori as well as a posteriori concepts, and comprising the following five key stages: (a) familiarizing, (b) identifying a thematic framework, (c) indexing, (d) charting, and (e) mapping and interpreting
27. Qualitative Secondary Data Analysis	Analyzing non-naturalistic data or artifacts that were derived from previous studies
28. Interpretative Phenomenological Analysis (IPA)	Analyzing in detail how one or more persons, in a given context, make sense of a given phenomenon—often representing experiences of personal significance (e.g., major life event)
29. Consensual Qualitative Research	Using open-ended questions in semi-structured data collection techniques that facilitate the collection of consistent data across individuals coupled with a more in-depth examination of individual experiences; using several judges throughout the data analysis process to yield multiple perspectives; using consensus to reach judgments about the meaning of the data; using one auditor to check the work of the team of judges and minimize the effects of groupthink; and using domains, core ideas, and cross-analyses in the data analysis
30. Situational Analysis	Assessing key social processes through cartographic situational analyses emphasizing (a) maps of key elements of the situation, variation, and difference (s), (b) maps of social worlds or arenas in mesolevel discursive negotiations, and (c) maps of issues and discursive axes focused around difference (s) of positionality and relationality
31. Micro-Interlocutor Analysis	Analyzing information stemming from one or more focus groups about which participant(s) responds to each question, the order that each participant responds, the characteristics of the response, the nonverbal communication used, and the like
32. Rhetorical Analysis	Analysis of the persuasiveness of discourses that are conventionally and/or socially purposeful. It follows five classical canons of rhetoric composition: (a) invention (i.e., discovering most optimal means of persuasion through purposive devices of ethos, pathos, and logos), (b)

	disposition (i.e., arrangement of arguments), (c) style, (d) memory (e.g., use of mnemonic devices), and (e) delivery (e.g., body movements, posture, or volume)
33. Systematic Data Integration	Interweaving observation data and interview data obtained from sequences of interactive situations
34. Nonverbal Communication Analysis	Analyzing nonverbal communication in interviews, focus groups, and observations

Note. Adapted from "Quantitative data analysis approaches," by A. J. Onwuegbuzie and M. A. Denham, 2014. Copyright 2014 by A. J. Onwuegbuzie and Onwuegbuzie and M. A. Denham.

Table 2. Miles and Huberman's (1994) within-case displays

Type of Display	Description
Partially Ordered:	
Poem	Composition in verse
Context Chart	Networks that map in graphic form the interrelationships among groups and roles that underlie the context of individual behavior
Checklist Matrix	Way of analyzing/displaying one major concept, variable, or domain that includes several unordered components
Time-Ordered:	
Event Listing	Matrix or flowchart that organizes a series of concrete events by chronological time periods and sorts them into multiple categories
Critical Incident Chart	Maps a few critical events
Event-State Network	Maps general states that are not as time-limited as events, and might represent moderators or mediators that link specific events of interest
Activity Record	Displays a specific recurring activity that is limited narrowly in time and space
Decision Modeling Flowchart	Maps thoughts, plans, and decisions made during a flow of activity that is bounded by specific conditions
Growth Gradient	Network that maps events that are conceptualized as being linked to an underlying variable that changes over time
Time-Ordered Matrix	Maps when particular phenomena occurred
Role-Ordered:	
Role-Ordered Matrix	Maps the participant's "roles" by sorting data in rows and columns that have been collected from or about a set of data that reflect their views, beliefs, expectations, and/or behaviors

Role-By-Time Matrix	Maps the participant's "roles," preserving chronological order
Conceptually Ordered:	
Conceptually Clustered Matrix	Text table with rows and columns arranged to cluster items that are related theoretically, thematically, or empirically
Thematic Conceptual Matrix	Reflects ordering of themes
Folk Taxonomy	Typically representing a hierarchical tree diagram that displays how a person classifies important phenomena
Cognitive Map	Displays the person's representation of concepts pertaining to a particular domain
Effects Matrix	Displays data yielding one or more outcomes in a differentiated manner, focusing on the outcome/dependent variable
Case Dynamics Matrix	Displays a set of elements for change and traces the consequential processes and outcomes for the purpose of initial explanation
Causal Network	Displays the most important independent and dependent variables and their inter-relationships

Note. Adapted from *Mapping Miles and Huberman's within-case and cross-case analyses onto the literature review process*, by A. J. Onwuegbuzie and Rebecca K. Frels, 2014, unpublished manuscript, Sam Houston state University, Huntsville, TX, p. x. Copyright 2014 by A. J. Onwuegbuzie and Rebecca K. Frels.

Table 3. Miles and Huberman's (1994) cross-case displays

Type of Display	Description
Partially Ordered:	
Partially Ordered Meta-Matrices	Display descriptive data for each of several cases simultaneously
Case-Ordered:	
Case-Ordered Descriptive Meta-Matrix	Contains descriptive data from all cases but the cases are ordered by the main variable of interest
Two-Variable Case-Ordered Matrix	Displays descriptive data from all cases but the cases are ordered by two main variables of interest that are represented by the rows and columns
Contrast Table	Displays a few exemplary cases wherein the variable occurs in low or high form, and contrast several attributes of the basic variable
Scatterplot	Plot all cases on two or more axes to determine how close from each other the cases are

Case-Ordered Effects Matrix	Sorts cases by degrees of the major cause of interest, and shows the diverse effects for each case
Case-Ordered Predictor-Outcome Matrix	Arranges cases with respect to a main outcome variable, and provides data for each case on the main antecedent variables
Predictor-Outcome Consequences Matrix	Links a chain of predictors to some intermediate outcome, and then illustrates the consequence of that outcome
Time-Ordered:	
Time-Ordered Meta-Matrix	Table in which columns are organized sequentially by time period and the rows are not necessarily ordered
Time-Ordered Scatterplot	Display similar variables in cases over two or more time periods
Composite Sequence Analysis	Permit extraction of typical stories that several cases share, without eliminating meaningful sequences
Conceptually Ordered:	
Content-Analytic Summary Table	Which allows the researcher to focus on the content of a meta-matrix without reference to the underlying case
Substructing	Permits the identification of underlying dimensions
Decision Tree Modeling	Displays decisions and actions that are made across several cases
Variable-By-Variable Matrix	Table that displays two major variables in its rows and columns ordered by intensity with the cell entries representing the cases
Causal Models	Network of variables with causal connections among them in order to provide a testable set of propositions or hunches about the complete network of variables and their interrelationships
Causal Networks	Comparative analysis of all cases using variables deemed to be the most influential in explaining the outcome or criterion
Antecedents Matrix	Display that is ordered by the outcome variable, and displays all of the variables that appear to change the outcome variable

Note. Adapted from *Mapping Miles and Huberman's within-case and cross-case analyses onto the literature review process*, by A. J. Onwuegbuzie and Rebecca K. Frels, 2014, unpublished manuscript, Sam Houston state University, Huntsville, TX, p. x. Copyright 2014 by A. J. Onwuegbuzie and Rebecca K. Frels.

Table 4. A Summary of Saldaňa's (2012) 32 coding methods

	Coding Method	Definition
1	Attribute Coding	Provide essential information about data for future reference
2	Axial Coding	Develop a category by grouping/ sorting / reducing the number of

		codes generated from the first cycle of coding
3	Causation Coding	Analyze the causality by identifying causes, outcome, and links between them
4	Descriptive Coding	Describe the topic of data with descriptive nouns (i.e., topic coding)
5	Domain and Taxonomic Coding	Analyze the cultural knowledge participants use and organize them into categories and reorganize them through further analysis into a taxonomic tree diagram
6	Dramaturgical Coding	Apply dramaturgical terms to qualitative data to analyze interpersonal and intrapersonal participant experiences
7	Eclectic Coding	Combine two or more similar First Cycle of coding methods purposefully
8	Elaborative Coding	Develop codes to refine theoretical constructs emerged from previous research or investigations
9	Emotion Coding	Apply codes accompanying emotion(s) to explore the interpersonal and/or intrapersonal participants' experiences
10	Evaluation Coding	Apply non-quantitative codes (e.g., +/-) to qualitative data for the evaluative purpose
11	Focused Coding	Develop categories with significant or frequent codes that emerged from In Vivo, Process, and/or Initial Coding
12	Holistic Coding	Analyze the data corpus as a whole and identify the basic themes or issues in the data
13	Hypothesis Coding	Apply pre-established codes to qualitative data to examine a researcher-generated hypothesis
14	In Vivo Coding	Apply the words verbatim that participants use to examine the possible dimensions or ranges of categories
15	Initial Coding	Apply provisional and tentative codes in the First Cycle of coding
16	Longitudinal Coding	Organize collected qualitative data across time; Categorize data into matrices for further analysis and interpretation
17	Magnitude Coding	Apply supplemental or sub- codes to quantitize or qualitize the phenomenon's intensity, frequency, direction, presence, or evaluative content
18	Motif Coding	Apply original index codes utilized to classify the elements of folk talks, myths, and legends; This method can be utilized for story-based data such as journals or diaries
19	Narrative Coding	Develop codes representing participant narratives from literary perspectives (e.g., storied, structured forms)

20	Outline of Cultural Materials Coding (OCM)	It was created as a specialized index for anthropologists and archeologists; Provide coding for the categories of social life
21	Pattern Coding	Develop meta-codes that identify similarly coded data by grouping them and generate major themes; Appropriate for Second Cycle coding
22	Process Coding	Apply codes by using -ing words to indicate actions
23	Protocol Coding	Apply codes or categories in a previously developed system to qualitative data (e.g., ALCOH= alcoholism or drinking)
24	Provisional Coding	Utilize the preset codes emerged from preliminary investigations or literature review and anticipated to be modified, revised, or deleted during the data analysis
25	Simultaneous Coding	Apply two or more different codes to a single qualitative datum in the different dimensions
26	Structural Coding	Categorize the data corpus into segments by similarities, differences, relationships by using conceptual phrases
27	Subcoding	Develop sub categories in the hierarchies and taxonomies added to the primary codes
28	Theoretical Coding	Develop the central category that covers all other codes and categories by integrating and synthesizing them
29	Values Coding	Apply codes consisting of three elements, *value, attitude,* and *belief* to examine a participant's perspectives or worldviews
30	Verbal Exchange Coding	Interpret data through the researcher's experience and reflection to explore cultural practices; Extensive written reflection is preferred to traditional margined coding methods
31	Versus Coding	Identify phenomena in a dichotomy terms and exhibit itself as X VS. Y
32	Theme, Theming the Data	Identify codes in the form of sentences capturing the essence and essentials of participant meanings

Note. Adapted from "Mapping Saldaňa's coding methods onto the literature review process," by A. J. Onwuegbuzie, R. K. Frels, and E. Hwang, 2016, *Journal of Educational Issues, 2*, pp. 136-139. Copyright 2016 by A. J. Onwuegbuzie, R. K. Frels, and E. Hwang.

1.2 Crossover Mixed Analyses

Contrastingly, in a crossover mixed analysis, one form of data (e.g., qualitative) collected can be analyzed utilizing techniques historically associated with the another tradition (e.g., quantitative) (Greene, 2007, 2008; Onwuegbuzie & Teddlie, 2003; Teddlie & Tashakkori, 2009), thereby yielding a higher level of integration of quantitative and qualitative analyses than would be the case if a mixed researcher had conducted a non-crossover mixed analysis (Onwuegbuzie & Combs, 2010). That is, a crossover mixed analysis involves what can be called a *between-tradition analysis*. Thus, crossover analyses are not only more complex than are non-crossover mixed analyses, but also they are much more integrated, leading Teddlie and Tashakkori (2009) to declare that "We believe that this is one of the more fruitful areas for the further development of MM [mixed methods] analytical strategies" (p. 281).

2. Qualitative Analysis and Quantitative Analysis Continua

Both the array of qualitative analysis approaches and the array of quantitative analysis approaches can be viewed as lying on continua (Onwuegbuzie et al., 2011). Specifically, qualitative analysis approaches can be placed on a qualitative analysis continuum and quantitative analysis approaches can be placed on a quantitative analysis continuum. Each continuum is discussed in the following sections.

2.1 Qualitative Analysis Continuum

Figure 2 presents what Onwuegbuzie et al. (2011) referred to as the *qualitative analysis continuum*. In this figure, qualitative analyses are placed on the continuum based on the degree to which qualitative analytical assumptions are combined with quantitative analytical assumptions (i.e., level of integration). Thus, for example, on the left side of the continuum are approaches like word count, in which a quantitative analysis (i.e., descriptive analysis) is used to analyze qualitative data (e.g., words that are extracted from individual interviews, focus group, documents). In contrast, on the right side of the continuum are approaches like constant comparison analysis that represent purely a qualitative analysis of qualitative data. Lying between these two extremes are qualitative analyses that involve the (strong) use of both quantitative analysis (i.e., reflecting quantitative-based assumptions [i.e., postpositivist]) and qualitative analysis assumptions (i.e., reflecting qualitative-based assumptions [e.g., constructivist-based]), such as classical content analysis and qualitative comparative analysis (cf. Table 1). For example, with classical content analysis, qualitative data first are analyzed qualitatively to yield categories (e.g., sub-themes, themes, meta-themes), and then these emergent categories are subjected to a quantitative analysis—specifically, a descriptive analysis (i.e., frequency count) of the categories. Interestingly, this continuum also captures the extent to which the approach is tied directly to a research design. For example, constant comparison analysis (Glaser, 1965) is the analysis of choice for the Glaserian version of grounded theory research (Glaser & Strauss, 1967). In contrast, word count is not linked directly to any qualitative research tradition.

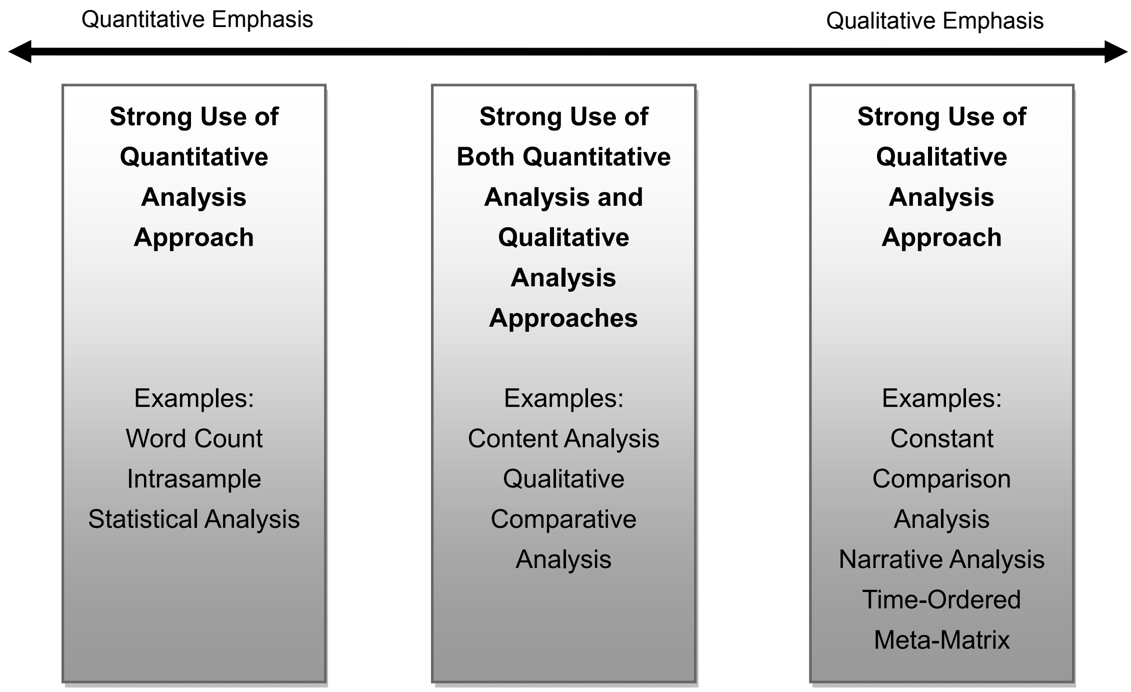

Figure 2. Qualitative analysis continuum

Note. Adapted from "Toward a new era for conducting mixed analyses: The role of quantitative dominant and qualitative dominant crossover mixed analyses," by A. J. Onwuegbuzie, N. L. Leech, and K. M. T. Collins, 2011, in M. Williams & W. P. Vogt (Eds.), *The Sage handbook of innovation in social research methods*, p. 358. Copyright 2011 by Sage Publications.

2.2 Quantitative Analysis Continuum

Figure 3 presents what Onwuegbuzie et al. (2011) referred to as the *quantitative analysis continuum*. In this figure, quantitative analyses are placed on the continuum based on the level of complexity. Consequently, on the left side of the continuum are descriptive statistics techniques that are not associated with any statistical modeling assumptions. Moving towards the right of the continuum, the next class of analyses represents exploratory analyses such as exploratory factor analysis, cluster analysis, correspondence analysis, and multidimensional scaling. These analyses are exploratory in nature because they do not involve null hypotheses statistical significant testing (i.e., no *p* values are involved). The remaining classes of quantitative analyses on the continuum represent inferential analyses that are governed by statistical modeling assumptions (i.e., distributional assumptions, structural assumptions, and cross-variation assumptions). Building on Onwuegbuzie et al.'s (2011) typology, Ross and Onwuegbuzie (2014) categorized the array of established quantitative analysis techniques into eight levels of complexity (cf. Figure 4).

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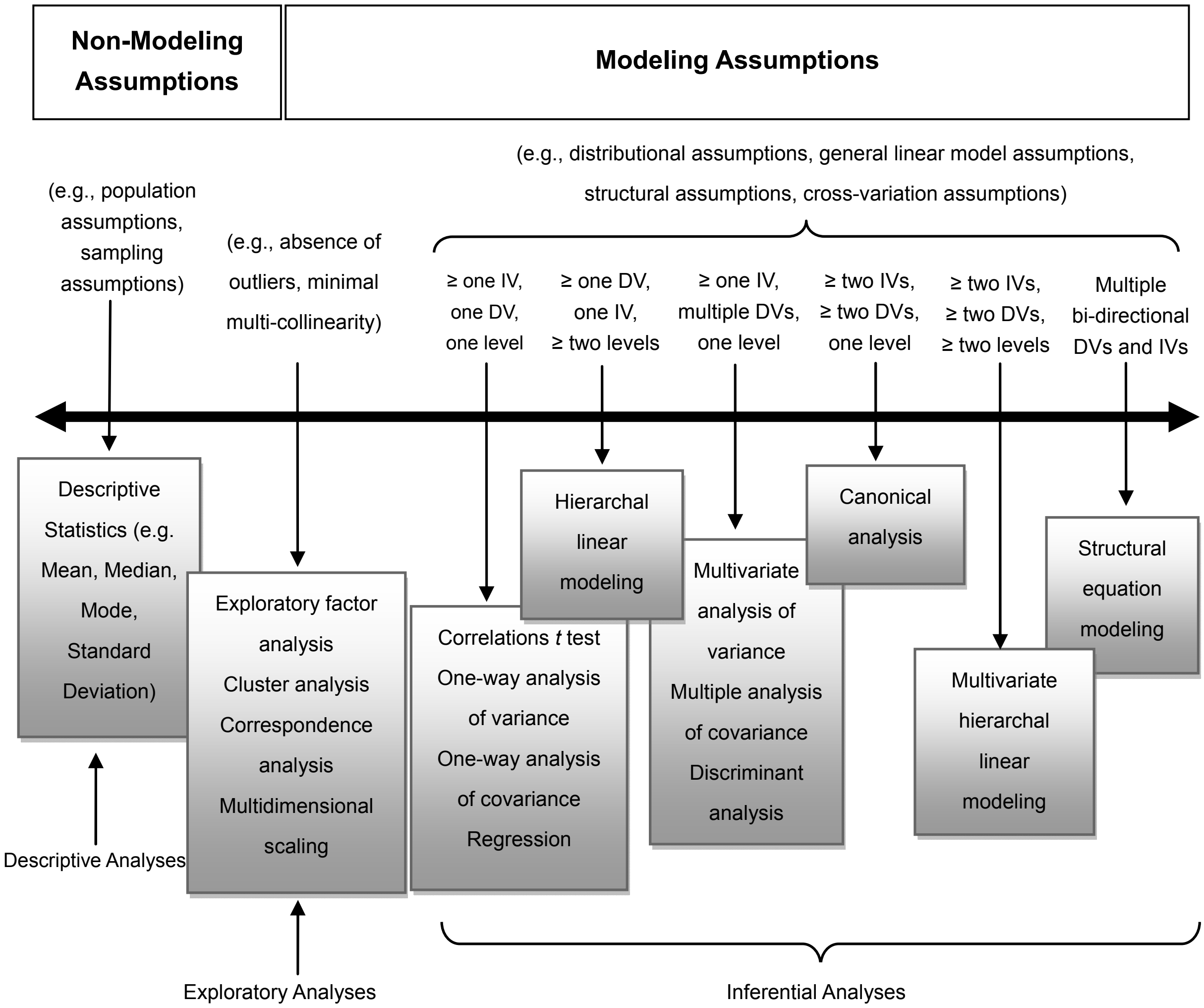

Figure 3. Quantitative analysis continuum

Note. Adapted from "Toward a new era for conducting mixed analyses: The role of quantitative dominant and qualitative dominant crossover mixed analyses," by A. J. Onwuegbuzie, N. L. Leech, and K. M. T. Collins, 2011, in M. Williams & W. P. Vogt (Eds.), *The Sage handbook of innovation in social research methods*, p. 359. Copyright 2011 by Sage Publications.

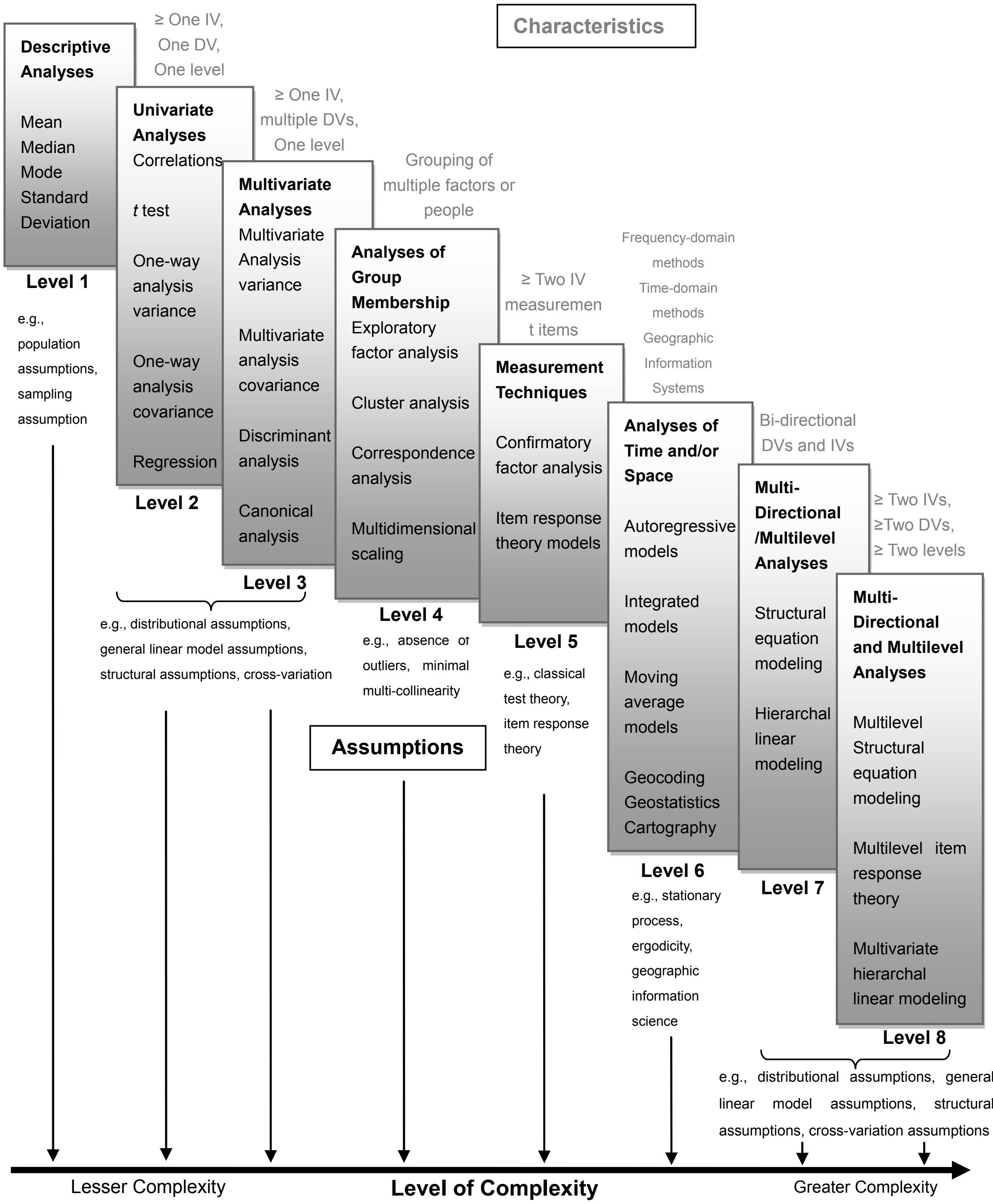

Figure 4. Quantitative analysis complexity continuum

Note. Adapted from "A typology of quantitative analyses," by A. Ross and A. J. Onwuegbuzie, 2014. Copyright 2014 by A. Ross and A. J. Onwuegbuzie.

However, to date, when conducting mixed analyses in general and crossover mixed analyses in particular, mixed researchers have not taken full advantage of the range of complexity available—tending to utilize lower levels of quantitative analysis complexity, when used alongside qualitative procedures. Consistent with this assertion. Ross and Onwuegbuzie (2014), who examined the complexity of quantitative analyses, within mixed research approaches, utilized in a flagship mathematics education publication (i.e., *Journal for Research in Mathematics Education*) over a 5-year period, documented that the mixed researchers used only the lowest three levels of the quantitative analysis continuum (cf. Figure 4)—with virtually all the studies involving the use of either descriptive analyses or univariate analyses (i.e., Levels 1-2), which supports Bazeley's (2010) observation that "there are surprisingly few published studies reporting results from projects which make more than very elementary use of the capacity to integrate data and analyses using computers" (p. 434). With this gap in the literature in mind, the purpose of this article is to introduce the concept of *multivariate mixed analyses*, which represents a complex form of both non-crossover and crossover mixed analyses.

3. Conceptual Framework

Multivariate mixed analyses represent a class of mixed analyses wherein at least one of the quantitative analyses and at least one of the qualitative analyses *both* involve the simultaneous analysis of multiple variables. These analyses can be conducted in a non-crossover manner whereby the selected complex qualitative analysis is used to analyze the qualitative data and a complex quantitative analysis is used to analyze the quantitative data. Alternatively, and representing an even more advanced form of mixed analysis, multivariate mixed analysis can be conducted in a crossover manner whereby qualitative data are analyzed utilizing a complex quantitative analysis *and* quantitative data are analyzed using a qualitative analysis in which multiple variables are analyzed simultaneously. For the purpose of this article, an exemplar of a *crossover multivariate mixed analysis* will be provided.

4. Heuristic Example

Setting the Scene: The example of a crossover multivariate mixed analysis involves an embedded mixed research study in which the purpose was to examine the relationship between the statistics anxiety and coping strategies among graduate students enrolled in quantitative-based research methods courses. The quantitative phase involved 115 graduate students from various education disciplines (e.g., special education, elementary education, secondary education, educational administration) who were enrolled in six sections of a quantitative-based educational research course at a mid-southern university. These participants were administered the Statistical Anxiety Rating Scale (STARS) and the Coping Strategies Inventory for Statistics (CSIS). The STARS (Cruise & Wilkins, 1980), which is a 51-item, 5-point Likert-format instrument assessing statistics anxiety in a wide variety of academic situations, has six subscales: (a) worth of statistics, (b) interpretation anxiety, (c) test and class anxiety, (d) computational self-concept, (e) fear of asking for help, and (f) fear of the statistics instructor. For the present study, the reliability of the STARS subscale scores, as measured by coefficient alpha, was as follows: worth of statistics (.95; 95% confidence interval [CI] = .94, .96), interpretation anxiety (.91; 95% CI = .87, .93), test and class anxiety (.90; 95% CI = .88, .93), computational self-concept (.91; 95% CI = .87, .93), fear of asking for help (.89; 95% CI = .85, .92), and fear of the statistics instructor (.80; 95% CI = .74, .85). The CSIS (Jarrell & Burry, 1989) is a 40-item, 10-point Likert-format instrument that assesses non-facilitative study coping strategies and examination-taking strategies of students enrolled in quantitative-based courses (e.g., statistics). This instrument comprises two scales that evaluate study coping strategies and examination-taking coping strategies. For the present study, the study coping strategies subscale and the examination-taking coping subscale generated scores that had a classical theory alpha reliability coefficient of .77 (95% CI = .70, .83) and .82 (95% CI = .77, .86), respectively.

The embedded mixed research phase comprised 18 students selected via convenience sampling (Onwuegbuzie & Leech, 2005), who represented three cohorts of a doctorate of education program at a university located in the southern United States, who had taken a doctoral-level statistics course within the past 6 months at the time of the study. These students were interviewed via three focus groups to ascertain the role that coping strategies played in the context of learning statistics.

5. Method

The multivariate analysis conducted to analyze the quantitative phase was a canonical correlation analysis (Cliff & Krus, 1976; Darlington, Weinberg, & Walberg, 1973; Onwuegbuzie & Daniel, 2003; Thompson, 1980, 1984, 1988). This analysis was used to identify a combination of coping strategy dimensions that might predict a combination of statistics anxiety dimensions. The multivariate analysis conducted to analyze the qualitative phase was qualitative comparative analysis (Ragin, 1987), which is a case-oriented qualitative data analysis approach that involves a systematic analysis of similarities and differences across cases of interest. Qualitative comparative analysis facilitates theory-building by allowing the analyst to examine links among multiple themes or variables that have been previously identified by the analyst or by another researcher, as well as by testing and developing the themes/variables to a greater extent.

6. Results

6.1 Quantitative Phase

The canonical correlation analysis revealed that the two canonical correlations when combined were statistically significant ($F[12, 214] = p < .0001$). However, when the first canonical root was excluded, the remaining canonical root was statistically non-significant. Together, these results suggested 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 (Cohen, 1988). However, the second canonical correlation was not statistically significant. Consequently, only the first canonical correlation was interpreted.

Table 5 displays the canonical solution for the first function. Using a cutoff correlation of 0.3 (Lambert & Durand, 1975), an examination of the standardized canonical function coefficients revealed that examination-taking coping strategies (-1.09) made a very important contribution to the set of statistics anxiety variables, with study coping strategies playing a small role (0.15). With respect to the statistics anxiety variable set, interpretation anxiety made a substantial contribution; with the remaining variables making a small contribution. The structure coefficients pertaining to the first canonical function revealed that both examination-taking coping strategies and study coping strategies made important contributions to the set of statistics anxiety variables, with examination-taking coping strategies again playing the biggest role. The square of the structure coefficient indicated that these variables explained 98.9% and 29.2% of the variance, respectively. With regard to the statistics anxiety variable cluster, all six variables made an important contribution, with, again, interpretation anxiety making the greatest contribution, explaining 34.8% of the variance.

Table 5. Canonical solution for first function: relationship between coping strategies dimension scores and statistics anxiety dimension scores

Variable	Standardized Coefficient	Structure Coefficient	Structure Coefficient^2 (%)
Coping Strategy Dimension:			
Examination-taking Coping Strategies	-1.09*	-0.99*	98.01
Study Coping Strategies	0.15	-0.54*	29.16
Statistics Anxiety Dimension:			
Worth of Statistics	0.22	0.41*	16.81
Interpretation Anxiety	0.83*	0.59*	34.81
Test and Class Anxiety	0.01	0.46*	21.16
Computational Self-Concept	0.04	0.42*	17.64
Fear of Asking for Help	0.04	0.37*	13.69
Fear of the Statistics Instructors	-0.03	0.30*	9.00

Note. * Coefficients with effect sizes larger than .3 (Lambert & Durand, 1975).

Comparing the standardized and structure coefficients identified some multicollinearity involving study coping strategies of the coping strategy set of variables and worth of statistics, test and class anxiety, computational self-concept, fear of asking for help, and fear of the statistics instructors of the statistics anxiety set of variables because for each of these variables, the standardized coefficient associated with the variable was small, whereas the corresponding structure coefficient was relatively large (Onwuegbuzie & Daniel, 2003; Tabachnick & Fidell, 2007).

Overall, the quantitative findings indicated a multivariate relationship between coping strategies and statistics anxiety. Examination-taking coping strategies represented a much more important predictor of statistics anxiety than did study coping strategies. However, study coping strategies also played a role in the canonical correlation function, albeit a smaller one.

6.2 Qualitative Phase

With regard to the qualitative phase, a constant comparison analysis (Glaser, 1965) of the focus group data yielded six themes related to statistics anxiety (i.e., lack of understanding, class anxiety, anxiety due to multiple responsibility, fear of performance expectations, fear based on prior experience, and fear of the professor/asking for help) and five themes related to coping strategies (i.e., peer support; professor support; personal management, organization, routine, and time; class structure and materials provided; and study skills; cf. Table 6). Each coping strategy theme then was quantitized (Tashakkori & Teddlie, 1998) by assigning a score of "1" if the participant provided a response that was categorized under that theme and a score of "0" otherwise—yielding an *inter-respondent matrix* (i.e., Student × Theme Matrix; cf. Table 7) (Onwuegbuzie, 2003; Onwuegbuzie & Teddlie, 2003) that consisted only of 0s and 1s. The statistics anxiety theme was quantitized into one meta-theme by first determining the number of codes assigned to each statistics theme for each participant and then totaling the number of codes assigned across the six statistics themes. This total then was converted to a "1" if it was above the median total and a "0" if it was below the median.

Table 6. Description of emergent 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, you emailed all the time, you really got to work well with everybody."
Instructor support	Asks for and receives help from the instructor	"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."

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Note. Adapted from "Relationships among attitudes, coping strategies, and achievement in doctoral-level statistics courses: A mixed research study," by J. P. Combs and A. J. Onwuegbuzie, 2012, *International Journal of Doctoral Studies, 7*, p. 361. Copyright 2012 by the Informing Science Institute.

Table 7. Inter-respondent matrix for lack of statistics anxiety as a function of coping strategies among 18 doctoral students

	← Conditions →					Outcome
Pseudonym	Peer Support	Instructor Support	Personal Management	Class Structure	Study Skills	Low Levels of Statistics Anxiety
Alpha	1	0	0	0	0	1
Bravo	0	0	0	0	0	0
Charlie	1	1	1	0	1	1
Delta	1	0	1	0	1	1
Echo	0	0	0	0	1	0
Foxtrot	0	0	0	1	0	0
Golf	1	1	0	1	0	1
Hotel	1	0	0	0	1	1
India	0	1	0	0	1	1
Juliet	0	0	0	1	0	0
Kilo	0	0	0	0	0	1
Lima	0	0	1	0	1	1
Mike	0	0	1	1	1	1
November	0	0	0	1	0	0
Oscar	0	1	1	1	0	1
Papa	0	1	0	1	1	1
Quebec	1	1	1	0	0	0
Romeo	0	0	0	1	0	0

Table 7 then served as what qualitative comparative analysts refer to as a *truth table*, which, in this case, lists all unique configurations of the 18 study participants and the five emergent coping themes that have been extracted from the data, along with the corresponding outcome (i.e., presence or absence of high levels of statistics anxiety) that have been observed for each configuration (Miethe & Drass, 1999). This truth table specifies which configurations are unique to a category of the construct of interest (i.e., classification variable) and which configurations appear in multiple categories. By comparing the numbers of configurations in these groups, the qualitative comparative analyst is able to estimate the degree that types of outcomes are unique or similar. Next, the researcher "compares the configurations within a group, looking for commonalities that allow configurations to be combined into simpler, yet more abstract, representations" (Miethe & Drass, 1999, p. 8). This step is conducted by identifying and removing unnecessary variables from these configurations. Specifically, a variable is deemed as unnecessary if its presence or absence within a configuration has no effect on the outcome that is associated with that configuration. The qualitative comparative analyst repeats these comparisons until no further reductions can be made. Next, all redundancies that are identified among the remaining reduced configurations are removed, thereby leading to the final solution, specifically, a statement of the unique characteristics of each category of the typology or theme.

Using the free qualitative comparative software called fsQCA (http://www.u.arizona.edu/~cragin/fsQCA/) to analyze the truth table (i.e., Table 7; standard analyses) revealed a combination of conditions linked to the outcome of high levels of overall statistics anxiety, yielding the following two logical equations:

$$SA = (PS) + (IS) + (PM) + (SS) \tag{1}$$

$$(PS) + (is) + (PM) + (cs) + (ss) \tag{2}$$

Where,

SA = low levels of statistics anxiety; PS = peer support; IS = instructor support; PM = personal management; CS = class structure; SS = study skills.

The first solution (i.e., Equation 1) indicates that for low levels of statistics anxiety to occur, peer support, instructor support, personal management, and study skills must be present. The fsQCA software program revealed a *consistency* score of 1.0 for the first solution, which indicates that this condition did not include any case (i.e., doctoral student) that did not display the outcome (i.e., low levels of statistics anxiety).

The second solution indicates that low levels of statistics anxiety to occur, peer support and personal management must be present regardless of whether instructor support, class structure, and study skills are present. As for the first solution, the *consistency* score of 1.0 for the second solution indicates that this condition did not include any case (i.e., doctoral student) that did not display the outcome (i.e., low levels of statistics anxiety). *Raw coverage* measures the proportion of memberships in the outcome explained by each term of the solution. The finding from the fsQCA output that the raw coverage for the first solution (.57) is higher than is the raw coverage (.14) indicates that the first solution covers more cases (i.e., more of the 18 doctoral students) in the data set.

Solution consistency of qualitative comparison analysis indicates the combined consistency of the causal conditions. That is, solution consistency measures the degree to which membership in the solution (the set of solution terms) is a subset of membership in the outcome. The fsQCA output revealed a solution consistency of 1.0, which indicates that the membership in the solution (the set of solution terms) is a subset of membership in the outcome (i.e., lack of statistics anxiety). *Solution coverage* indicates the proportion of membership in the outcome that can be explained by membership in the causal recipes. The fsQCA output revealed a solution coverage of 0.76, which indicates that most of the doctoral students for which the outcome is present (i.e., low levels of statistics anxiety) are a member of either of the solutions and, thus, are explained by the model. That both the solution consistency and solution coverage are greater than .75 (Ragin, 2008) indicates a correctly specified model. Therefore, in summary, the qualitative comparative analysis of the truth table in Table 7 suggests, in particular, the importance of peer support and personal management in minimizing statistics anxiety.

7. Meta-Inferences from the Multivariate Mixed Analysis

The multivariate mixed analysis, which comprised a quantitative multivariate analysis and an embedded multivariate mixed analysis, not only indicated a multivariate relationship between coping strategies and statistics anxiety but also identified the nature of this relationship in terms of the specific coping and anxiety variables involved. If in the quantitative phase, the relationship between a general measure of statistics anxiety and a general measure of coping was examined—via a correlation coefficient (i.e., Level 2 analysis)—then, at best, the conclusion would have been that these two constructs are related to some degree. Although this information would have been useful, by increasing the complexity by just one level (i.e., from Level 2 analysis to Level 3 analysis) via a multivariate analysis (i.e., canonical correlation analysis), a substantially richer understanding of the relationship between statistics anxiety and coping for the underlying sample was obtained. The findings from the quantitative phase of the heuristic example show the (potential) benefit of mixed researchers using more complex quantitative analyses within their mixed analysis frameworks.

Interestingly, even higher levels of quantitative analysis could have been used in this quantitative phase. For example, because other demographic variables (e.g., gender, ethnicity, age), achievement-related variables (e.g., number of statistics courses taken, number of research methodology courses taken, statistics performance), and affective variables (e.g., academic self-concept) also were collected from these 115 graduate students, a structural equation modeling (SEM) analysis (i.e., Level 7 analysis) could have been conducted. For example, this SEM analysis could have been used to test further Combs and Onwuegbuzie's (2012) Expectancy-Value Coping Strategies Model of statistics achievement that they had hypothesized using the frameworks of Eccles and Wigfield (2002) and Ramirez, Emmioglu, and Schau (2010); and they had tested and confirmed using qualitative data (cf. Figure 5). Alternatively, because information also was available regarding the students' place of abode and where their undergraduate institutions were located, a geospatial analysis (i.e., Level 6 analysis) could have been conducted to assess the potential role that location played in students' coping strategies. Such a geospatial analysis could have yielded what Onwuegbuzie (2015) referred to as spatial effect sizes. Alternatively still, a cluster analysis (i.e., Level 4 analysis) could have been conducted to ascertain how the students grouped together with respect their responses to the CSIS.

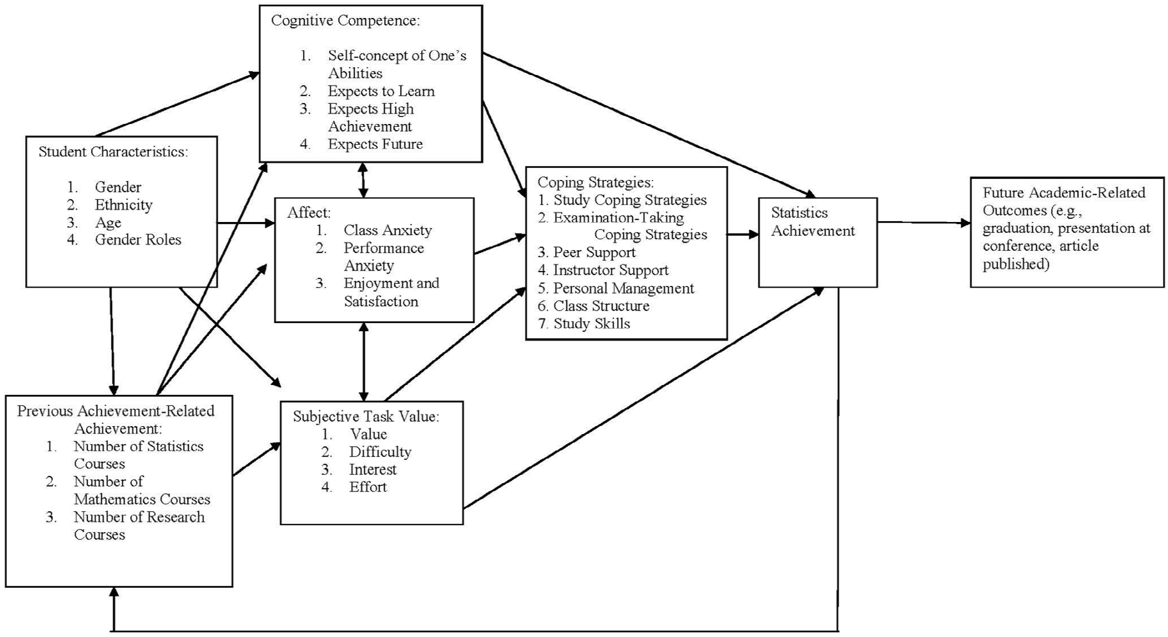

Figure 5. Combs and Onwuegbuzie's (2014) emergent Expectancy-Value Coping Strategies Model of statistics achievement using the frameworks of Eccles and Wigfield (2002) and Ramirez, Emmioglu, and Schau (2010)

Note. Adapted from "Relationships among attitudes, coping strategies, and achievement in doctoral-level statistics courses: A mixed research study," by J. P. Combs and A. J. Onwuegbuzie, 2012, *International Journal of Doctoral Studies, 7*, p. 364. Copyright 2012 by the Informing Science Institute.

The point here is that conducting a higher level of quantitative analysis enables mixed researchers to get more out of their data, thereby enhancing meta-inference quality. In other words, conducting higher levels of quantitative analyses allows mixed researchers to ask increasingly complex questions within a mixed analysis framework. Unfortunately, the vast majority of researchers do not appear to use multivariate statistical analyses in their mixed research studies (Onwuegbuzie & Corrigan, 2016; Ross & Onwuegbuzie, 2014).

With regard to qualitative analyses, our multivariate mixed analysis example has shown not only the utility of using multiple qualitative analysis approaches—as advocated by Leech and Onwuegbuzie (2007)—but also the benefit of using a qualitative analysis (i.e., qualitative comparative analysis) that allows the simultaneous analysis of multiple categories (e.g., sub-themes, themes, meta-themes)—yielding what I am terming a *multivariate qualitative analysis*. In the current example, an analysis that involved the strong use of a qualitative analysis approach (i.e., constant comparison analysis) was followed up with an analysis that involved the strong use of both quantitative analysis and qualitative analysis approaches (i.e., qualitative comparative analysis). Moreover, this follow-up qualitative analysis led to a crossover analysis in which the emergent themes (cf. Table 6) were quantitized (cf. Table 7) and then subjected to a qualitative comparative analysis.

Greene, Caracelli, and Graham (1989) conceptualized five purposes for mixing or combining quantitative and qualitative data, which, in essence, provide a purpose for mixing or combining quantitative and qualitative data analysis approaches, as follows:

(a) *triangulation* (i.e., compare findings from the qualitative data with the quantitative results), (b) *complementarity* (i.e., 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]), (c) *development* (i.e., use the results from one analytical strand to help inform the other analytical strand), (d) *initiation* (i.e., discover paradoxes and contradictions that emerge when findings from the two analytical strands are compared that might lead to a re-framing of the research question), and (e) *expansion* (i.e., expand breadth and range of a study by using multiple analytical strands for different study phases). In this multivariate mixed analysis example, the findings from both the multivariate quantitative analysis (i.e., canonical correlation analysis) and multivariate qualitative analysis (i.e., qualitative comparative analysis) provided *triangulation* inasmuch as they both revealed a multivariate relationship between statistics anxiety and coping strategies. Further, findings from both phases of the multivariate mixed analysis yielded *complementarity* by revealing different coping strategies that were related to statistics anxiety. Finally, the use of multiple qualitative analysis approaches represented *development*. As such, the multivariate mixed analysis facilitated the coming to fruition of three of Greene et al.'s (1989) five purposes—thereby facilitating quality meta-inferences.

8. Conclusions

The notion of multivariate mixed analyses has not been described in any published work, thereby providing compelling evidence of the significance and innovation of the article. Some mixed researchers might view my call for the conduct of multivariate mixed analyses as representing a paradigm shift. However, I would argue that rather than representing a paradigm shift, this advanced form of mixed analyses represents an extension of existing mixed analysis approaches (see, for e.g., Leech & Onwuegbuzie, 2010). Thus, I hope that mixed researchers keep in mind this analytical concept (i.e., multivariate mixed analyses) when developing research questions in the future so that they can ask increasingly complex questions that, when answered using multivariate mixed analyses, will help mixed researchers to come closer to verstehen.

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