Mixed Methods Analysis and Information Visualization: Graphical Display for Effective Communication of Research Results

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In this paper, we introduce various graphical methods that can be used to represent data in mixed research. First, we present a broad taxonomy of visual representation. Next, we use this taxonomy to provide an overview of visual techniques for quantitative data display and qualitative data display. Then, we propose what we call "crossover" visual extensions to summarize and integrate both qualitative and quantitative results within the same framework. We provide several examples of crossover (mixed research) graphical displays that illustrate this natural extension. In so doing, we contend that the use of crossover (mixed research) graphical displays enhances researchers' understanding (i.e., increased Verstehen) of social and behavioral phenomena in general and the meaning that underlies these phenomena in particular. Key Words: Graphic Methods, Visual Techniques, Graphical Displays, Crossover Graphical Displays, and Mixed Research

Overview of Graphical Display

> *As knowledge increases among mankind, and transactions multiply, it becomes more and more desirable to abbreviate and facilitate the modes of conveying information from one person to another, and from one individual to many.*

While written by William Playfair in 1801, the idea of conveying information still is regarded as timely and valuable in today's world. Images can be visual renditions or representations of ideas, dimensions, and events (Dickinson, 2001). Representing statistical ideas and information is a complex task, and as Tufte (1990) stated, "all communication between the readers of an image must take place on a two-dimensional surface" (p. 12).

Historically, quantitative data have facilitated graphical display techniques, offering a visual one-to-one correspondence of number to graphical element. A typical example of this one-to-one correspondence is the scatterplot, with each Cartesian

coordinate pair represented by a plotted point, providing a visual summary of the measure of association among the variables of interest.

Visual methods of quantitative data display have been extensively developed for more than 200 years (Chernoff, 1973; Friendly, 1995; Playfair, 1801/2005; Tufte, 1990, 1997a, 1997b, 2001, 2006; Tukey, 1972, 1989; Wainer, 1992, 2005). Playfair, a prolific graphical innovator, developed techniques such as divided surface area charts, bar charts, time series line charts, gridlines, and differentiated line qualities (broken and solid lines, and line weight [thickness]). In fact, Playfair developed or improved all four major types of graphical display: data maps, time series, space-time-narrative, and relational graphics (Tufte, 2001). After Playfair, "graphs popped up everywhere, being used to convey information in the social, physical, and natural sciences" (Wainer, 2005, p. 9).

Chernoff (Chernoff, 1973; Chernoff & Rizvi, 1975) developed a multivariate display technique known as Chernoff's Faces, whereby each facial feature reflected a corresponding numeric variable value. Tukey developed stem-and-leaf plots, while Wainer often and eloquently described the inherent pictorial connections between graphical display techniques and effective communication. Wainer (2005) wrote, "an efficacious way to add context to statistical facts is by embedding them in a graphic" (p. 86). The challenge remains to develop and apply new methods of graphical exploration and display in order to translate effectively qualitative data into a visual format, thereby providing a powerful visual tool for effective communication of research results. Unfortunately, although there is a myriad of literature on graphical displays of statistical data, with the exception of Miles and Huberman (1994), scant attention has been paid regarding graphical displays of *qualitative* data.

In an attempt to redress this balance, Onwuegbuzie, Dickinson, Leech, and Zoran (2007) conceptualized an array of graphical techniques for analyzing focus group interviews. For example, these authors showed how the communication patterns of focus group interviewees can be displayed. In addition, they showed how various modes of non-verbal behaviors such as the following can be mapped: proxemic (i.e., use of interpersonal space to communicate attitudes), chronemic (i.e., use of pacing of speech and length of silence in conversation), kinesic (i.e., body movements or postures), and paralinguistic (i.e., all variations in volume, pitch, and quality of voice).

If graphical methods can be used for both quantitative and qualitative data, then it follows that graphical methods can used in mixed research, which involves the mixing of quantitative and qualitative approaches within the same study (Johnson & Onwuegbuzie, 2004; Johnson, Onwuegbuzie, & Turner, 2007). Yet, to date, virtually no guidance has been given as to how graphical methods can enhance mixed methods data analyses (also referred to as mixed analyses); particularly the second and third steps of the mixed analysis process, namely, data display and data transformation (Onwuegbuzie & Teddlie, 2003). This is the focus of the current paper. Specifically, the purpose of this article is to introduce various graphical methods that can be used to represent data in mixed research. First, we present a broad taxonomy of visual representation (Tufte, 2001). Second, we use this taxonomy to provide an overview of visual techniques for quantitative data display. Third, we use this taxonomy to provide an overview of visual techniques for qualitative data display. Fourth, we propose what we call "crossover" visual extensions to summarize and integrate both qualitative and quantitative results within the same framework. We provide several examples of crossover graphical displays that illustrate

this natural extension. We classify each example using Tufte's (2006) six fundamental principles of analytical design. In so doing, we contend that the use of crossover graphical displays enhances researchers' understanding (i.e., increased *Verstehen*; Outhwaite, 1975*)* of social and behavioral phenomena in general and the meaning that underlies these phenomena in particular.

Taxonomy of Visual Representation

Using Tufte's (2001) framework, we contend that there are five broad levels of visual display that are pertinent to both quantitative and qualitative data analysis: (a) text (i.e., level 1), (b) tables (i.e., level 2), (c) text-tables (i.e., level 3), (d) supertables (i.e., level 4), and (e) graphics (i.e., level 5). Each of these levels is discussed in the next section. Further, Tufte (2006) identifies six fundamental principles of analytical design: (a) comparison; (b) causality, mechanism, structure, and explanation; (c) multivariate analysis; (d) integration of evidence; (e) documentation; and (f) content. These are not ordered by levels of complexity; rather, each principle represents a discrete idea. As noted by Tufte (2006), "Visual displays, if they are to assist thinking, should show comparisons" (p. 127). Based on the scientific method, "the reason we examine evidence is to understand causality, process, and systemic structure" (Tufte, 2006, p. 128). By incorporating multiple variables into our graphics, we can analyze the relationship among variables, based on the resultant visual patterns of their observed values. These multiple pieces of evidence provide documentation of our dataset, and a visual summary of narrative content. Graphics give data a "voice"; enabling our data to speak to us in a non-verbal way (Dickinson, Hines, & Onwuegbuzie, 2006).

Visual Techniques for Quantitative Data Display

Quantitative data can be represented using each of the five levels of visual display previously identified. For example, numbers can be represented as figures or words, depending on the style guide (e.g., American Psychological Association, 2001; Chicago Manual of Style, 2003), within a sentence or paragraph. However, text ("the conventional sentence") is "a poor way to show more than two numbers because it prevents comparisons within the data" (Tufte, 2001, p. 178). Tables in quantitative research "are clearly the best way to show exact numerical values," whereas text-tables summarize numeric data by type and source of information (i.e., demographic information, data source and time, group membership) by "arranging the type to facilitate comparison" (Tufte, 2001, p. 178). Supertables, "a type of elaborate table," may be used to "attract readers through its organized, sequential detail, and reference-like quality" (Tufte, 2001, p. 179). Finally, graphics make "complexity accessible: combining words, numbers, and pictures;" giving "access to the richness of data makes graphics more attractive to the viewer" (Tufte, 2001, p. 180). Typical examples of graphics for quantitative data summary include the scatterplot, stem-and-leaf plot, and the box and whisker plot.

Visual Techniques for Qualitative Data Display

Qualitative data can be represented using each of the five levels of visual display discussed previously. Text, or what some qualitative researchers refer to as extended text, the lowest level of visual data, is the most common way of representing data in qualitative research (Miles & Huberman, 1994), likely because they represent the most direct way of capturing words that are based on observation, interviews, and/or documents. However, extended text can yield cognitive overload, especially when it is extensive (Faust, 1982; Miles & Huberman), as often is the case in ethnographic research, grounded theory, and phenomenological research. Thus, it is surprising that with the exception of fields such as visual anthropology, visual displays are under-utilized in qualitative research. Yet, as noted by Miles and Huberman, such visual displays can be "designed to assemble organized information into an immediately accessible, compact form so that the analyst can see what is happening and either draw justified conclusions or move on to the next step of analysis the display suggests may be useful" (p. 11).

Moreover, in addition to aiding data display, visual displays can enhance the other two major forms of qualitative data analysis, namely: data reduction and conclusion drawing/verification (Leech & Onwuegbuzie, in press; Miles & Huberman, 1994). With respect to data reduction, graphical displays provide a way of organizing, simplifying, focusing, summarizing, documenting, sorting, transforming, and discarding text (Leech & Onwuegbuzie; Miles & Huberman). With regard to conclusion drawing/verification, visual displays not only can help qualitative researchers make inferences and conclusions, they can aid researchers assess, on a continual basis, the trustworthiness, credibility, dependability, confirmability, and/or transferability of the inferences made. As such, whatever its goal, visual display potentially is an important part of the analysis process because the decisions made as to how to construct the visual display represent analytical processes. Further, visual display can serve as a thread that interweaves data reduction, data display, and conclusion drawing/verification in the tapestry (i.e., report) that emerges from the qualitative study.

Like quantitative researchers, qualitative researchers have numerous ways of displaying data. These visual displays could be constructed for one case at a time (i.e., within-case displays) or for two or more cases at a time (i.e., cross-case displays). Within-case displays include the following: partially ordered displays, time-ordered displays, role-ordered displays, and conceptually ordered displays (Miles & Huberman, 1994). Partially ordered displays are visual representations that uncover and portray what is occurring in a local setting or context by imposing minimal conceptual structure on the data, —such as poems (level 1 display); context charts (i.e., networks that map in graphic form the interrelationships among groups and roles that underlie the context of individual behavior; level 5); and checklist matrices (i.e., way of analyzing/displaying one major concept, variable, or domain that includes several unordered components; level 3). Time-ordered displays are visual representations that order data by time and sequence, maintaining the historical chronological order of events and facilitating an analysis of when the events occurred and their antecedents, such as event listing (i.e., matrix or flowchart that organizes a series of concrete events by chronological time periods and sorts them into multiple categories; levels 3-5); critical incident chart (i.e., maps a few critical events; level 3); event-state network (i.e., maps general states that are not as time-

limited as events, and might represent moderators or mediators that link specific events of interest; levels 3-5); activity record (i.e., displays a specific recurring activity that is limited narrowly in time and space; levels 3-5); decision modeling flowchart (i.e., maps thoughts, plans, and decisions made during a flow of activity that is bounded by specific conditions; level 5); growth gradient (i.e., network that maps events that are conceptualized as being linked to an underlying variable that changes over time; level 5); and time-ordered matrix (i.e., maps when particular phenomena occurred; level 3).

Role-ordered displays order information according to the participant's roles in a formal or informal setting, such as role-ordered matrix (i.e., 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; level 3) and role-by-time matrix (i.e., maps the participant's "roles," preserving chronological order; level 3). Conceptually ordered displays order the display by concepts or variables, such as a conceptually clustered matrix (i.e., a text table with rows and columns arranged to cluster items that are related theoretically, thematically, or empirically; level 3); thematic conceptual matrix (i.e., reflects ordering of themes; level 3); folk taxonomy (e.g., typically representing a hierarchical tree diagram that displays how a person classifies important phenomena; level 5); cognitive maps (e.g., displays the person's representation of concepts pertaining to a particular domain; levels 3-5); effects matrix (i.e., displays data yielding one or more outcomes in a differentiated manner, focusing on the outcome/dependent variable; level 3); case dynamics matrix (i.e., displays a set of elements for change and traces the consequential processes and outcomes for the purpose of initial explanation; level 3); and causal network (i.e., displays the most important independent and dependent variables and their inter-relationships; level 5).

Cross-case displays include partially ordered displays, case-ordered displays, time-ordered displays, and conceptually ordered displays (Miles & Huberman, 1994). Partially ordered displays include partially ordered meta-matrices (i.e., display descriptive data for each of several cases simultaneously; level 3). Case-ordered displays include case-ordered descriptive meta-matrix (i.e., contains descriptive data from all cases but the cases are ordered by the main variable of interest; level 3); two-variable case-ordered matrix (i.e., 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; level 3); contrast table (i.e., displays a few exemplary cases wherein the variable occurs in low or high form, and contrast several attributes of the basic variable; level 3); scatter plot (i.e., plot all cases on two or more axes to determine how close from each other the cases are: level 5); case-ordered effects matrix (i.e., sorts cases by degrees of the major cause of interest, and shows the diverse effects for each case; level 3); case-ordered predictor-outcome matrix (i.e., arranges cases with respect to a main outcome variable, and provides data for each case on the main antecedent variables; level 3); predictor-outcome consequences matrix (i.e., links a chain of predictors to some intermediate outcome, and then illustrates the consequence of that outcome; level 3). Time-ordered displays include time-ordered meta-matrix (i.e., table in which columns are organized sequentially by time period and the rows are not necessarily ordered; level 3); time-ordered scatterplots (i.e., display similar variables in cases over two or more time periods; level 5); and composite sequence analysis (i.e., permit extraction of typical stories that several cases share, without eliminating meaningful sequences; levels 3-5). Conceptually

ordered displays include content-analytic summary table (i.e., which allows the researcher to focus on the content of a meta-matrix without reference to the underlying case; level 3); substructing (i.e., permits the identification of underlying dimensions; level 3); decision tree modeling (i.e., level 5); variable-by-variable matrix (i.e., table that displays two major variables in its rows and columns ordered by intensity with the cell entries representing the cases; level 3); causal models (i.e., 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; level 5); causal networks (i.e., comparative analysis of all cases using variables deemed to be the most influential in explaining the outcome or criterion; level 5); and antecedents matrix (i.e., a display that is ordered by the outcome variable, and displays all of the variables that appear to change the outcome variable; levels 3-5).

Graphical Methods that Transform Data in Mixed Research

Information (and meaning) is conveyed through the composition and integration of multiple lines within an image. One technique for conveying meaning is using multiple lines within an image would be geographical maps: using multiple lines, with differentiated line thickness, colors, and weight to portray three-dimensional information on a two-dimensional surface. Tufte (2006) noted that "maps show information with differentiated lines all the time, with greater richness" (p. 71). By incorporating differentiated line qualities within data display techniques, we can illustrate research information with enhanced clarity, thereby providing a visual summary of our phenomena of interest.

Another way to convey meaning is advocated through the creation of unique visual elements to summarize and highlight important data characteristics and research implications. An example of creating a unique visual element is the utilization of bubble plots to show the amount of agreement in response to a survey or interview item. The diameter of the bubble reflects the corresponding numeric variable values. Thus, a larger bubble portrays a larger value. For instance, when administering an instrument that contains both closed- and open-ended items, bubble plots can represent both the results of a summated rating scale, and then be modified to represent open-ended item responses. Graphical research extensions to mixed research approaches are shown in Table 1.

Table 1

Extensions of Graphical Display Techniques to Mixed Methods Research

Graphical Display Technique	Current use Within Quantitative Research	Application and Extension to Mixed Research
Bubble plot	show selected variable value by subject	show level of agreement in response to survey or interview item; show composition of focus groups; use differentiated line qualities

Pictogram	display frequencies by variable of interest	development of iconic symbols to represent nested sample characteristics; sorted by categorical variables; new pictograms utilized symbols to represent school, teacher, and classroom relationships
Scatterplot	display one-to-one correspondence	display demographic characteristics of study participants by matching linked variables (e.g., ethnicity, gender)

Tufte's principles for the design of statistical graphics provided a theoretical framework for our extension of visual display techniques to mixed analyses. These principles include documenting the sources and characteristics of data, enforcing appropriate comparisons, demonstrating mechanisms of cause and effect, expressing those mechanisms quantitatively and qualitatively, recognizing the inherent multivariate nature of data and analyses, and evaluating alternative explanations (Tufte, 1997b).

Quantitizing

One of the two most common ways of transforming data in mixed research is via quantitizing data. Quantitizing involves transforming qualitative data to a numerical form (Tashakkori & Teddlie, 1998). More specifically, in quantitizing, "qualitative 'themes' are numerically represented, in scores, scales, or clusters, in order more fully to describe and/or interpret a target phenomenon" (Sandelowski, 2001, p. 231). For example, Onwuegbuzie, Witcher, Collins, Filer, Wiedmaier, and Moore (2007) illustrated how emergent qualitative themes could first be quantitized and then subjected to a statistical display. These researchers examined perceptions of characteristics of effective college teachers among 912 undergraduate and graduate students from various academic majors enrolled at a university in a mid-southern state.

A qualitative analysis revealed the following nine characteristics that students considered to reflect effective college teaching: responsive, enthusiast, student-centered, professional, expert, connector, transmitter, ethical, and director. These themes then were quantitized. Specifically, for each study participant, a score of a "1" was given for a theme if it represented a significant statement or observation pertaining to that individual; otherwise, a score of "0" was given. That is, for each participant, each theme was *quantitized* to a score of "1" or "0." This *quantitizing* led to the formation of what Onwuegbuzie (2003) called an *inter-respondent matrix* (*participant x theme matrix*). The inter-respondent matrix indicated which individuals contributed to each emerging theme. This matrix allowed various statistical analyses to be undertaken. In particular, Onwuegbuzie, Witcher, et al. (2007) converted the inter-respondent matrix to a matrix of bivariate associations among the responses pertaining to each of the emergent themes. These bivariate associations represented tetrachoric correlation coefficients because the

themes had been quantitized to dichotomous data (i.e., "0" vs. "1"), and tetrachoric correlation coefficients are appropriate to use when one is determining the relationship between two (artificial) dichotomous variables (cf. Nelson, Rehm, Bedirhan, Grant, & Chatterji, 1999). This matrix of tetrachoric correlation coefficients then formed the basis of an exploratory factor analysis, which determined the number of factors underlying the themes. These factors, or latent constructs, yielded *meta-themes* (Onwuegbuzie) such that each meta-theme contained one or more of the emergent themes. These meta-themes then were displayed as in Figure 1.

Figure 1. *Thematic structure pertaining to students' perceptions of the characteristics of effective college instructors: Graphical display of quantitized data.*
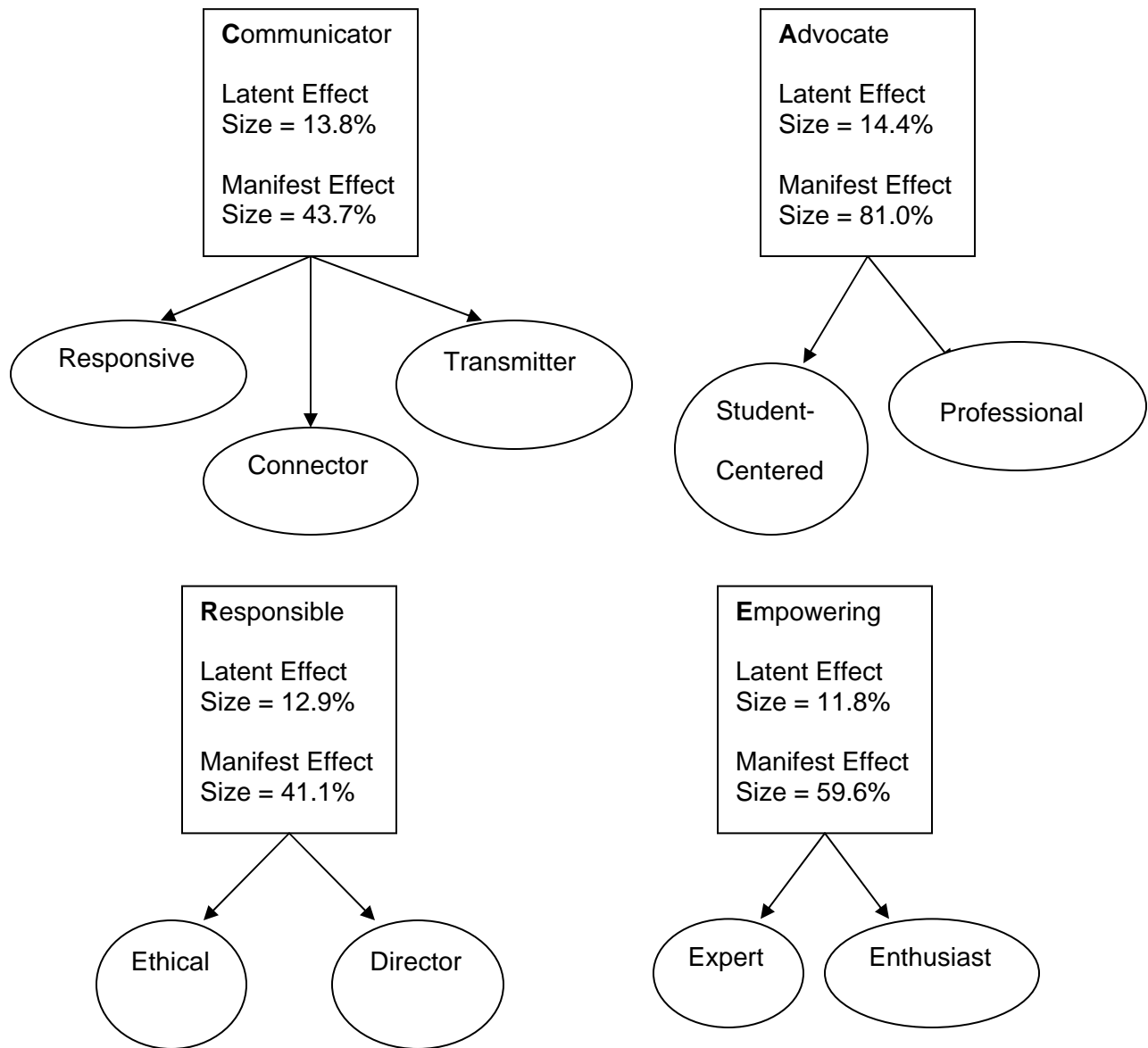
This figure was adapted from Onwuegbuzie, Witcher, et al. (2007). Reprinted with kind permission of Sage Publications.

The graphical display in Figure 1 vividly shows the relationship among the themes. Thus, this graphical display provides a powerful way of displaying emergent themes. Using Tufte's (2006) fundamental principles of analytical design, this graphic is designed to provide multiple sources of information based on these six ideas: (a) comparison; (b) structure and explanation; (c) multivariate analysis; (d) integration of evidence; (e) documentation; and (f) content.

Qualitizing

The other common way of transforming data in mixed research is by qualitizing data. Qualitizing data is a process by which quantitative data are transformed into data that can be analyzed qualitatively (Tashakkori & Teddlie, 1998). The study of Daley and Onwuegbuzie (2004) provides an example of displaying qualitized data. These researchers examined juvenile offenders ($n = 82$) with respect to the proportions of inaccurate causal attributions (i.e., violence attributional errors) they make for others' violent behaviors, and the salient pieces of information they utilize in arriving at their attributions (i.e., reasons for violence attributions). The researchers defined violence attribution errors as errors that occur when an offender does not blame the perpetrator of a violent act (e.g., rape), but instead blames either the victim or the circumstance (e.g., fate). Additionally, the researchers were interested in developing a typology of reasons for violence attributions, as well as to ascertain whether these reasons predict juvenile delinquents' violence attributional errors. Also, the researchers sought to determine the antecedent correlates of juvenile offenders' causal attributions. Finally, these researchers examined whether the profiles of juvenile delinquents could be developed based on their violence attribution reasons.

Daley and Onwuegbuzie (2004) conducted what the researchers termed a *concurrent mixed methods analysis* (CMMA). This analysis involved using qualitative and quantitative data analytic techniques in a concurrent manner. The CMMA involved six stages. The first stage (i.e., exploratory stage) consisted of the recoding of the multiple-choice responses (i.e., person, stimulus, and circumstance). Specifically, a score of 1 was given if the offender indicated a stimulus or circumstance response (i.e., external attribution), representing a violence attribution error and a score of 0 if the offender indicated a person option (i.e., person attribution) and dispositional attributions were given a score of 0. Responses to the 12 items of the VAS were summed to produce an index of violence attributional errors (range = 0-12), with high scores being indicative of juveniles who committed a high proportion of attributional errors. These scores then were used to determine the juvenile delinquents' overall violence attributional error rate. The second stage (i.e., exploratory stage) involved using the method of constant comparison (Glaser & Strauss, 1967) to analyze the open-ended responses, from which themes emerged relating to the offenders' reasons for their attributions.

The third stage (i.e., exploratory stage) of the CMMA involved utilizing descriptive statistics to analyze the hierarchical structure of the emergent themes. In particular, each theme was quantitized (i.e., creation of inter-respondent matrix, as described previously) in order to determine the frequency of each theme, as well the relationship between responses to each theme (i.e., 0 vs. 1) and the violence attributional error rate. The fourth CMMA stage (i.e., exploratory stage) involved using the inter-

respondent matrix to conduct an exploratory factor analysis to ascertain the underlying structure of these themes, as described earlier. The fifth stage (i.e., confirmatory stage) of the CMMA involved the determination of antecedent correlates of the relationship between responses to each theme (i.e., 0 vs. 1) and selected demographic variables (e.g., age, ethnicity, number of prior arrests).

The sixth and final stage (i.e., exploratory stage) of the CMMA involved narrative profile formation. Specifically, the number of average profiles (Tashakkori & Teddlie, 1998) was determined using an ipsative approach, in which the juveniles' responses to each theme were interpreted in relation to their responses to the other themes (Allport, 1937, 1962, 1966; Block, 1957) in the following manner: (a) for each offender, the emergent theme scores (i.e., 0 or 1) were ranked such that each scale took on a value from 1 through the number of emergent themes (i.e., 7) and (b) the index of similarity used for the analysis was based on the theme scores ranked from lowest to highest within each profile. An intra-individual correlation matrix then was formed by correlating each pair of profiles, yielding $(n)(n\text{-}1)/2$ Spearman Rho values (where n was the number of respondents). This correlation matrix was cluster-analyzed in order that individualistic patterns could be characterized for each offender sample member. Offenders having similar profiles were clustered together. The criterion of percentage variation explained by each cluster decided the most meaningful cluster solution. More specifically, the eigenvalues for each cluster-solution were compared to ascertain the number of interpretable and meaningful profiles. The formation of average profiles thus represented the *qualitizing* of previously quantitized themes (Tashakkori & Teddlie).

The profiles for the resulting three clusters are displayed pictorially in Figure 2. The seven themes (i.e., conflict resolution, fate, irresponsibility, poor judgment, provocation, self-control, and violation of rights) are presented on the horizontal axis, whereas the proportion of juveniles who provided a significant statement (i.e., an attribution reason) belonging to each theme is presented on the vertical axis. As such, each of the three emergent profiles represented an average set of responses across each theme. As can be seen in Figure 2, members of Cluster 1 ($n = 35$) were extremely unlikely to endorse the self-control (probability (p) = .20) and conflict resolution (p = .20) themes. These offenders were moderately likely to endorse the violation of rights (p = .43) and fate (p = .40) themes. However, they were very likely to endorse the provocation (p = .80), irresponsibility (p = .80), and poor judgment (p = .86) themes. Juveniles in Cluster 2 ($n = 23$) highly endorsed self-control (p = .83), violation of rights (p = .70), provocation (p = .83), irresponsibility (p = .83), and poor judgment (p = .74) themes. Also, they were moderately likely to endorse the conflict resolution theme (p = .57). However, they were unlikely to provide a reason associated with fate (p = .17). Finally, members of Cluster 3, like Cluster 2, highly endorsed the self-control (p = 1.00), provocation (p = .70), irresponsibility (p = .90), and poor judgment (p = .95) themes. Also, they were moderately likely to endorse fate (p = .63). However, this group was highly unlikely to endorse the violation of rights (p = .10) and conflict resolution (p = .15) themes. Thus, this graphical display provides a powerful way to compare the profiles of participants and to depict them qualitatively.

Figure 2. *Average profiles relating to juvenile delinquents' reasons for violence attributions: Graphical display of qualitized data.*
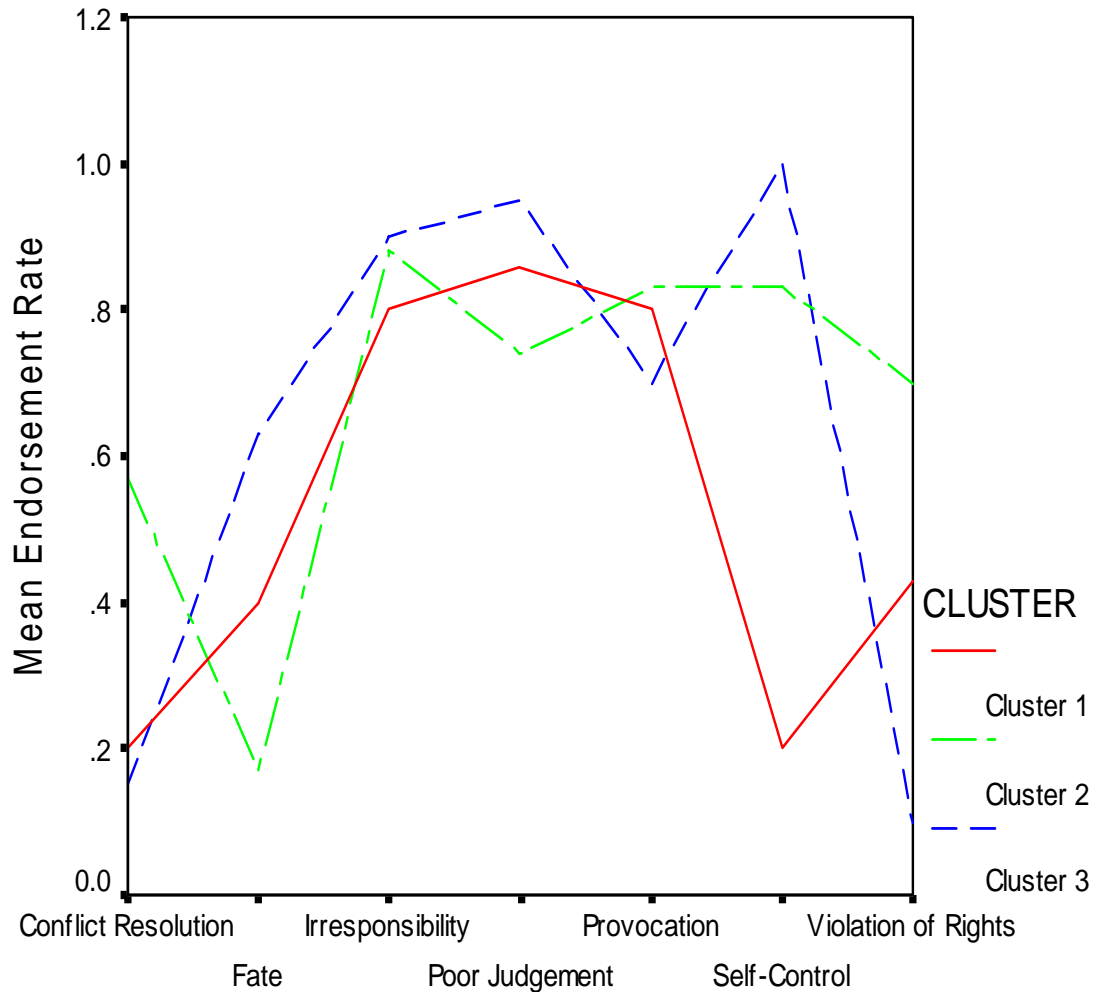

This figure was adapted from Daley and Onwuegbuzie (2004). Reprinted with kind permission of Heldref Publications.

The study of Witcher, Onwuegbuzie, and Minor (2001) provides another example of a graphical display of qualitized data. These researchers examined preservice teachers' perceptions ($n = 219$) of characteristics of effective teachers. The cluster analysis yielded a three-cluster solution, which explained nearly 59% of the variation. The profiles for the resulting three clusters are displayed pictorially in Figure 3. The six emergent themes (i.e., student-centeredness, enthusiastic about teaching, ethicalness, classroom and behavior management, teaching methodology, and knowledge of subject) are presented on the horizontal axis, whereas the proportion of students who provided an attribution reason belonging to each theme is presented on the vertical axis. As can be seen in Figure 3, preservice teachers' perceptions of characteristics of effect teachers were represented by the following three meta-themes: (a) classroom atmosphere (comprising the classroom and behavior management and enthusiasm for teaching themes); (b) knowledge of subject and student (comprising the knowledge of subject and student-centeredness themes); (c)

ethicalness (comprising the ethicalness theme); and (d) teaching methodology (comprising the teaching methodology theme). Using Tufte's (2006) fundamental principles of analytical design, the two profile graphics are designed to provide multiple sources of information based on these six ideas: (a) comparison; (b) structure and explanation; (c) multivariate analysis; (d) integration of evidence; (e) documentation; and (f) content.

Figure 3. *Average profiles relating to preservice teachers' perceptions of the characteristics of effective teachers: Graphical display of qualitized data.*
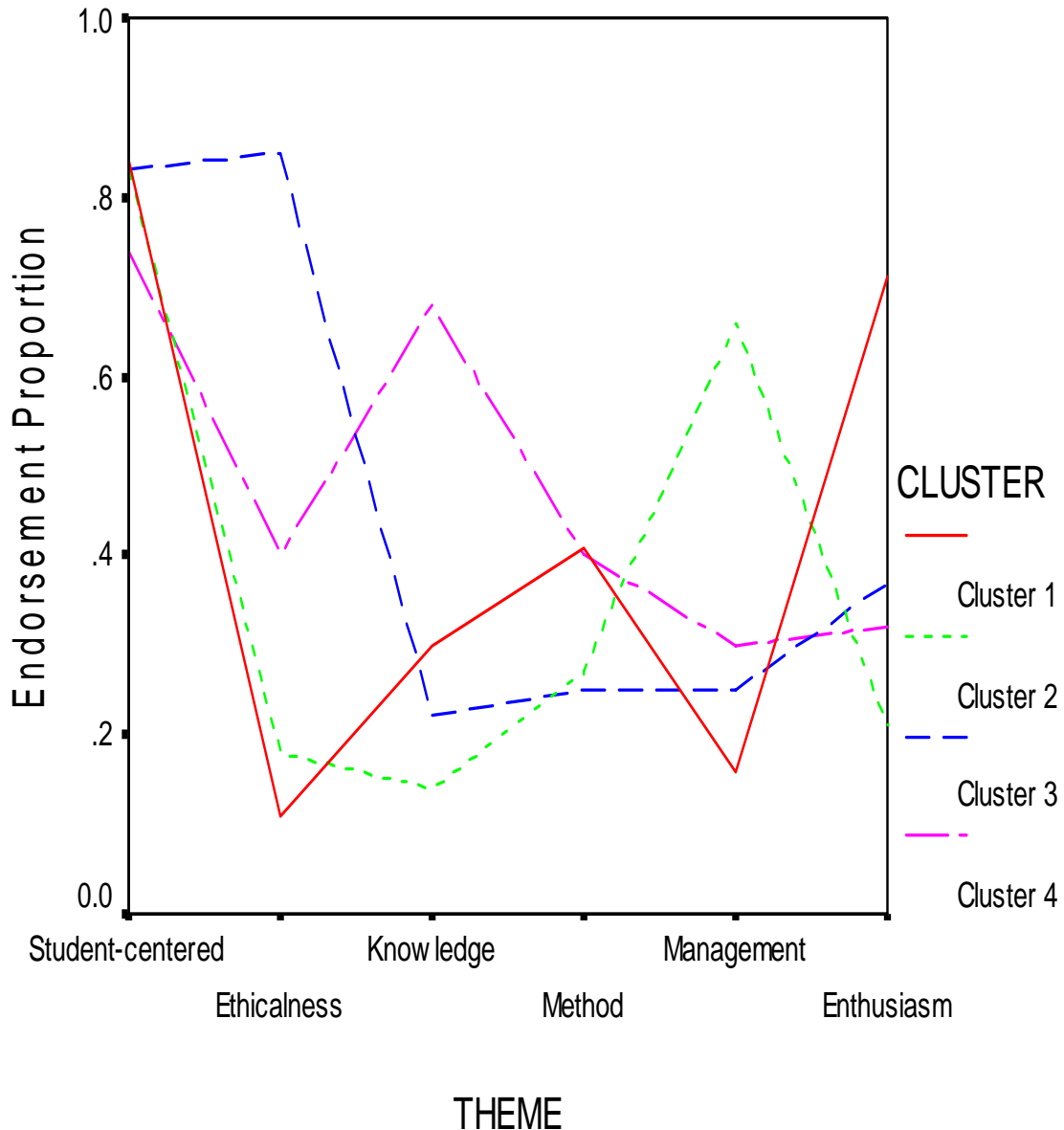
This figure was adapted from Witcher et al. (2001). Reprinted with kind permission of the Mid-South Educational Research Association and the Editors of *Research in the Schools*.

Archival Data Map: The Broad Street Pump

The Broad Street Pump (Figure 4), rendered by Dr. John Snow, documents an "early use of a map to chart patterns of disease" (Tufte, 2001, p. 24). It was 1854, and central London was beset by a cholera outbreak within the Golden Square neighborhood. The exact cause of cholera was still unknown, and Dr. Snow decided he "would try to find the killer through an indirect route: by looking at the patterns of lives and deaths on the streets of Golden Square" (Johnson, 2006, p. 100). Dr. Snow used a map of the London neighborhood as a geographical matrix, recording the location of each death with a dot, and marking the location of each water pump, by street, with an X. A city-wide, sanitary public water system was not in place in London, so the inhabitants relied on water drawn up from these public wells by a hand-pump. He noticed the largest number of deaths occurring on Broad Street, which had its own water pump. The number of deaths was described as follows,

> In Broad Street, on Monday evening, when the hearses came round to remove the dead, the coffins were so numerous that they were put on top of the hearses as well as inside. Such a spectacle has not been witnessed in London since the time of the plague. (Johnson, 2006, p. 109)

By examining the dot pattern of deaths by location, Snow "observed that cholera occurred almost entirely among those who lived near (and drank from) the Broad Street Pump" (Tufte, 2001, p. 24). Snow called for the removal of the handle from the Broad Street Pump (so that people could not raise up water from the well). This simple action effectively ended the cholera outbreak in London; an outbreak that had caused in excess of 500 deaths.

Within this graph, we see all six of Tufte's (2006) principles*:* comparison, structure and explanation, multivariate analysis, integration of evidence, documentation, and content. The location of death, location of pumps, and number of deaths provide documentation of multivariate data from the cholera outbreak, whereas the dot pattern of death-by-location integrates the evidence and provides both narrative content and a visual basis for comparison.

Figure 4. *Broad Street pump.*

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Trends in Methamphetamine Abuse: Mapping Clandestine Activity and Seizure Across the United States

Dickinson et al. (2006) provide a very contemporary illustration of a crossover (mixed research) graphical display. By combining data from two sources, the National Clandestine Laboratory Database and the Drug Enforcement Agency (DEA) website, these researchers developed a visual inventory representing both frequency and location of illicit laboratory activity across the United States, combining quantitative information

with geographical referents to create a summative visual mapping of illicit drug activity. The raw data pertaining to the number of kilograms of methamphetamine (meth) seized and number of laboratories seized by the state are shown in Table 2. The researchers reported a statistically significant and large positive relationship between the number of kilos of meth seized and the number of meth labs seized ($r_s = .53$, $p < .0001$).

Table 2

Numeric Summary of Drug and Laboratories Seizures by State

State	Kilos Seized 2005	Labs seized 2005	State	Kilos Seized 2005	Labs seized 2005
AR	22.9	346	MT	6.1	25
AK	1.5	37	NC	16.1	322
AL	51	248	ND	3.8	163
AZ	551.3	76	NE	22.4	223
CA	1508.7	433	NH	0	6
CO	34.1	145	NJ	10.2	3
CT	0.9	3	NM	78.6	29
DE	0.2	0	NV	59.5	50
FL	37	230	NY	9.5	20
GA	218.1	130	OH	3.6	316
HI	91.6	6	OK	30.7	220
IA	24.6	719	OR	49.7	130
ID	11.1	21	PA	32.6	63
IL	14.2	917	RI	0	0
IN	35.1	880	SC	11.4	88
KS	123.9	353	SD	2	16
KY	5.8	563	TN	15.7	786
LA	8.5	98	TX	970.9	250
MA	0.7	3	UT	49.3	38
MD	0.7	2	VA	17.8	50
ME	0	3	VT	0	1
MI	356.5	342	WA	74.4	500
MN	49.6	88	WI	0.2	55
MO	23.8	2151	WV	1.9	212
MS	54.3	173	WY	1.8	9

Although providing useful information, knowledge that there was a large relationship between these two indices of meth seizure did not help the researchers identify which states experience the most/least meth activities. Therefore, they utilized surface maps to combine a geographic map of the United States with the corresponding frequencies of clandestine methamphetamine laboratories and drug seizures by state. The frequency of the labs by state was displayed by the height of each graphical element (spike). In each graph, there was one spike drawn per state, as state represented the unit

of analysis. The composite visual mapping for clandestine laboratory seizures by state and methamphetamine seizures by state, in kilos, is shown in Figure 5.

Figure 5. *Clandestine methamphetamine laboratories and kilo seizures.*
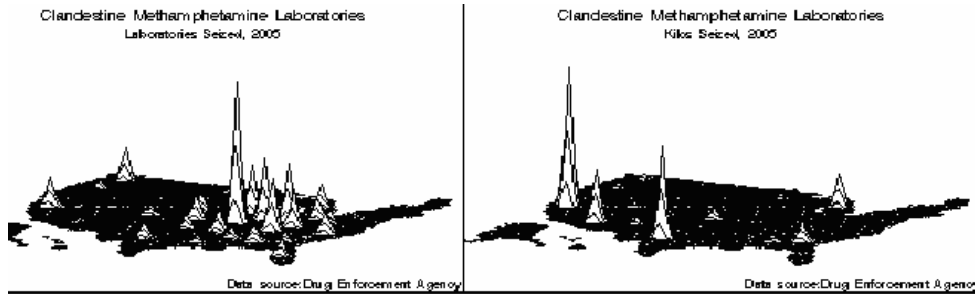
SOURCE: This figure was reproduced from Dickinson et al. (2006). Reprinted with kind permission of SAS Institute..

From these visual mappings, Dickinson et al. extracted three themes. The first theme was a Border theme, wherein the states that experienced a large number of kilos seized represented Border states (i.e., California, Texas, Arizona, Michigan, and Georgia, respectively). The second theme was a Midwest theme, wherein the states that experienced a large number of labs seized tended to represent the Midwest (i.e., Missouri, Illinois, Indiana, and Iowa, respectively). The third theme was a New England theme, wherein New England states had the least number of combined laboratory and drug seizures. Consequently, this graphical technique led to the identification of the geographic patterns of drug use and illicit laboratory activities that were not readily apparent from the numeric format. In addition to providing valuable information that could help guide law enforcement agencies in determining how to allocate resources to address these illegal drug activities, the visual mapping provided important research questions that should be the subject of future studies that employ qualitative techniques, such as the following: Why did Border states experience the largest number of kilos seized? Why did Midwestern states experience the largest number of labs seized? Why did New England states experience the least number of combined laboratory and drug seizures? As such, the visual mapping provided an important bridge between quantitative and qualitative research approaches, thereby promoting mixed research procedures.

Conclusions

An area of concern in pictorial graphics is the idea of scaling. In art, scaling refers to the relationship between an object and the way the object is depicted. In graphics, scaling refers to the relationship between the data and the manner in which the data are depicted. Tufte (1997a) refers to the "constant scale factor" (p. 19) as an ideal way to depict accurately data in a graphical format. By using the idea of a constant scale factor, we can accurately (and representatively) depict both the amount and meaning that our data indicate. Thus, a possible limitation can be controlled for in our graphical representations.

Graphs, like other communication forms, serve different purposes, with the most common goals being visual summary and exposure (Friendly, 1995). Summary refers to the visual inventory of data created to present the viewer with an informed understanding of the underlying information. Depending on the initial format or source, visual summary may embrace a variety of structural composites. Powsner and Tufte (1997) advocated the creation of effective visual summaries, while encouraging the researcher to retain a diversity of methods for data representation. Exposure refers to the illustration of narrative meaning within an image (Dickinson et al., 2006). Narrative meaning helps provide evidence and confirmation for research efforts. Tufte (2006) reports, "Evidence that bears on questions of any complexity typically involves multiple forms of discourse; …whether words, numbers, images, or diagrams, still or moving" (p. 9). Graphical display, like mixed research designs, provides this essential multiplicity of investigation, form, and discourse. Thus, combining graphical display with these multiple modes of inquiry enhances the narrative power of both.

Wainer reminds us of the power of graphical displays, stating the "unrelenting forcefulness inherent in the character of a good graphic is its greatest virtue" (1992, p. 14). Graphical displays can help us discover patterns and recognize important truths about our data not readily apparent in a table or text. Graphs can easily show us elements that might not have been seen otherwise (Wainer, 1990).

As Tukey (1989) declared, the greatest possibilities of visual display lie in the vibrancy and the accessibility of the intended message. Facilitating the graphical delivery of this message is crucial for dissemination of mixed research results. By continuing to develop new, non-text visual methods for mixed methods data display, we aid in the expansion of the visual display knowledge base.

A perusal of the majority of quantitative and qualitative articles published in journals representing the social and behavioral sciences reveals scant use of graphical displays. In quantitative research articles, data displays typically are limited to tables (i.e., level 2), whereas in qualitative research, data displays usually are represented, at best, by text-tables (i.e., level 3). In general, quantitative researchers have an over-reliance in presenting numbers in raw form (i.e., with or without tables), whereas qualitative researchers have an over-dependence in presenting text in raw form (i.e., often without tables). Yet, as noted earlier, the extensive use of numbers and text can yield cognitive overload. Moreover, the tradition of presenting data in the form of raw numbers and/or text is occurring despite the advances in technology (e.g., ability of software to generate complex graphical representations). Thus, we believe that with a few notable exceptions (e.g., visual anthropology), in the social and behavioral science field, in general, the visual representation of data by researchers is lagging far behind the technological advances.

Within the space of merely 100 years, fields such as aerospace (originating circa 1903) have left our social and behavioral science field far behind with respect to the representation of data. Our ability to improve the appropriateness and meaningfulness of our data interpretations will depend, to a large part, on our ability to improve the quality of information visualization in our field by keeping pace with rapid technological innovation. For example, geographic information system (GIS) can play an important role in social and behavioral science research by helping researchers to think spatially. GIS can integrate, relate, and accentuate many forms of data with a spatial component,

regardless of the source of the data. For instance, in the field of education, an array of quantitative and qualitative school-based variables (e.g., achievement, attitudes, perceptions, attendance, suspension/expulsion, ethnic composition, socioeconomic status) can be integrated with GIS to enhance researchers' understanding of phenomena by providing more context. In the field of sociology, researchers could use GIS, or other graphing applications, to map immigration activity across the United States over a period of time (see, for e.g., Dickinson, Hines, & Onwuegbuzie, 2007), and then link these data to other quantitative- and/or qualitative-based sociological data (e.g., housing, health, income and poverty, labor force participation, wealth distribution, social justice, marriage quality, social structure, social transformation, religion).

  In addition to GIS, other visual representations can be used to enhance the analysis of quantitative and/or qualitative data, such as hierarchical clustering, dendograms, multidimensional scaling, proximity plots, heatmaps, and correspondence analysis (see, for e.g., Dickinson & Hall, 2008). These analyses can be used to facilitate both case-oriented analyses (i.e., analyses that focus primarily on the selected case(s), which have a tendency toward particularizing and analytical generalizations; Onwuegbuzie, Slate, Leech, & Collins, 2008) and variable-oriented analyses (i.e., analyses that involve identifying relationships, often probabilistic in nature, among entities, which are conceived as variables, and which have a proclivity toward statistical generalizations; Onwuegbuzie et al., 2008). Space prevents us from providing more detail about these and other visual representations. However, many of these visual representations are discussed in Onwuegbuzie, Collins, Leech, and Slate (in press). In any case, the use of such visual displays goes far beyond the reporting of *p*-values and effect sizes in quantitative research and the documentation of themes and quotations in qualitative research.

  In an era wherein technology in general, and computers and computer software in particular dominate our lives,

> the way we think about what and how and why we are generating data *must* be addressed in a large way so that countless decisions can be made to move the ball forward in terms of real lives, not mere academic doodling. (Dr. Joseph Yeager, personal communication, September 4, 2007)

Moreover, the use of visual representations can help researchers take more of a bird's eye view of research data and findings, by allowing interpretations to be made in a larger context of information science and data displays used for decision making (Dr. Joseph Yeager, personal communication, November 19, 2007). In turn, the ability to take a bird's eye view of research data and findings can transform a researcher from being a passive transmitter of knowledge, who collects and analyzes data that merely are archived, to an active researcher who co-constructs knowledge with research participants via information visualization techniques; knowledge that is used in action-oriented decision environments.

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Article Citation

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*(2), 204-225. Retrieved from http://www.nova.edu/ssss/QR/QR13-2/onwuegbuzie.pdf