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Towards Full (er) Integration in Mixed Methods Research: The Role of Canonical Correlation Analysis for Integrating Quantitative and Qualitative Data

Hacia la plena integración en la investigación con métodos mixtos: El papel del análisis de correlación canónica en la integración de datos cuantitativos y cualitativos

在混合方法研究中实现全面整合：典型相关分析在整合定量和定性数据中的作用

На пути к полной интеграции в исследованиях смешанных методов: Роль канонического корреляционного анализа для интеграции количественных и качественных данных

Anthony J. Onwuegbuzie
University of Cambridge
tonyonwuegbuzie@aol.com
https://orcid.org/0000-0002-4569-5796

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Abstract

One of the biggest developments in mixed methods research has been the conceptualization of one or more analysis types associated with one tradition (e.g., qualitative analysis) being used to analyze data associated with a different tradition (e.g., quantitative data)—what Onwuegbuzie and Combs (2010) called *crossover mixed analyses*, or, more simply, *crossover analyses*. A hallmark of crossover analyses is the notion of *quantitizing*, which, in its simplest form, involves converting qualitative data into numerical forms that can be analyzed statistically. The focus on quantitizing has been on *descriptive-based quantitizing* approaches such as counting the occurrence of emergent themes. Unfortunately, scant guidance exists on *inferential-based quantitizing*, which refers to the quantitizing of qualitative data for the purpose of prediction or estimation (Onwuegbuzie, in press). Although recent literature has emerged on a few inferential-based quantitizing approaches (i.e., multiple linear regression analysis, structural equation modeling, hierarchical linear modeling), there still remains some general linear model analyses for which mixed methods researchers, in pursuit of conducting crossover analyses, can benefit from guidelines. One such analysis is canonical correlation analysis. Its importance stems from the fact that the analysis of qualitative data typically yields multiple patterns of meaning (e.g., codes, themes), which then can be correlated with other available variables (e.g., demographic variables, personality variables, affective variables) via the use of canonical correlation analysis. Therefore, the purpose of this article is (a) to describe canonical correlation analysis and (b) to illustrate how canonical correlation analyses can serve as an inferential-based quantitizing using a heuristic example.

Keywords: emergent themes, mixed methods research, descriptive-based quantitizing, exploratory-based quantitizing, inferential-based quantitizing, measurement-based quantitizing, canonical correlation analysis, 1 + 1 = 1 integration approach, full(er) integration.

Resumen

Uno de los mayores avances en la investigación con métodos mixtos ha sido la conceptualización de uno o más tipos de análisis asociados con una tradición (por ejemplo, el análisis cualitativo) que se utilizan para analizar datos asociados con una tradición diferente (por ejemplo, datos cuantitativos), lo que Onwuegbuzie y Combs (2010) denominaron análisis mixtos cruzados o, más sencillamente, análisis cruzados. Una característica distintiva de los análisis cruzados es la noción de cuantificación, que, en su forma más simple, implica la conversión de datos cualitativos en formas numéricas que puedan analizarse estadísticamente. La cuantificación se ha centrado en enfoques descriptivos, como el recuento de temas emergentes. Lamentablemente, apenas existen orientaciones sobre la cuantificación inferencial, que se refiere a la cuantificación de datos cualitativos con fines de predicción o estimación. Aunque ha aparecido literatura reciente sobre unos pocos enfoques de cuantificación basados en la inferencia (es decir, análisis de regresión lineal múltiple, modelización de ecuaciones estructurales, modelización lineal jerárquica), todavía quedan algunos análisis de modelos lineales generales para los que los investigadores de métodos mixtos, en la búsqueda de la realización de análisis cruzados, pueden beneficiarse de las directrices. Uno de estos análisis es el análisis de correlación canónica. Su importancia radica en el hecho de que el análisis de datos cualitativos suele arrojar múltiples patrones de significado (ej., códigos, temas), que luego pueden correlacionarse con otras variables disponibles (ej., variables demográficas, variables de personalidad, variables afectivas) mediante el uso del análisis de correlación canónica. Por lo tanto, el propósito de este artículo es (a) describir el análisis de correlación canónica e (b) ilustrar cómo los análisis de correlación canónica pueden servir como cuantificación basada en la inferencia utilizando un ejemplo heurístico.

Palabras clave: temas emergentes, investigación con métodos mixtos, cuantificación basada en la descripción, cuantificación basada en la exploración, cuantificación basada en la inferencia, cuantificación basada en la medición, análisis de correlación canónica, enfoque de integración 1 + 1 = 1, integración(es) completa(s).

概要

混合方法研究的最大发展之一是将与一种传统（例如，定性分析）相关的一种或多种分析类型概念化，用于分析与不同传统（例如，定量数据）相关的数据——Onwuegbuzie 和 Combs（2010）称为交叉混合分析，或者更简单地说，交叉分析。交叉分析的一个标志是量化的概念，其最简单的形式涉及将定性数据转换为可以进行统计分析的数字形式。量化的重点是基于描述的量化方法，例如计算出现的主题。不幸的是，基于推理的量化缺乏指导，推理量化是指为了预测或估计的目的对定性数据进行量化（Onwuegbuzie，出版中）。尽管最近出现了一些基于推理的量化方法（即多元线性回归分析、结构方程建模、层次线性建模）的文献，但仍然存在一些通用线性模型分析，混合方法研究人员在进行交叉分析时进行分析，　可以从指南中受益。一种这样的分析是典型相关分析。它的重要性源于这样一个事实，即定性数据的分析通常会产生多种意义模式（例如，代码、主题），然后可以通过使用将其与其他可用变量（例如，人口变量、性格变量、情感变量）相关联典型相关分析。因此，本文的目的是 (a) 描述典型相关分析和 (b) 使用启发式示例说明典型相关分析如何用作基于推理的量化。

关键词：新兴主题，混合方法研究，基于描述的量化，基于探索的量化，基于推理的量化，基于测量的量化，典型相关分析，1 + 1 = 1 整合方法，全整合.

Аннотация

Одним из самых значительных достижений в области исследований смешанных методов стала концептуализация одного или нескольких видов анализа, связанных с одной традицией (например, качественный анализ), которые используются для анализа данных, связанных с другой традицией (например, количественных данных) - то, что Onwuegbuzie и Combs (2010) назвали перекрестным смешанным анализом, или, проще говоря, перекрестным анализом. Отличительной чертой перекрестного анализа является понятие квантификации, которое в своей простейшей форме предполагает преобразование качественных данных в числовые формы, которые могут быть проанализированы статистически. Основное внимание при количественном анализе уделялось количественным подходам, основанным на описательном подходе, таким как подсчет встречаемости возникающих тем. К сожалению, существует мало рекомендаций по количественному анализу на основе инференции, который относится к количественному анализу качественных данных с целью прогнозирования или оценки. Хотя в последнее время в литературе появилось несколько подходов к количественной оценке на основе инференции (например, множественный линейный регрессионный анализ, моделирование структурных уравнений, иерархическое линейное моделирование), все еще остаются некоторые общие линейные модельные анализы, для которых исследователи смешанных методов, стремящиеся провести перекрестный анализ, могут воспользоваться рекомендациями. Одним из таких анализов является канонический корреляционный анализ. Его важность обусловлена тем, что анализ качественных данных, как правило, дает множество моделей смысла (например, коды, темы), которые затем могут быть соотнесены с другими доступными переменными (например, демографическими переменными, переменными личности, аффективными переменными) с помощью канонического корреляционного анализа. Поэтому целью данной статьи является (а) описание канонического корреляционного анализа и (б) иллюстрация того, как канонический корреляционный анализ может служить в качестве квантификации на основе инференции на эвристическом примере.

Ключевые слова: эмерджентные темы, смешанные методы исследования, квантификация на основе описаний, квантификация на основе исследований, квантификация на основе заключений, квантификация на основе измерений, канонический корреляционный анализ, подход интеграции 1 + 1 = 1, полная(эр) интеграция.

As described by Onwuegbuzie (2022) during an invited public lecture honouring the memory and work of the late Dr. Vimala Judy Kamalodeen—a prolific mixed methods researcher—the origin of mixed methods research can be traced back to what Johnson and Gray (2010) referred to as *proto-empiricists*. Essentially, these proto-empiricists—which included Aristotle [384-322 BCE]—were realists who posited that the goal of inquiry was to obtain understandings of what humans observe and experience in their everyday lives. More specifically, they championed reliance on deduction, induction, dialectics, and opinion as potentially complementary approaches to understanding; they also viewed intersubjectivity as representing an essential component of truth. These proto-empiricists later paved the way for the *proto-mixed methods* movement, who adopted a middle position between the

(proto-) quantitative and *(proto-) qualitative* stances by adopting standpoints such as knowledge construction emanates from the combination of reason and imagination (Johnson & Gray, 2010). In the Western world, this proto-mixed methods movement, although representing a minority position compared to both the (proto-)quantitative and (proto-)qualitative movements, continued to occupy this middle position throughout the *middle ages* (circa 5th century to 16th century) and the *modern times* (circa 17th century to early 20th century) that included part of the *Renaissance period* (i.e., circa 17th century), the *Enlightenment period* (i.e., circa 17th century through the late 18th century), and the *Romantic period* (i.e., circa late 18th century through mid-19th century).

During the modern times, the use of quantitative and qualitative strategies within the same inquiry occurred more in the natural sciences than in the social sciences (Maxwell, 2016). For instance, as noted by Maxwell (2016), during these modern times, the fields of astronomy (e.g., Galileo's use of observational description and mathematics to demonstrate that sunspots actually were characteristics of the sun, instead of planets) and geology (e.g., Charles Lyell's classification of the chronological order of different European rock strata) provide some examples of the use of qualitative and quantitative approaches within the same investigation, as did the fields of medicine and epidemiology.

With respect to the social and behavioral sciences, Hesse-Biber (2010) traced the use of both qualitative and quantitative research approaches in modern times back to LePlay's (1855) studies of poverty among families in Europe. Another notable use of both qualitative and quantitative research approaches was W. E. B. DuBois's (1899) study, which represents "one of the first works to combine urban ethnography, social history, and descriptive statistics" (Anderson, 1996, p. ix).

With the formal emergence of the social and behavioral sciences at the turn of the 20th century (Onwuegbuzie et al., 2022; Teddlie & Johnson, 2009), the number of studies involving the use of both qualitative and quantitative research approaches increased significantly, although they still represented the minority of empirical research studies. However, it was not until 1972 that the first mixed methods-declared work, across all fields and disciplines, which was identified by Collins et al. (2007) (i.e., Parkhurst et al., 1972), was published. This work represented the field of education. In the 50 years that have followed, the publication of mixed methods-declared works has increased exponentially (Onwuegbuzie et al., 2023). During these 50 years, the use of mixed methods research has evolved substantially. One of the biggest developments has been the conceptualization of one or more analysis types associated with one tradition (e.g., qualitative analysis) being used to analyze data associated with a different tradition (e.g., quantitative data)—what Onwuegbuzie and Combs (2010) coined as "cross-over mixed analyses" (p. 422)—hereafter referred to as *crossover mixed analyses*, or, more simply, *crossover analyses*. As identified by Onwuegbuzie and Combs (2010), crossover analyses can be used to reduce, to display, to transform, to correlate, to consolidate, to compare, to integrate, to assert, or to import data—yielding nine crossover analysis types, which are presented in Table 1.

Table 1

Crossover Mixed Analysis Strategies

Analysis Step	Cross-Case Analysis Strategy
Integrated Data Reduction	Reducing the dimensionality of qualitative data/findings using quantitative analysis (e.g., exploratory factor analysis of qualitative data) and/or quantitative data/findings using qualitative techniques (e.g., thematic analysis of quantitative data) (Onwuegbuzie, 2003; Onwuegbuzie & Teddlie, 2003)
Integrated Data Display	Visually presenting both qualitative and quantitative results within the same display (Lee & Greene, 2007; Onwuegbuzie & Dickinson, 2008)
Data Transformation	Converting quantitative data into data that can be analyzed qualitatively (i.e., *qualitizing* data; Tashakkori & Teddlie, 1998), and/or qualitative data into numerical codes that can be analyzed statistically (i.e., *quantitizing* data; Tashakkori & Teddlie, 1998)
Data Correlation	Correlating qualitative data with quantitized data and/or quantitative data with qualitized data (Onwuegbuzie & Teddlie, 2003)
Data Consolidation	Combining or merging multiple data sets to create new or consolidated codes, variables, or data sets (Louis, 1982; Onwuegbuzie & Teddlie, 2003)
Data Comparison	Comparing qualitative and quantitative data/findings (Onwuegbuzie & Teddlie, 2003)
Data Integration	Integrating qualitative and quantitative data/findings either into a coherent whole or two separate sets (i.e., qualitative and quantitative) of coherent wholes (McConney, Rudd, & Ayres, 2002; Onwuegbuzie & Teddlie, 2003)
Warranted Assertion Analysis	Reviewing all qualitative and quantitative data to yield meta-inferences (M. L. Smith, 1997)

Analysis Step	Cross-Case Analysis Strategy
Data Importation	Utilizing follow-up findings from qualitative analysis to inform the quantitative analysis (e.g., qualitative contrasting case analysis, qualitative residual analysis, qualitative follow-up interaction analysis, and qualitative internal replication analysis; Li, Marquart, & Zercher, 2000; Onwuegbuzie & Teddlie, 2003) or follow-up findings from quantitative analysis to inform the qualitative analysis (e.g., quantitative extreme case analysis, quantitative negative case analysis; Onwuegbuzie & Teddlie, 2003)

Note. Adapted from "Emergent Data Analysis Techniques in Mixed Methods Research: A Synthesis," by A. J. Onwuegbuzie and J. P. Combs, 2010, *Handbook of mixed methods in social and behavioral research,* p. 422. Copyright 2010 by Sage Publications.

The hallmarks of crossover analyses are the notion of *qualitizing* and *quantitizing*. The technique of *qualitizing* involves transforming quantitative data into a qualitative form (e.g., obtaining narratives to explore the meaning of numerical data; Onwuegbuzie and Teddlie, 2003; Sandelowski et al., 2009; Tashakkori & Teddlie, 1998) that can be analyzed qualitatively. An effective way of qualitizing data is via narrative profile formation (Tashakkori & Teddlie, 1998), wherein narrative descriptions are constructed from quantitative data. Narrative profile formation includes modal profiles, average profiles, holistic profiles, comparative profiles, and normative profiles. Broadly speaking, modal profiles are detailed narrative descriptions of a group of individuals, which are based on the most commonly occurring attributes in the group that they represent. Holistic profiles are the overall impressions of the researcher(s) relating to the unit of investigation. Average profiles represent profiles that are based on the mean (i.e., average) number of attributes of the individuals or situations. Comparative profiles are formed by comparing one unit of analysis to one or more other units, and includes possible similarities/differences between/among them. Finally, normative profiles are similar to narrative profiles; however they are obtained by comparing an individual or a group to some standard, such as a normative group (Onwuegbuzie & Teddlie, 2003; Tashakkori & Teddlie, 1998). Very recently, Onwuegbuzie and Leech (2019) expanded the definition of qualitizing wherein qualitizing can involve five major elements (Onwuegbuzie & Leech, 2021). Specifically, qualitizing:

1. can yield numerous representations,
2. can stem not only from quantitative data but also from qualitative data,
3. can involve qualitative analyses and/or quantitative analyses,
4. can involve a single analysis or multiple analyses, and
5. can yield a fully integrated analysis.

In other words, Onwuegbuzie and Leech's (2019) comprehensive definition of qualitizing is as follows:

> The technique of qualitizing involves transforming data into qualitative form. The data that are qualitized can either stem directly from quantitative data, or from qualitative data that are converted to numeric form (i.e., quantitized), or both. The qualitizing process can involve one or more qualitative analysis and/or one or more quantitative analysis (e.g., descriptive analyses, exploratory analyses, inferential analyses) that represent either a single analysis (i.e., single qualitizing) or multiple analyses (i.e.,

> multi-qualitizing*)*, which, optimally, involves the full integration of qualitative and quantitative research approaches (i.e., 1 + 1 = 1 integration formula) that yield fully integrated analysis. Some form of qualitizing can be undertaken by quantitative researchers, qualitative researchers, and mixed researchers that represent a variety of ontological, epistemological, and methodological assumptions and stances. The qualitizing process can yield numerous representations that include codes, categories, sub-themes, themes, figures of speech, meta-themes, and narratives (i.e., prose or poetry). (p. 122)

In contrast, in its simplest form, *quantitizing* involves converting qualitative data into numerical codes or representations that can be analyzed statistically (Miles & Huberman, 1994; Onwuegbuzie & Teddlie, 2003; Sandelowski et al., 2009; Tashakkori & Teddlie, 1998). Recently, Onwuegbuzie (in press) and Onwuegbuzie and Johnson (2021a) deconstructed quantitizing into the following four types that potentially are available for use as part of the meaning-making process: *descriptive-based quantitizing*, *exploratory-based quantitizing*, *measurement-based quantitizing*, and *inferential-based quantitizing*. Broadly speaking, descriptive-based quantitizing represents quantitizing that involves the use of descriptive analyses that are characterized by the following four measures: measures of central tendency (e.g., mean, median, mode), measures of variation/dispersion (e.g., range, standard deviation, variance, interquartile range), measures of position/relative standing (e.g., percentile, quartile, decile, z score, t score), and measures of distributional shape (e.g., skewness, kurtosis) (Onwuegbuzie & Johnson, 2021a). Exploratory-based quantitizing refers to the quantitizing of qualitative data in order to identify group membership, whereby the grouping could be participants or variables (Onwuegbuzie & Johnson, 2021a). This form of quantitizing can be utilized via analyses such as exploratory factor analysis, correspondence analysis, cluster analysis, multidimensional scaling, and spatial analysis. Measurement-based quantitizing involves the quantitizing of qualitative data for the purpose of instrument development or construct validation. This type of quantitizing can be employed via analyses such as confirmatory factor analysis, Rasch analysis, or item response theory. Finally, inferential-based quantitizing refers to the quantitizing of qualitative data for the purpose of prediction or estimation. This class of quantitizing can be conducted via analyses such as analyses (e.g., multiple regression, structural equation modeling) that are of the general linear model (GLM).

Over the last quarter of a century, the focus on quantitizing has been on descriptive-based quantitizing techniques such as counting the occurrence of emergent codes, categories, sub-themes, themes, and meta-themes (Miles & Huberman, 1994; Tashakkori & Teddlie, 1998). As a result, scant guidance is available from the literature on the other types of quantitizing techniques (i.e., exploratory-based quantitizing, measurement-based quantitizing, and inferential-based quantitizing). Enter *The Routledge Reviewer's Guide to Mixed Methods Analysis*! As the title suggests, this book—edited by Onwuegbuzie and Johnson (2021b)—is the first book that is devoted solely to mixed analyses. The biggest section of the four sections of this book is the first section, which is represented by 11 of the 30 chapters in the book, and which is entitled, *Quantitative Approaches to Qualitative Data*—or what can be referred to as *qualitative-dominant crossover mixed analyses*. These 11 chapters comprise exploratory-based quantitizing of qualitative data (i.e., exploratory factor analysis, correspondence analysis, multidimensional scaling, cluster analysis), measurement-based quantitizing of qualitative data (i.e., item response theory), and inferential-based quantitizing of qualitative data (i.e., chi-square automatic interaction detection analysis, multiple linear regression analysis, structural equation modeling, hierarchical linear modeling, Bayesian analyses, diachronic analysis). Although there are six outstanding chapters representing inferential-based quantitizing, only three of them (i.e., multiple linear regression analysis, structural equation modeling, hierarchical linear modeling) represent commonly used GLM analyses. Consequently, there still remain some GLM analyses for which mixed methods researchers, in pursuit of conducting crossover analyses, can benefit from guidelines. One such analysis is canonical correlation analysis. Indeed, canonical correlation analysis has been found to play an especially important role in promoting full(er) integration in mixed methods research studies (Anderson et al., 2012; Benge et al., 2010; Burgess et al., 2012; Daley & Onwuegbuzie, 2004; McClure et al., 2021; Onwuegbuzie & Ojo, 2021; Onwuegbuzie et al., 2007, 2020; Witcher et al., 2001, 2008). Its importance stems from the fact that the analysis of qualitative data—which often represents the starting point for a quantitative-dominant crossover mixed analysis—typically yields two or more patterns of meaning (e.g., codes, categories, sub-themes, themes, meta-themes). These multiple patterns of meaning then can be correlated with other available variables (e.g., demographic variables [e.g., gender, race/ethnicity]; personality variables [e.g., resilience]; affective variables [e.g., motivation]; nonverbal communication variables [e.g., proxemics, chronemics, kinesics]) via the use of canonical correlation analysis. Therefore, the purpose of the remainder of this article is (a) to describe canonical correlation analysis and (b) to illustrate how canonical correlation analyses can serve as an inferential-based quantitizing using a heuristic example.

Canonical Correlation Analysis

Canonical correlation analysis is a statistical approach that is used to examine the multivariate relationship between two sets of variables wherein both sets contain at least two variables (Cliff & Krus, 1976; Darlington et al., 1973; Onwuegbuzie & Daniel, 2003; Thompson, 1984, 1991). As such, this analysis represents a multivariate statistical analysis. Because it is a multivariate analysis member of the GLM, it can be used to conduct all univariate statistical analyses that also belong to the GLM. In other words, canonical correlation analysis can be used to undertake all the parametric tests that canonical correlation analysis approaches subsume as special cases, including Pearson correlation, *t* tests, analysis of variance, analysis of covariance, simple linear regression, and multiple regression (Henson, 2000; Roberts & Henson, 2002; Onwuegbuzie & Daniel, 2003; Thompson, 1991). Consistent with this assertion, Knapp (1978) concluded that "virtually all of the commonly encountered tests of significance can be treated as special cases of canonical correlation analysis" (p. 410).

In terms of types of quantitative variables that are eligible for use in a canonical correlation analysis, variables can represent the interval scale of measurement, the ratio scale of measurement, or the nominal scale of measurement—specifically, a dichotomous variable. That is, both the independent (i.e., predictor) variable set and the dependent (i.e., criterion) variable set of any canonical correlation model can contain interval-scaled, ratio-scaled, and/or dichotomous variables. This makes canonical correlation analysis a great choice for explaining or predicting patterns of meaning that are extracted from qualitative data—that is, data stemming from one of the following four sources of qualitative data identified by Leech and Onwuegbuzie (2008): *talk* (e.g., individual-based [interviews] vs. group-based [focus group discussions]; face-to-face vs. virtual; synchronous vs. asynchronous; verbal vs. non-verbal), *observations* (e.g., emic-based vs. etic-based; interactive vs. non-interactive; first-hand vs. second-hand), *documents* (i.e., digital vs. non-digital), and images (e.g., still [e.g., drawings, paintings] vs. moving [e.g., videos]; two-dimensional [e.g., drawings, paintings] vs. multidimensional [e.g., movies]; non-virtual [e.g., drawings] vs. virtual [e.g., I-phone, I-Pad, Youtube, Panoramio, Flickr, iMovie, Instagram]). Specifically, by qualitizing patterns of meaning (e.g., codes, categories, sub-themes, themes, meta-themes) extracted from the qualitative data to dichotomous form, canonical correlation analyses can be used quantitatively to predict or to explain these patterns of meaning. The following section provides an exemplar of the use of canonical correlation analysis in a mixed methods research study further to contextualize themes that emerge from qualitative data (i.e., emergent themes).

Heuristic Example

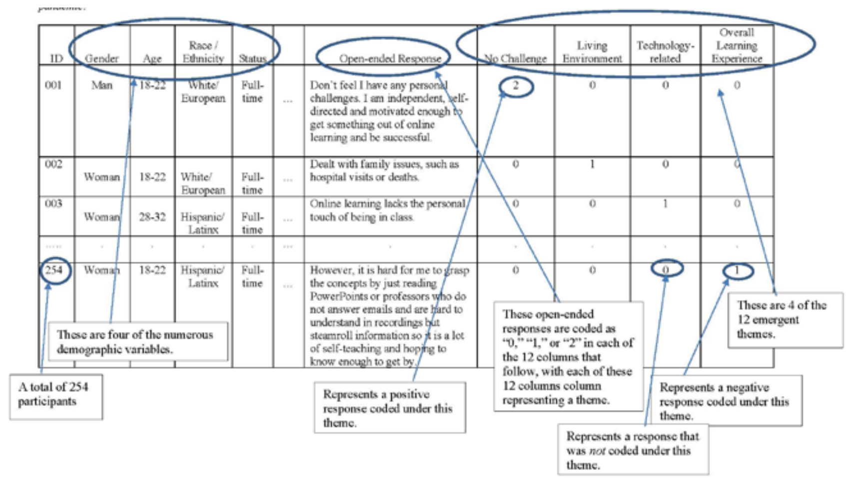
In this section, I provide a real example from the extant literature that exemplifies the use of canonical correlation analysis for the purpose of disaggregating the emergent themes by identifying predictors of these themes. This study represents an investigation conducted by McClure et al. (2021) to examine how the emergency remote teaching and learning that was implemented at a university in New York City in March 2020 due to the COVID-19 pandemic, impacted the students. Specifically, the researchers emailed a Qualtrics survey—containing both closed- and open-ended items—to undergraduate and graduate students at the university that included the following open-ended question: What, if any, challenges did you face that hindered your ability to learn successfully online? A total of 254 students responded.

The students' responses were analyzed via a fully integrated, four-phase mixed methods analysis. During the first phase, constant comparison analysis (Glaser, 1965) was used to analyze the responses to the open-ended question to identify themes. In total, 12 emergent themes were identified. During the second phase, each emergent theme was quantitized by two coders such that if a participant provided a negative response relating to challenges to online learning, then a score of "1" was given to the theme for that response; otherwise, a score of "0" was given. This quantitizing process led to the formation of what Onwuegbuzie (in press) refers to as an intensity-based, inter-respondent matrix of themes (i.e., participant x theme matrix), consisting only of 0s and 1s for each of the 12 emergent themes. Onwuegbuzie (in press) defines an *intensity-based, inter-respondent matrix*, which is a matrix that is used to assess the intensity of a phenomenon, event, incidence, experience, or the like, via participants' responses that are assumed to reflect their individual attitude or opinion and that are coded in a reliable manner. Figure 1 shows a partial intensity-based, inter-respondent matrix provided by McClure et al. (2021) to represent the quantitized data.

During the third phase, the inter-respondent matrix of themes was used to undertake descriptive-based quantitizing. Specifically, descriptive analyses—namely, frequencies and proportions—were used to ascertain the prevalence of the 12 emergent themes. These prevalence rates, respectively, were as follows: No Challenges (34.26%), Living Environment (25.93%), Technology-Related (20.37%), Overall Learning Experience (19.44%), Feelings (12.04%), Professor-Related (9.26%), Motivation (8.33%), Mental Health (7.41%), Time Management (4.63%), Communication (3.70%), Finances (1.85%), and Health-Related (1.85%).

Figure 1

A partial intensity-based, inter-respodent Matrix used to conduct a mixed analysis from responses to the following open-ended survey question: what, if any, challenges did university student in the New York city area experience that hindered their ability successfully to learn online during the COVID-19.



ID	Gender	Age	Race / Ethnicity	Status		Open-ended Response	No Challenge	Living Environment	Technology-related	Overall Learning Experience
001	Man	18-22	White/ European	Full-time	…	Don't feel I have any personal challenges. I am independent, self-directed and motivated enough to get something out of online learning and be successful.	2	0	0	0
002	Woman	18-22	White/ European	Full-time	…	Dealt with family issues, such as hospital visits or deaths.	0	1	0	0
003	Woman	28-32	Hispanic/ Latinx	Full-time	…	Online learning lacks the personal touch of being in class.	0	0	1	0
.....	.	.	.	.	…	.	.	.	.	.
254	Woman	18-22	Hispanic/ Latinx	Full-time	…	However, it is hard for me to grasp the concepts by just reading PowerPoints or professors who do not answer emails and are hard to understand in recordings but steamroll information so it is a lot of self-teaching and hoping to know enough to get by.	0	0	0	1

Note. Adapted from "Online learning challenges experienced by university students in the New York City area during the COVID-19 pandemic: A mixed methods study," by D. R. McClure, E. O. Ojo, M. B. Schaefer, D. Bell, S. S. Abrams, and A. J. Onwuegbuzie, 2021, *International Journal of Multiple Research Approaches, 13*(2), p. 154.

During the fourth phase—the phase of particular interest for the purposes of the present article—the inter-respondent matrix of themes was used to undertake inferential-based quantitizing. As noted by the researchers, the goal of this inferential-based quantitizing was to disaggregate the emergent themes by selected socio-demographic variables via the conduct of a canonical correlation analysis. This analysis was undertaken to examine simultaneously the relationship between six socio-demographic variables (i.e., *gender* [men vs. women]; *age group* [18-37 vs. ≥ 38]; *race* [White vs. Non-White]; *full-time status* [full-time vs. part-time]; *level of student* [undergraduate vs. graduate]; and *technology access* [full access to a computer and reliable Internet vs. not full access to a computer and/or non-reliable Internet]) and the following three most prevalent challenge themes: Living Environment, Technology-Related, and Overall Learning Experience. Now, the number of canonical functions (i.e., factors) that are yielded from a canonical correlation analysis is determined by the number of variables contained in the smaller of the two sets (i.e., independent and dependent set) of variables (Thompson, 1984). As such, because six socio-demographic variables simultaneously were correlated with three themes, a total of three canonical functions were produced. Each of these three canonical functions should be tested for statistical significance (i.e., via *p* values) as well as for practical significance (i.e., via a measure of effect size, namely, the squared canonical correlation coefficient, which explains the proportion of variance in the dependent variable set that are explained by the independent variable set). Each canonical function is associated with unique standardized coefficients and structure coefficients, both of which also facilitate assessment of practical significance (Onwuegbuzie & Daniel, 2003).

When conducting a canonical correlation analysis, it is essential for researchers to report and to interpret both the standardized coefficients and the structure coefficients (Onwuegbuzie & Daniel, 2003; Thompson, 1984). This strategy is important because by comparing these two sets of coefficients, the analyst will be able fully to determine the importance (i.e., significance) of each variable in both variable sets that characterize the canonical correlation solution. These comparison yields four possible outcomes. First, when both the standardized coefficient and the structure coefficient of a variable are large (e.g., ≥ .30), then that variable is considered to be *practically significant*. Second, when both the standardized coefficient and the structure coefficient of a variable are negligible (i.e., near-zero) or even small (e.g., < .30), then that variable is deemed to be *not practically significant*. In other words, that (independent or dependent) variable is considered not to be a practicable predictor of the other (i.e., dependent or independent) set of variables. (Both these scenarios [i.e., both variables practically significant, both variables not practically significant] yield clear interpretations of the canonical correlation model.) Third, if a variable has a trivial/small standardized coefficient but a large structure coefficient, then that variable is deemed to be important in explaining/predicting the variables in the other set; however, that variable is *collinear* with one or more variables from the same set. Finally, if a variable has a trivial/small structure coefficient but a large standardized coefficient, then this indicates that that variable represents what is called a *suppressor variable*. Specifically, suppressor variables are variables that improve the prediction of variables in the other set (i.e., by increasing the effect size) due to their relationship with other variables in the same set (Onwuegbuzie & Daniel, 2003). Alternatively stated, suppressor variables improve the predictive power of the other variables in the same set by suppressing variance that is not relevant to the prediction of the other set of variables, as a result of the suppressor variable's relationship with the other same-set variables.

Figures 2-5 provide screenshots showing how McClure et al. (2021) conducted the canonical correlation analysis via SPSS (version 28). Specifically, Figure 2 shows the path for accessing the canonical correlation analysis dialog box. Figure 3 shows the dialog box for moving the selected variables from the left-hand box to the two boxes on the right-hand side comprising to where the independent variable set (e.g., Set 1) and the dependent variable set (e.g., Set 2) are moved. Figure 4 shows the selected independent variables and dependent variables. Figure 5 shows the available options that the analyst can select for the canonical correlation analysis, such as displaying in the resultant statistical output the coefficients of each of the variables in both sets.

Figure 2

Path for Accessing the Canonical Correlation Analysis Dialog Box

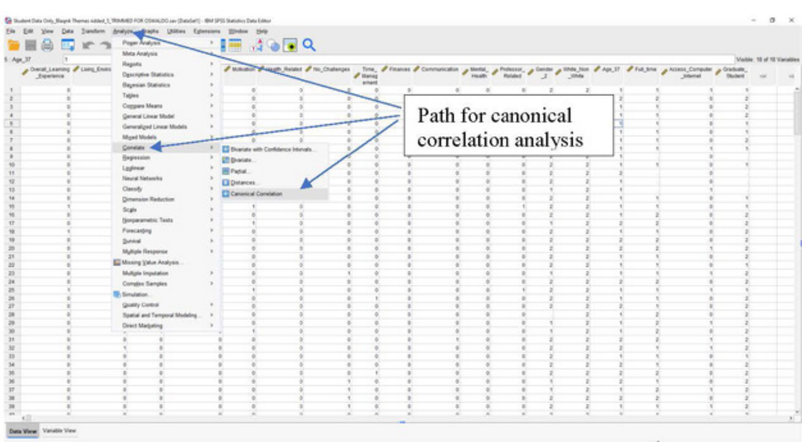


Figure 3

Variables for Selection for the Canonical Correlation Analysis

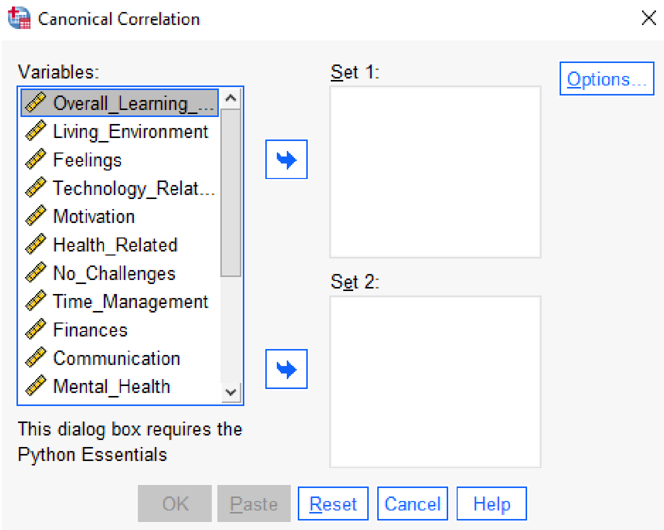


Figure 4

Independent and Dependent Variables Selected for the Canonical Correlation Analysis

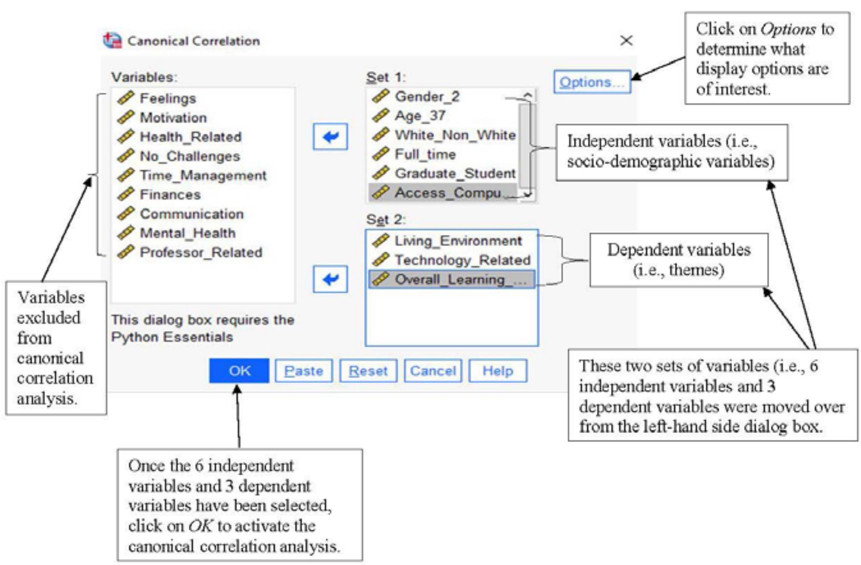
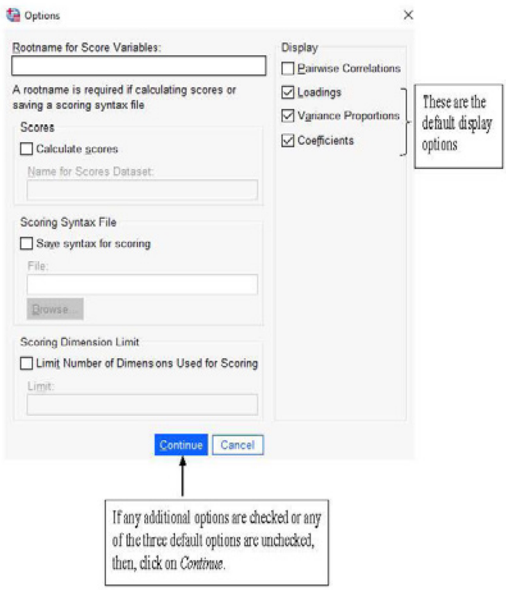


Figure 5

Available Options for the Canonical Correlation Analysis



Rather than conducting a traditional canonical correlation analysis, McClure et al. (2021) conducted what is known as an *all possible subsets* (APS) canonical correlation analysis. This form of analysis involves separate canonical correlation analyses being conducted for all different combinations of variable sets that contain at least two variables, until the best subset of variable sets is identified according to some prespecified criteria (Onwuegbuzie & Daniel, 2003). For this study, the criteria used were Wilks's lambda, the probability level (i.e., *p* value), the squared canonical correlation coefficient (primary effect-size measure), the standardized coefficient for each variable, and the structure coefficient for each variable. This analysis yielded a final canonical correlation solution that involved four socio-demographic variables (i.e., age group, race, student status, technology access) and two emergent themes (i.e., Overall Learning Experience, Technology-Related). Figure 6 shows the final independent variables and dependent variables selected in their dialog boxes. Figure 7 shows the SPSS syntax for this analysis. The useful aspect of this syntax is that all the analyst(s) would need to do is to replace the names of the independent variables and dependent variables with the names of her/his/their variables and then, with the dataset open in SPSS, paste this syntax. Figure 8 shows the path for accessing the canonical correlation analysis syntax dialog box. Figure 9 shows the canonical correlation analysis syntax dialog box, whereas Figure 10 shows the canonical correlation analysis syntax dialog box with the syntax pasted in. Finally, Table 11 shows the standardized coefficients and structure coefficients pertaining to the four socio-demographic variables (i.e., age group, race, student status, technology access) and two emergent themes (i.e., Overall Learning Experience, Technology-Related) that were extracted from the ensuing SPSS output. Based on Table 11, McClure et al. (2021) made the following conclusion:

Overall, the selected canonical correlation solution, which was statistically significant (*F*[8, 196] = 2.52, p = .013) and practically significant (Canonical R_{c1} = .42; moderate effect size) (see Fable 2), indicated that the multivariate relationship was mostly characterized by the relationship between age, race, full- time status, and technology access on the socio-demographic side and Technology-Related and Overall Learning Experience on the challenge themes side. (p. 157)

Figure 6

Final Independent and Dependent Variables Selected for the Canonical Correlation Analysis

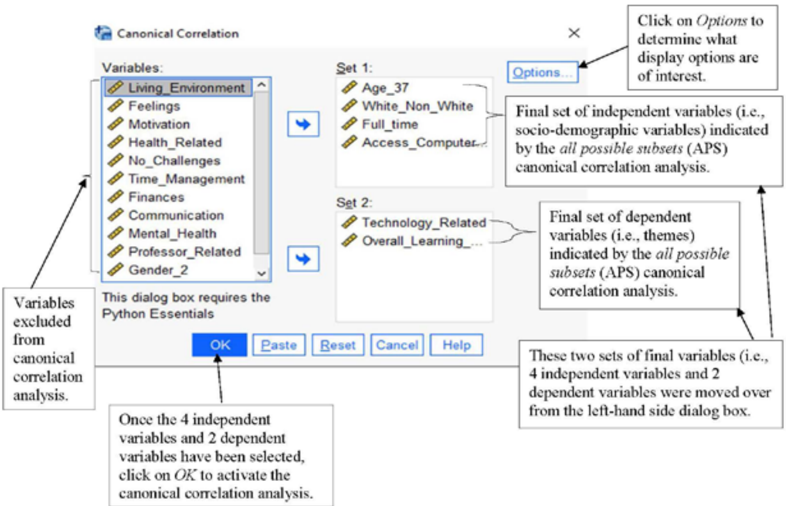


Figure 7

SPSS Syntax for Canonical Correlation Analysis for Final Canonical Correlation Solution

```
DATASET ACTIVATE DataSet1.
STATS CANCORR SET1=Age_37 White_vs_NonWhite Fulltime_vs_Parttime
Access_Computer_and_Reliable_Internet
   SET2=Technology_Related Overall_Learning_Experience
/OPTIONS  COMPUTECVARS=NO
/PRINT PAIRWISECORR=NO LOADINGS=YES VARPROP=YES
COEFFICIENTS=YES.
```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Onwuegbuzie, A. J. (2022). Towards Full (er) Integration in Mixed Methods...

Figure 8

Path for Accessing the Syntax Dialog Box

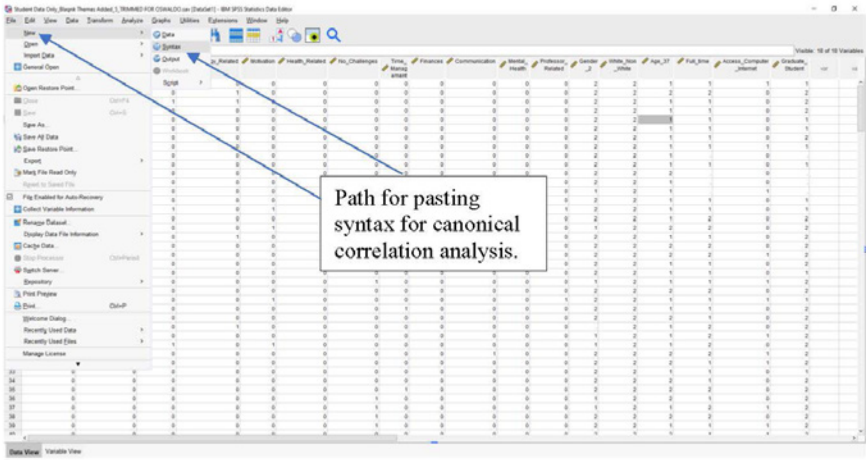

Figure 9

Syntax Dialog Box for Pasting the Canonical Correlation Analysis Syntax

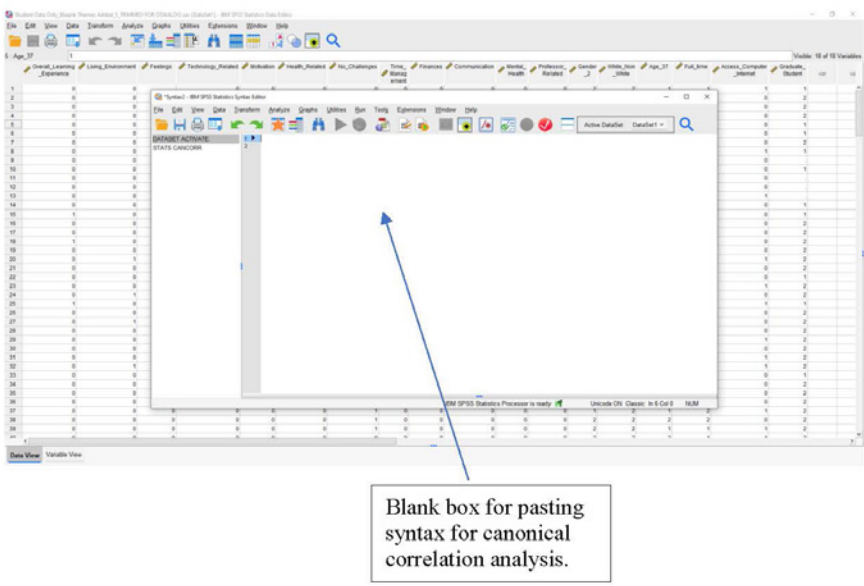

Figure 10

Syntax Dialog Box with the Canonical Correlation Analysis Syntax Pasted

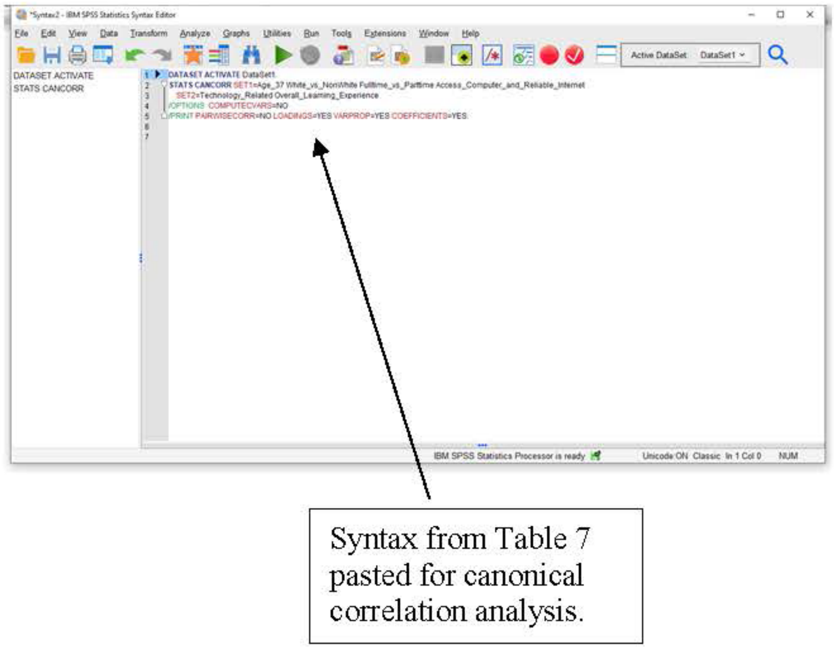

Table 11

Canonical Solution for the First Function: Relationship Between the Selected Final Four Socio-Demographic Variables and Two of the Four Most Prevalent Emergent Themes

Variable	Standardized Coefficient	Structure Coefficient	Structure^2 (%)
Demographic:			
Age group (18-37 vs. 38+)	-.48*	-.71*	50.4
Race (White vs. Non-White)	.46*	.30*	10.9
Status (Full-time vs. Part-time)	-.45*	-.73*	53.3
Technology Access (full access vs non-full access)	-.39*	-.50*	25.0
Theme:			
Overall Learning Experience	.85*	.95*	90.3
Technology-Related	.34*	.57*	32.5

Note. Adapted from "Online learning challenges experienced by university students in the New York City area during the COVID-19 pandemic: A mixed methods study," by D. R. McClure, E. O. Ojo, M. B. Schaefer, D. Bell, S. S. Abrams, and A. J. Onwuegbuzie, 2021, *International Journal of Multiple Research Approaches, 13*(2), p. 158.
*Coefficients with the effect sizes larger than .3.

McClure et al. (2021) followed up their canonical correlation analysis with another inferential-based quantitizing approach via the use of a series of Fisher's Exact Test. This test, which is more appropriate to use than is the chi-square test when sample sizes are small (Fisher, 1922, 1954), was used to determine whether or not there was a statistically significant relationship between each of the four socio-demographic variables (i.e., age group, race, student status, technology access) and the two emergent themes (i.e., Overall Learning Experience, Technology-Related) that characterized the final canonical correlation analysis model. This second inferential-based quantitizing approach led to the following observations:

> Most interestingly, full-time students were 4.32 times (95% CI = 1.85, 10.07) more likely to indicate challenges associated with Overall Learning Experience than were part-time students. Additionally, students 18-37 years old were 8.93 times (95% CI = 1.30, 61.42) more likely to indicate challenges associated with Overall Learning Experience than were students older than 37 years of age. Also, students without full access to a computer and/or reliable Internet were 2.17 times (95% CI = 1.10, 5.43) more likely to indicate challenges associated with Overall Learning Experience than were their counterparts with full access to both. Finally, and intuitively, students without full access to a computer and/or reliable Internet were 3.16 times (95% CI = 1.07, 9.29) more likely to indicate challenges associated with technology than were their counterparts. Therefore, with respect to personal challenges that hindered students' ability to learn online successfully, a *computer meta-theme*, a *computer and reliable Internet connection meta-theme*, an *age meta-theme*, and a *full-time meta-theme* emerged. (McClure et al., 2021, pp. 157-158)

Therefore, as can be seen, these two inferential-based quantitizing approaches, spearheaded by the canonical correlation analysis, not only served to contextualize the most frequent emergent themes by disaggregating them, but also led to the identification of several meta-themes. In general, meta-themes involve integrating themes from across cultures, participants, cases, sites, settings, or other defining grouping foci (Leech & Onwuegbuzie, in press; Wutich et al., 2021). As such, as can be seen, canonical correlation analysis provided a pathway for full(er) integration of the qualitative and quantitative data.

Conclusions

As concluded by Onwuegbuzie (2021),

> until very recently, the overwhelming majority of quantitizing has involved descriptive-based quantitizing, and scant attention has been paid to more advanced types of quantitizing, which include exploratory-based quantitizing, measurement-based quantitizing, and inferential-based quantitizing, as described by Onwuegbuzie (in press) and Onwuegbuzie and Johnson (2021[a]). Yet, these forms of quantitizing help to enhance the quality of meta-inferences in mixed methods research studies, which, in turn, enhance the meaning-making process. (p. 146)

Onwuegbuzie and Johnson's (2021b) 30-chapter book represents an important step towards advancing exploratory-based quantitizing, measurement-based quantitizing, and inferential-based quantitizing. However, much more guidance is needed on all three of these forms of quantitizing. Therefore, the goal of the present article was to continue the conversation on inferential-based quantitizing.

Specifically, in this article, I have outlined and demonstrated how canonical correlation analysis can help (mixed methods) researchers to contextualize emergent themes that have been subjected to descriptive-based quantitizing via the process of unitizing—specifically, dichotomizing—themes. As noted elsewhere (e.g., Onwuegbuzie, 2021), one potential pitfall in relying exclusively on the descriptive-based quantitizing technique of simple counting to contextualize themes is that it could lead easily to qualitative findings (e.g., codes, categories, sub-themes, themes, meta-themes) being overgeneralized. For example, with regard to McClure et al.'s (2021) findings, it is very useful to know the prevalence rate of each of the 12 emergent themes as a result of descriptive-based quantitizing. However, without further information—particularly stemming from inferential-based quantitizing—these prevalence rates might be somewhat misleading because it can lead to these rates being over-generalized by consumers of the research findings, with these consumers incorrectly assuming that these emergent themes apply across all subgroups. For example, reporting that a theme associated with challenges faced by students that hindered their ability to learn successfully online was Overall Learning Experience (i.e., a qualitative finding stemming from the constant comparison analysis) provides useful information. However, it is even more useful to know from the descriptive-based quantitizing that this theme represented a challenge for approximately one in five students (i.e., 19.44%). Moreover, it is even more helpful to know from the inferential-based quantitizing that students who indicated challenges associated with Overall Learning Experience were significantly more likely to be the following: full-time students (4.32 times more likely, on average), students aged between 18 and 37 (8.93 times more likely, on average), and students without full access to a computer and/or reliable Internet were (2.17 times more likely, on average). Such information facilitates a disaggregation of the thematic structure, which, in turn, would help to determine which subgroups of participants were most at-risk for experiencing challenges, and would help to ensure that no study subgroup is misrepresented—consistent with a major tenet of critical dialectical pluralism (Onwuegbuzie & Frels, 2013; Onwuegbuzie et al., in press).

Further, such information from inferential-based quantitizing offers greater implications for intervention. As such, compared to descriptive-based quantitizing approaches, inferential-based quantitizing approaches have great potential for yielding value-added information that enhances the meaning-making process. Importantly, the heuristic example in the present article has demonstrated that the use of canonical correlation analysis in the context of inferential-based quantitizing is consistent with Onwuegbuzie's (2017) and Onwuegbuzie and Hitchcock's (2019) 1 + 1 = 1 integration approach that represents full(er) integration of qualitative and quantitative approaches by replacing the quantitative–qualitative dichotomy inherent in Fetters and Freshwater's (2015) 1 + 1 = 3 integration approach—that is characterized by one or more distinct quantitative phases and one or more distinct qualitative phases, but which promotes synergy at the data interpretation stage—with continua that facilitate this full[er] integration (Hitchcock & Onwuegbuzie, 2022; Natesan et al., 2019; Newman et al., 2015; Onwuegbuzie & Hitchcock, 2019) and that represent a synechist (i.e., anti-dualistic) approach to mixed methods research that transcends the qualitative-quantitative divide (Mason, 2006).

Typically, when each study participant is asked within the same data collection framework (e.g., via a questionnaire) to provide both quantitative responses (e.g., via Likert-format scales, rating scales, socio-demographic items) *and* qualitative responses (e.g., via open-ended survey questions, observations, interview questions), what typically occurs at the data analysis stage under the 1 + 1 = 3 framework is that

- one or more quantitative analyses are used to analyze the quantitative data separately to provide quantitative findings;
- one or more qualitative analyses are used to analyze the qualitative data separately to provide qualitative findings; and
- once the quantitative findings and qualitative findings have been obtained separately, then the interpretations obtained from both strands are combined into some coherent whole—a process known as obtaining *meta-inferences* (Tashakkori & Teddlie, 1998)

However, bearing in mind the fact that each study participant (optimally) provides the full set of data, this 1 + 1 = 1 strategy of analyzing the quantitative data separately and the qualitative data separately results in some form of *unmixing* rather than what Onwuegbuzie (2012) advocates as *putting the mixed back into quantitative and qualitative research* (p. 202). And even employing descriptive-based quantitizing approaches on the qualitative data (e.g., determining the prevalence of themes) does not integrate directly the ensuing qualitized data with the quantitative data until the data interpretation stage—which still represents an unmixing of mixed data. In contrast, this unmixing is avoided by treating all the data—whether it be qualitative data, quantitative data, or what Onwuegbuzie et al. (2017) referred to as *multidata* (i.e., representing *both* quantitative data and quantitative data)—as representing a set and applying a fully integrated analysis on this set. This fully integrated analysis involves a crossover mixed analysis in general and, when the sample size permits, as was the case for McClure et al.'s (2021) study, lends itself to some form of inferential-based quantitizing. And because canonical correlation analysis represents a multivariate analysis approach, I suggest that this analysis should be a serious contender for use—reflecting the multivariate nature of reality that many researchers are interested in studying. Simply put, applying a fully integrated analysis motivates the adoption of *fully integrated thinking* such that synergy occurs in most, if not all, phases of the mixed methods research process. That is, full(er) integrated thinking optimally can occur

> during all four *research-producer* stages of the mixed research process—namely: *research conceptualization* (e.g., extracting information via an integrated research synthesis, determining the integrated goal of the study, identifying the integrated objective[s], determining the research/integration rationale[s], determining the research/integration purpose[s], determining the integrated research question[s]); *research planning* (e.g., selecting the integrated sampling design, selecting the integrated research design), *research implementation* (e.g., collecting the integrated data, conducting an integrated analysis, legitimating/validating the integrated data and data interpretations, interpreting the integrated data via meta-inferences), and *research dissemination* (e.g., writing the final integrated research report, re-conceptualizing the integrated research question[s])—as well as the *research-consumer* stage of *research utilization* (e.g., the consumer of the integrated research report using the findings in an integrated manner for practical or research purposes). (Onwuegbuzie & Hitchcock, 2019, p. 14)

In conclusion, as can be seen from the heuristic example, use of canonical correlation analysis as an inferential-based quantitizing approach provides a powerful way to promote full(er) integration in mixed methods research. In turn, such an approach has the potential not only to answer research questions in a more in-depth manner, but also to answer more complex and complicated questions. Therefore, I encourage (mixed methods) researchers to consider using this canonical correlation analysis approach to inferential-based quantitizing whenever appropriate (e.g., sample size large enough to ensure adequate statistical power) to enhance the meaning-making process.

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