Article

Organizational Research Methods
2018, Vol. 21(4) 877-904

DOI: 10.1177/1094428117752466
journals.sagepub.com/home/orm
SAGE

Fuzzy Profiles: Comparing and Contrasting Latent Profile Analysis and Fuzzy Set Qualitative Comparative Analysis for Person-Centered Research

Allison S. Gabriel[1], Joanna Tochman Campbell[2], Emilija Djurdjevic[3], Russell E. Johnson[4], and Christopher C. Rosen[5]

Abstract

Person-centered approaches to organizational scholarship can provide critical insights into how sets of related constructs uniquely combine to predict outcomes. Within micro topics, scholars have begun to embrace the use of latent profile analysis (LPA), identifying constellations of constructs related to organizational commitment, turnover intentions, emotional labor, recovery, and well-being, to name a few. Conversely, macro scholars have utilized fuzzy set qualitative comparative analysis (fsQCA) to examine numerous phenomena, such as acquisitions and business strategies, as configurations of explanatory conditions associated with firm-level outcomes. What remains unclear, however, is the extent to which these two approaches deliver similar versus unique insights when applied to the same topic. In this paper, we offer an overview of the ways these two methods converge and diverge, and provide an empirical demonstration by applying both LPA and fsQCA to examine a multidimensional personality construct—core self-evaluations (CSE)—in relation to job satisfaction. In so doing, we offer guidance for scholars who are either choosing between these two methods, or are seeking to use the two methods in a complementary, theory-building manner.

[1]Department of Management and Organizations, Eller College of Management, University of Arizona, Tucson, AZ, USA
[2]Department of Management, Carl H. Lindner College of Business, University of Cincinnati, Cincinnati, OH, USA
[3]Department of Entrepreneurial Management and Law, College of Business Administration, University of Rhode Island, Kingston, RI, USA
[4]Department of Management, Eli Broad College of Business, Michigan State University, East Lansing, MI, USA
[5]Department of Management, Sam M. Walton College of Business, University of Arkansas, Fayetteville, AR, USA

Corresponding Author:
Allison S. Gabriel, Department of Management and Organizations, Eller College of Management, University of Arizona, Tucson, AZ 85704, USA.
Email: asgabriel@email.arizona.edu

Keywords
person-centered methodology, latent profile analysis, fuzzy set qualitative comparative analysis, core self-evaluations

Over the past 5 years, organizational scholars have increasingly argued for the importance of adopting person-centered approaches (Wang & Hanges, 2011). Compared to variable-centered approaches (e.g., regression, ANOVA), person-centered analytic approaches enable researchers to understand how variables operate conjointly and within persons; that is, person-centered approaches emphasize *people* as opposed to *variables*. Although variable-centered approaches have their merits in terms of specifying relationships of focal predictors with criteria (Cohen, Cohen, West, & Aiken, 2003), the goal of a person-centered approach is to identify individuals who express certain profiles, or constellations, of characteristics and ascertain whether and how antecedents and outcomes diverge across these different clusters of individuals (Wang & Hanges, 2011). Importantly, person-centered approaches are more aligned with the applied side of organizations, where organizations make decisions about people—for example, who to hire or promote—as a whole (e.g., across a set of traits), rather than considering individual traits in isolation (De Fruyt, 2002). Thus, moving from a variable-centered approach to a person-centered approach represents a "revolutionary departure from traditional thinking by prompting a more extreme reconceptualization of an object of study" (Zyphur, 2009, p. 678) and has the potential to disrupt and/or advance many well-established research areas.

For micro organizational behavior (OB) and human resources (HR) topics, researchers originally relied upon cluster analysis (e.g., *K* means cluster analysis; Schmitt et al., 2007) to understand how certain constructs combined to form various classes. Perry-Smith and Blum (2000), for example, applied cluster analysis to the study of work-family HR practices, identifying "bundles" of polices (e.g., leave policies, day care, flexible scheduling, monetary assistance for dependent care) that pertained to firm performance. More recently, Moran, Diefendorff, Kim, and Liu (2012) used cluster analysis to examine how different forms of motivation based on self-determination theory (SDT; Deci & Ryan, 1985) combined and related to correlates (e.g., social support, job characteristics, performance). Yet, as highlighted by Wang and Hanges (2011), traditional cluster analysis (a) does not have formal criteria that can aid researchers in identifying the best fitting solution and (b) forces individuals in a sample to belong to only one cluster. However, it is possible that individuals have a probability of belonging to multiple clusters within a given solution. In light of these limitations, scholars have recently turned toward latent profile analysis (LPA), which is equipped to model the likelihood (i.e., probability) that individuals belong to a profile (Wang & Hanges, 2011).

Interestingly, for macro topics, scholars also once heavily relied on cluster analysis, especially in the stream of research on strategic groups (e.g., Cool & Schendel, 1987; Dess & Davis, 1984; Fiegenbaum & Thomas, 1995; Lewis & Thomas, 1990; Reger & Huff, 1993). This literature, active in the 1980s and 1990s, sought to identify groups of firms that followed similar strategies based on a number of proxy variables, ultimately examining the performance consequences of cluster membership. Nonetheless, scholars gradually worried that cluster analysis was a suboptimal way of approaching this question, with Barney and Hoskisson (1990) stating, "Given the limitations of cluster analysis as a way to test the existence of strategic groups, one is forced to wonder whether strategic groups really exist, or are an artifact of clustering analysis" (p. 190). More explicitly, because the technique always identified clusters, it was difficult to establish whether the groupings generated were meaningful and represented conscious strategies. Following Ketchen and Shook's (1996) review and critique of strategy scholars' use of cluster analysis, the use of this technique declined. A decade later, a promising alternative emerged in the form of set-theoretic methodology (Fiss, 2007), and fuzzy set qualitative comparative analysis (fsQCA) in particular.

Given the historical evolution of micro and macro scholarship, and the increasing use and popularity of these two emergent approaches within each subfield, two key questions arise. First, are the conclusions garnered from the two approaches consistent or divergent? Second, and related to the previous question, how can scholars utilize LPA and fsQCA in a complementary fashion? No work to date has integrated these configurational analytic approaches to highlight how they potentially align, nor has work considered how the approaches are distinct. As such, across both fields of study, there is little understanding of which approach may be better suited to answer particular research questions, or how the approaches can be combined. For instance, do both approaches follow similar underlying theoretical assumptions (e.g., identifying subpopulations) and analytical approaches (e.g., testing profiles/configurations separate from the criterion variable)? In addition, can the same research questions be addressed with LPA and fsQCA? And, perhaps most interesting, if the same data are analyzed using LPA and fsQCA, will researchers reach the same conclusions in regard to which combinations or configurations of constructs yield the most optimal outcomes for employees and organizations?

In this study, we clarify the similarities and differences between LPA and fsQCA. In so doing, we provide an overview of past research that has utilized each analytic approach across micro and macro domains, highlighting the types of research questions that are common to each analytic approach. We then apply both analytic techniques to the study of the same data surrounding a popular organizational topic—core self-evaluations (CSE; Chang, Ferris, Johnson, Rosen, & Tan, 2012; Judge, Locke, & Durham, 1997)—in order to investigate whether the conclusions reached via LPA and fuzzy set analysis are similar. Through this, we also highlight how these analytic techniques can be used to test and advance theory, with CSE theory as an example. Last, we provide practical considerations and recommendations for future research.

Micro Scholarship and the Use of Latent Profile Analysis (LPA)

LPA allows researchers to identify constellations of constructs that exist within a sample by modeling the unobserved heterogeneity present within the data (for recent reviews of LPA, see J. P. Meyer & Morin, 2016; Morin, Meyer, Creusier, & Biétry, 2016; Morin & Wang, 2016; Wang & Hanges, 2011). This is in contrast to variable-centered approaches, which implicitly "ignore the fact that participants may come from different subpopulations in which the observed relations between variables may differ" (Morin, Morizot, Boudrias, & Madore, 2011, p. 59). Importantly, the profiles that emerge using LPA (a) account for possible error in classification and (b) can differ quantitatively or qualitatively. In regard to the former point, unlike cluster analysis, which "forces" an individual into a class, LPA accounts for the fact that the classification of an individual may be imperfect (Wang & Hanges, 2011): Although one person may have a strong likelihood of belonging to one profile, there is a probability that he or she could be assigned to an alternative profile. Regarding the latter point, profiles that emerge can vary in absolute level (i.e., quantitative differences) or shape (i.e., qualitative differences). For quantitatively distinct profiles, all profile indicators are at the same level (e.g., if four constructs are examined: profiles in which all four profile indicators are at high, moderate, or low levels). In contrast, qualitatively distinct profiles, which Wang and Hanges (2011) argue are the true value of LPA, reflect profiles in which individuals vary in their relative standing on each indicator (e.g., if four constructs are being examined, having one profile where people are high on one profile indicator and low on all others; having another where people are high on two of the profile indicators and low on others).

After identifying a profile solution, researchers can examine how profile membership is predicted by antecedent variables (i.e., whether being high/low on an antecedent makes people more or less likely to belong to a specific profile; Vermunt, 2010). Scholars can also examine how profiles exhibit mean differences on criteria of interest, or what Lanza, Tan, and Bray (2013) refer to as distal outcomes. A key point is that in conducting these analyses, researchers do *not* allow the antecedents and/or outcome variables to affect profile membership, which departs from how the analytic approach once was conducted. This approach of not letting correlates—antecedents or outcomes—affect profile assignment is known as the automatic three-step procedure (Asparouhov & Muthén, 2014; Vermunt, 2010), and the analysis of antecedents and outcomes in this manner continues to account for possible error in the profile classification (Wang & Hanges, 2011). Thus, profile solutions in LPA are selected separate from their correlates, meaning that the addition of correlates cannot alter the final profile structure.

LPA has been applied to an array of micro topics (see Supplemental Material 1 online for example topics). Most notably, organizational commitment researchers have embraced LPA, identifying profiles of commitment mindsets that vary in levels of affective, normative, and continuance commitment (Kabins, Xu, Bergman, Berry, & Willson, 2016; Morin et al., 2011; see J. P. Meyer & Morin, 2016, for a review). Likewise, leadership research by Foti, Bray, Thompson, and Allgood (2012) utilized LPA to identify profiles of self leader and ideal leader perceptions, arguing that LPA offered greater insight into leadership profiles compared to variable-centered analyses that would have "provided limited information about how response patterns across factors may manifest within an individual" (p. 713). Recently, Gabriel, Daniels, Diefendorff, and Greguras (2015) applied LPA to emotional labor, identifying five distinct profiles of employees who utilized surface and deep acting strategies at varying levels, with these profiles differentially relating to emotional exhaustion, felt inauthenticity, and job satisfaction. Scholars have further examined profiles that pertain to well-being, such as profiles of employee recovery experiences during nonwork time (e.g., psychological detachment, relaxation, mastery, control, problem-solving pondering) that predicted emotional exhaustion and engagement (Bennett, Gabriel, Calderwood, Dahling, & Trougakos, 2016), as well as profiles of actual psychological well-being constructs (Morin et al., 2017). Moreover, researchers are building upon work that was traditionally conducted with cluster analysis. For instance, Graves, Cullen, Lester, Ruderman, and Gentry (2015) identified profiles of managerial motivation grounded in SDT via LPA that built upon Moran et al.'s (2012) profiles derived from cluster analysis, with Howard, Gagné, Morin, and Van den Broeck (2016) further examining motivational profiles via LPA using two samples from different countries (i.e., Canada and Belgium).

HR-focused research has also embraced LPA. Woo and Allen (2014) took an inductive approach to the study of turnover intentions, identifying profiles of "stayers" and "leavers" in organizations based upon thoughts of leaving one's current job, plans to leave, job search behaviors, and social-emotional, economic, and external reasons for staying in one's current job. Woo and Allen also examined how job satisfaction, motivational forces (e.g., alternative, normative, moral), and dispositions (e.g., trait affectivity, personality) made individuals more or less likely to belong to a particular latent class. In addition, Kinnunen, Mäkikangas, Mauno, De Cuyper, and De Witte (2014) considered environmental and individual predictors of profiles of job insecurity, linking these profiles to psychological well-being and turnover intentions.

Macro Scholarship and the Use of Fuzzy Set Qualitative Comparative Analysis (fsQCA)

In recent years, macro researchers interested in configurational theory and testing, especially those studying complex phenomena (for a recent review, see Misangyi et al., 2017), have turned to set-theoretic methods. Such methods are grounded in set theory from mathematics (Smithson & Verkuilen, 2006), and the idea that the relationship between variables/constructs is "often best understood in terms of *set membership*" lies at the heart of set-theoretic approaches (Fiss, 2007,

p. 1183). Many view these methods as a middle ground between qualitative and quantitative methodological approaches (Ragin, 2008) due to their origins in case analysis, with the units of analysis being the cases under consideration (e.g., individuals, firms, political systems), which are conceptualized as set theoretic configurations (Misangyi et al., 2017). Accordingly, constructs—or attributes of interest—are conceptualized and operationalized in terms of membership in a relevant set (e.g., the set of high-performing individuals). This process of assigning set membership and conversion from raw data, referred to as calibration, is discussed in more detail later.

Fuzzy set qualitative comparative analysis (fsQCA, or fuzzy set analysis) gained the most popularity amongst set-theoretic approaches due to its flexibility in assigning set membership, allowing for multiple degrees of gradation and thus accounting for the essential "fuzziness" of many social science constructs. In fuzzy set analysis constructs are operationalized in terms of set membership ranging from 0 (fully outside of the set) to 1 (full membership), with multiple degrees of membership in between (e.g., 0.75 represents "more in than out," 0.25 is "more out than in"). This nonparametric method of examining configurations of attributes in relation to an outcome is rooted in Boolean algebra (i.e., AND, OR, NOT operators), and relies on necessity and sufficiency analyses, enabling researchers to uncover paths that consistently lead to a given outcome, or the absence of an outcome. In contrast to LPA, consistent configurations do not exist without concomitantly considering an outcome, and in contrast to both cluster analysis and LPA, meaningful configurations of attributes (that is, configurations of attributes consistently associated with an outcome or its absence) do not always emerge.

Two additional attributes have made fsQCA particularly appealing to macro scholars, especially when compared to regression analysis and its derivatives. Specifically, fsQCA allows for (a) equifinality, or the possibility of multiple "paths" to an outcome (e.g., multiple strategies for achieving high performance), and (b) causal asymmetry, or the possibility that the paths to the absence of the same outcome are diametrically different from the paths to its presence (e.g., low performing firms differ from high performers not only in level, but in kind). Equifinality implies that the outcome may result from a number of different "causal recipes" (Ragin, 2008). The property of causal asymmetry also stands in sharp contrast to correlational approaches because correlations are symmetric by nature; in fsQCA, the combinations of conditions that lead to the presence of a given outcome may often be different from the sets of conditions that lead to the reverse of the outcome (Fiss, 2007). Moreover, attributes found to be "causally related in one configuration may be unrelated or even inversely related in another" (A. D. Meyer, Tsui, & Hinings, 1993, p. 1178). In sum, fsQCA allows researchers to consider three aspects of causal complexity: conjunction, equifinality, and causal asymmetry (Misangyi et al., 2017; Ragin, 2008).

Similar to LPA in micro scholarship, fsQCA has been applied across macro topics (see a comprehensive review by Misangyi et al. [2017], and Supplemental Material 1 online for a selection). After laying out the theoretical foundations for set-theoretic methodology—including fsQCA—in the organizational sciences (e.g., Fiss, 2007), Fiss (2011) empirically examined configurations suggested by the influential Miles and Snow typology (1978), linking them to firm performance. Similarly, Aversa, Furnari, and Haefliger (2015) investigated configurations of business models associated with high performance, and/or lack thereof, across multiple time periods. Other topics addressed by strategy scholars using fsQCA include firm strategic orientation (Frambach, Fiss, & Ingenbleek, 2016), mergers and acquisitions (Campbell, Sirmon, & Schijven, 2016), firm adaptation (Vergne & Depeyre, 2016), innovation management (Meuer, 2014), and various aspects of stakeholder management (Crilly, 2011; Crilly, Zollo, & Hansen, 2012; García-Castro & Francoeur, 2014), among others. Yet, perhaps the most fertile ground to date for fuzzy set-based research in macro scholarship is the literature on corporate governance, where scholars have examined configurations of governance characteristics and their outcomes across a variety of settings, including S&P 1500 firms in the United States (Misangyi & Acharya, 2014), foreign initial public offerings (Bell, Filatotchev, & Aguilera, 2014), and different national systems across 31 countries (García-Castro, Aguilera, & Ariño, 2013).

Several set-theoretic studies in the strategy domain employ a higher level of analysis than the firm, such as distinct geographic regions within a country (Gilbert & Campbell, 2015) and across multiple countries (Greckhamer, 2011, 2016; Pajunen, 2008; Schneider, Schulze-Bentrop, & Paunescu, 2010). Notably, all of the aforementioned studies vary widely in the number of cases (i.e., observations) analyzed, ranging from as little as 10 to more than 2,400. This highlights the flexibility of fuzzy set analysis and its adaptability to both small-*N* and large-*N* situations, albeit with minor modifications depending on the type of setting (for a detailed discussion and recommendations in this regard, see Greckhamer, Misangyi, & Fiss, 2013).

A Comparison of LPA and fsQCA

Although researchers are increasingly using LPA and fsQCA, it is unclear to what extent these approaches differ or share conceptual space, and how the approaches could potentially be used in tandem. Thus, in order to understand how LPA and fsQCA results converge and diverge, we apply each of these two analytic techniques to the study of CSE—the "fundamental appraisals that people make of their own self-worth, competence, and capabilities" (Chang et al., 2012, p. 82)—and approach/avoidance motivation. In so doing, we can understand how these methods, when applied to the same data, may yield similar or unique insights.

As a brief overview, CSE is a multidimensional construct theorized to account for disposition-based effects on job satisfaction (Judge et al., 1997). CSE comprises four personality traits: (a) self-esteem (i.e., one's appraisal of one's self-worth), (b) generalized self-efficacy (i.e., one's estimate of one's ability to act effectively), (c) emotional stability (i.e., one's propensity to be less reactive to events, analogous to low neuroticism), and (d) locus of control (i.e., the extent to which one believes that one can impact one's environment to produce desired outcomes). Although meta-analytic findings suggest that these traits are among the strongest dispositional predictors of job satisfaction (Judge & Bono, 2001), CSE has since come under scrutiny. For example, Johnson, Rosen, and Levy (2008) highlighted that CSE traits are not necessarily interchangeable, with evidence suggesting that locus of control exhibits less convergent validity than the other traits (Erez & Judge, 2001; Judge, Bono, & Locke, 2000) and fails to load onto the higher-order CSE factor when common method variance is controlled for (Johnson, Rosen, & Djurdjevic, 2011). As such, it has been recommended that researchers pay more attention to how the individual CSE traits *combine* (Johnson, Rosen, Chang, & Lin, 2015).

Moreover, it has been suggested that CSE is broader than once conceptualized, including constructs such as approach and avoidance motivation that reflect self-regulatory capabilities (Ferris et al., 2011). As reviewed by Ferris et al. (2011), the CSE traits have been theorized as representing an approach temperament, in that they are seeking positive outcomes that can affect criteria such as job satisfaction. Conversely, CSE also appears to reflect low avoidance temperament, in which individuals are concerned with averting negative outcomes (Johnson et al., 2008; Judge, Locke, Durham, & Kluger, 1998). Indeed, research indicates a consistent pattern of relationships between CSE traits, approach and avoidance motivation, and job satisfaction (Ferris et al., 2011; Ferris et al., 2013). Owing to this pattern of relationships, further theoretical and empirical integration of CSE traits and approach/avoidance motivation is needed (Chang et al., 2012; Johnson et al., 2008).

To integrate these constructs, we focused on how constellations that emerge using LPA and fsQCA predict job satisfaction, the principal outcome of CSE (Judge et al., 1997). Using LPA, we explored whether profiles of the four CSE traits, approach motivation, and avoidance motivation exist that offer both quantitative and qualitative differences. Assuming that such profiles emerge, we further sought to examine whether these profiles exhibit significant mean differences in job satisfaction. Thus, we considered two research questions for LPA:

Research Question 1: Do profiles of CSE traits (self-esteem, generalized self-efficacy, emotional stability, and locus of control) and approach and avoidance motivations exist that vary quantitatively (i.e., in level) and qualitatively (i.e., in shape)?

Research Question 2: Do the uncovered profiles of CSE traits and approach and avoidance motivations differentially relate to job satisfaction?

Using fsQCA, we examined a slightly different set of research questions. Examining causal asymmetry is a unique advantage of fuzzy set analysis, which does not assume symmetric relationships. As such, the profiles that consistently predict job satisfaction need not be the mirror opposites of the profiles that predict a lack of satisfaction. In fact, it is quite possible that the traits which predict job satisfaction do not predict the absence of satisfaction, and vice versa.

Another key difference between LPA and fsQCA lies in the underlying goals of the two methods. The aim of fuzzy set QCA is to identify necessary and/or sufficient subset relations (Ragin, 2000, 2008). A cause is considered to be *necessary* if it is a subset of the outcome (here, job satisfaction); that is, it must be present for the outcome to occur (Ragin, 2000). A cause is considered *sufficient* if, by itself, it can produce the outcome. In theory, causes can be necessary *and* sufficient (i.e., they both are necessary for the outcome to occur and they consistently produce the outcome). For instance, increased temperature is both necessary to boil water, and is alone sufficient to produce this outcome. However, necessary causes are not always sufficient. For example, submitting a paper to a given journal is necessary to publish in that journal, yet doing so does not inevitably result in a publication. Instead, submitting a paper will lead to acceptance only in conjunction with other conditions (e.g., valuable research questions, robust research design, appropriate methods). FsQCA therefore helps researchers identify multiple and complex recipes by pointing to necessary and sufficient attributes of interest, sometimes referred to as "causal conditions" in QCA parlance.[1] Naturally, "social phenomena rarely result from single causes" (Ragin, 2000, p. 99); thus, fsQCA also allows one to examine combinations of attributes sufficient for the outcome to occur. As such, we examined the following with fsQCA:

Research Question 3: Are there any attributes that are empirically necessary for job satisfaction or the *absence* of job satisfaction (i.e., job dissatisfaction)?

Research Question 4a: Which, if any, theoretically possible configurations of CSE traits and approach and avoidance motivations are considered sufficient for job satisfaction?

Research Question 4b: Which, if any, theoretically possible configurations of CSE traits and approach and avoidance motivations are considered sufficient for the *absence* of job satisfaction?

Method and Results

Sample and Procedure

We utilized an archival dataset of 434 employees from the United States who were 28.5 years of age on average ($SD = 13.7$) and largely male (58.1%) and White (78.8%).[2] Participants worked 34.5 hours per week on average ($Mdn = 40.0$, $SD = 16.4$), and had worked in their current position for an average of 3.4 years ($SD = 4.6$). They were employed in a variety of industries, including service/retail, manufacturing, government, and education. Participants were recruited in MBA and undergraduate courses at two universities in the United States via snowball sampling. Specifically, students at both universities received course extra credit for participating in the study if they worked full-time and they could earn supplementary extra credit by recruiting another full-time employee. Additional participants were recruited via an online panel run by a nonprofit academic service known as StudyResponse (Stanton & Weiss, 2002). All participants completed online surveys (the order of the measures was counterbalanced).

Measures

All items were assessed on a 5-point scale (1 = *strongly disagree*, 5 = *strongly agree*).[3]

Self-esteem. We used 10 items from Rosenberg (1989; $\alpha = .96$). A sample item is "I feel that I have a number of good qualities."

Generalized self-efficacy. We used 9 items from Schwarzer and Jerusalem (1995; $\alpha = .97$). An example item is "I can always manage to solve difficult problems if I try hard enough."

Emotional stability. We used 10 items from Goldberg (1999; $\alpha = .93$). A sample item is "I feel comfortable with myself."

Locus of control. We used 10 items from Goldberg (1999; $\alpha = .86$). An example item is "I like to take responsibility for making decisions."

Approach and avoidance motivation. We assessed approach and avoidance motivation using Johnson, Chang, Meyer, Lanaj, and Way's (2013) scale. Six items each assessed approach motivation ($\alpha = .95$; "I think about the positive outcomes that my job can bring me") and avoidance motivation ($\alpha = .79$; "I am focused on failure experiences that occur while working").

Job satisfaction. We used 3 items from Seashore, Lawler, Mirvis, and Cammann (1982; $\alpha = .94$). An example item is "All in all, I am satisfied with my job."

Latent Profile Analysis: Analytic Approach

We conducted LPA using Mplus 7.31 (L. K. Muthén & Muthén, 1998-2015). We first specified one profile and increased the number of profiles until model fit no longer improved. Although hard-cut criteria for selecting a profile solution do not exist, we utilized several guidelines to determine appropriate model fit. Specifically, we relied on the following fit statistics: Akaike information criterion (AIC), Bayesian information criterion (BIC), consistent AIC (C-AIC; calculated as BIC plus the number of free parameters modeled), sample-size-adjusted Bayesian information criterion (SSA-BIC), Lo-Mendell-Rubin likelihood ratio test (LMR; Lo, Mendell, & Rubin, 2001; recommended by Tofighi & Enders, 2007), bootstrap likelihood ratio test (BLRT; recommended by Nylund, Asparouhov, & Muthén, 2007), and entropy. In interpreting model fit, scholars generally should consider solutions in which the AIC, BIC, C-AIC, and SSA-BIC are lower compared to other profile solutions; conversely, entropy—an index that summarizes the classification accuracy (ranges from 0.00 to 1.00; values closer to 1.00 indicating higher accuracy; Jung & Wickrama, 2008)—should be larger than other profile solutions. In addition, scholars should consider whether the LMR and BLRT statistics are significant ($p < .05$); these two statistics examine whether k profile solution is a better fit then the $k - 1$ profile solution.

Importantly, simulation evidence has suggested that the BIC, C-AIC, and SSA-BIC tend to be more optimal in identifying the best fitting profile solution compared to the LMR, BLRT, and AIC statistics (e.g., Diallo, Morin, & Lu, 2016, 2017; Nylund et al., 2007; Peugh & Fan, 2013, 2015; Tofighi & Enders, 2007). Following Howard et al. (2016), to aid in interpretation, we calculated "elbow plots" of the BIC and C-AIC values of each profile solution to illustrate the gains in model fit with each additional profile specified; scholars should select the profile solution at the point with which the slope of the plot flattens (Morin & Marsh, 2015). However, it is critical to note that the BIC and C-AIC tend to underestimate the number of profiles, and SSA-BIC and BLRT statistics tend to overestimate (Morin et al., 2016). Thus, in addition to statistical considerations, we kept theoretical and contextual considerations in mind (Foti et al., 2012; Lawrence & Zyphur, 2011). Specifically, we ensured that the profiles had theoretical meaning that fit within our larger theoretical CSE framework and were not redundant with each other; as stated by Howard et al. (2016), profiles that have the same theoretical meaning as other profiles in the solution can suggest selecting a smaller profile solution, particularly if fit indices offer support for a more parsimonious solution.

We also considered whether the profiles captured a small subpopulation of the sample. For instance, a profile of 1% in the current study ($n = 434$) would contain 4 people. Critically, this profile (a) may not have substantial theoretical meaning, and/or (b) create instability in the estimation of the model (e.g., Nylund et al., 2007). Yet, as found by Gabriel et al. (2015), a small profile that is extracted (e.g., 1.27%) can still be theoretically meaningful. As such, we considered all of the aforementioned criteria in a holistic manner versus relying on a single decision point.

In conducting our analyses, we followed the previously described automatic three-step approach for LPA (e.g., Asparouhov & Muthén, 2014; Lanza et al., 2013; Vermunt, 2010). We first conducted our profile enumeration process and selected the best fitting solution based upon the aforementioned criteria. We allowed profile indicators' intercepts and variances to be freely estimated across profiles (e.g., Morin et al., 2011; Morin & Marsh, 2015; Peugh & Fan, 2013).[4] Second, we obtained the most-likely class membership from the posterior distribution from the profile enumeration process in the prior step (Asparouhov & Muthén, 2014); as previously reviewed, this step is what differentiates LPA from other person-centered analytic approaches, such as cluster analysis, by accounting for error associated with the profile classification (Morin et al., 2011; Wang & Hanges, 2011). Third, and finally, we assessed our distal outcome (job satisfaction) in relation to the profiles, again accounting for possible error in the profile classification (Wang & Hanges, 2011). Following Lanza et al. (2013; see also Asparouhov & Muthén, 2014), the DCON auxiliary command was used to determine if there were statistically significant differences between the profiles on our job satisfaction outcome variable.

Latent Profile Analysis: Results

Profile enumeration fit statistics are provided in Table 1. We selected the five-profile solution as best fitting given lower BIC, C-AIC, and SSA-BIC solutions compared to the two-, three-, and four-profile solutions; in addition, LMR and BLRT were significant ($p < .05$), and the entropy value was larger than the four-, six-, and seven-profile solutions. Importantly, we note that six-profile solution also exhibited significant LMR and BLRT statistics, as well as slightly lower BIC, C-AIC, and SSA-BIC values. However, after inspecting the elbow plot (see Figure 1), the slope tapered around the five-profile mark, suggesting appropriate model fit.

Means of our six indicators per latent profile are in Table 2. The profiles are visually presented in Figures 2a and 2b following common practice amongst scholars (a histogram and a line chart, respectively). Each profile in the final solution was qualitatively distinct, though we note that there were two pairs of profiles that exhibited similar trends. Specifically, two profiles emerged that exhibited high positive self-evaluations along with high approach motivation and low avoidance motivation; these profiles were labeled as *assured strivers* (32.35%) and *high assured strivers* (23.47%). Interestingly, both profiles had similarly low levels of locus of control ($M = 3.36$ and

Table 1. Latent Profile Enumeration Fit Statistics.

Number of Profiles	LL	FP	AIC	C-AIC	BIC	SSA-BIC	LMR (p)	BLRT (p)	Entropy
1	–3354.149	12	6732.297	6793.174	6781.174	6743.092	—	—	—
2	–2214.327	25	4478.655	4605.481	4580.481	4501.144	.0000	.0000	.987
3	–2105.583	38	4287.166	4479.942	4441.942	4321.351	.1308	.0000	.967
4	–2008.992	51	4119.984	4378.709	4327.709	4165.863	.2410	.0000	.876
5	–1924.953	64	3977.905	4302.580	4238.580	4035.479	.0492	.0000	.890
6	–1862.705	77	3879.410	4270.035	4193.035	3948.678	.0289	.0000	.886
7	–1821.023	90	3822.045	4278.619	4188.619	3903.008	.5520	.0000	.873

Note: N = 434. LL = log-likelihood; FP = free parameters; AIC = Akaike information criterion; C-AIC = consistent Akaike information criterion (calculated as the number of free parameters plus the BIC value); BIC = Bayesian information criterion; SSA-BIC = sample-size-adjusted BIC; LMR = Lo, Mendell, and Rubin (2001) adjusted LRT test; BLRT = bootstrapped log-likelihood ratio test. LMR, BLRT, and entropy statistics are not available when only 1 profile is calculated. All profiles were modeled in which the means and variances per profile indicator were allowed to vary across profiles.

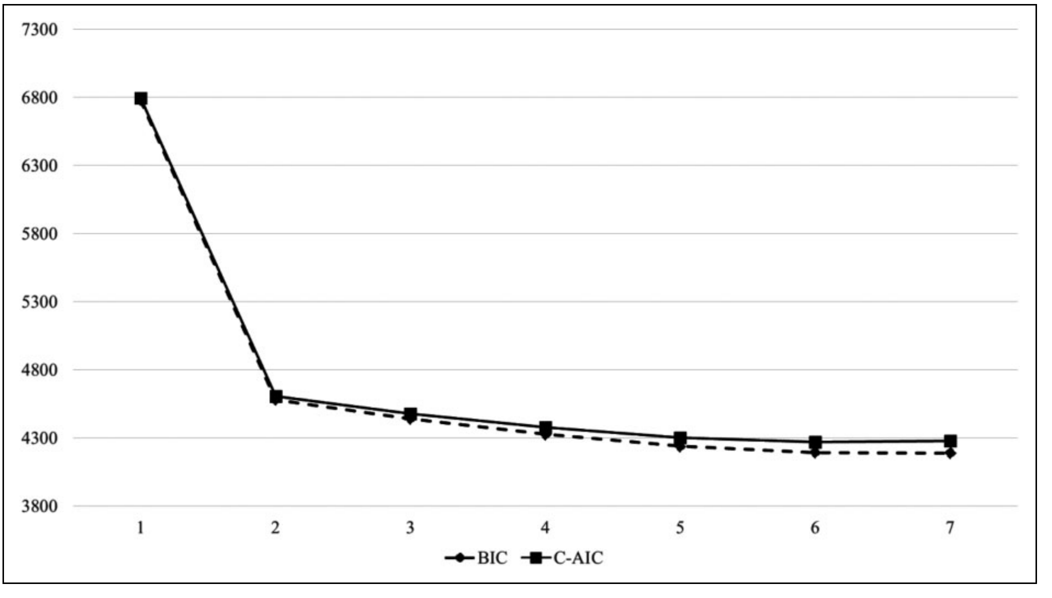

Figure 1. Elbow plot for BIC and C-AIC in determining profile solution.
Note: Values on the x-axis represent the number of profiles being extracted. BIC = Bayesian information criterion; C-AIC = consistent Akaike information criterion (calculated as the number of free parameters plus the BIC value).

Table 2. Descriptive Information per Latent Profile.

	% of Sample	Emotional Stability	Locus of Control	Self-Esteem	Self-Efficacy	Approach Motivation	Avoidance Motivation
High doubtful evaders	5.59	1.53	2.39	1.45	1.31	1.66	3.90
Doubtful evaders	27.35	2.22	2.56	2.23	1.99	2.04	3.42
Ambivalent enactors	11.24	2.98	2.85	2.91	2.84	2.85	3.05
Assured strivers	32.35	3.67	3.36	3.72	3.91	3.98	3.04
High assured strivers	23.47	4.25	3.39	4.17	4.34	4.26	2.47

Note: All CSE and approach/avoidance motivation constructs were on a 5-point scale (1 = *strongly disagree*, 5 = *strongly agree*).

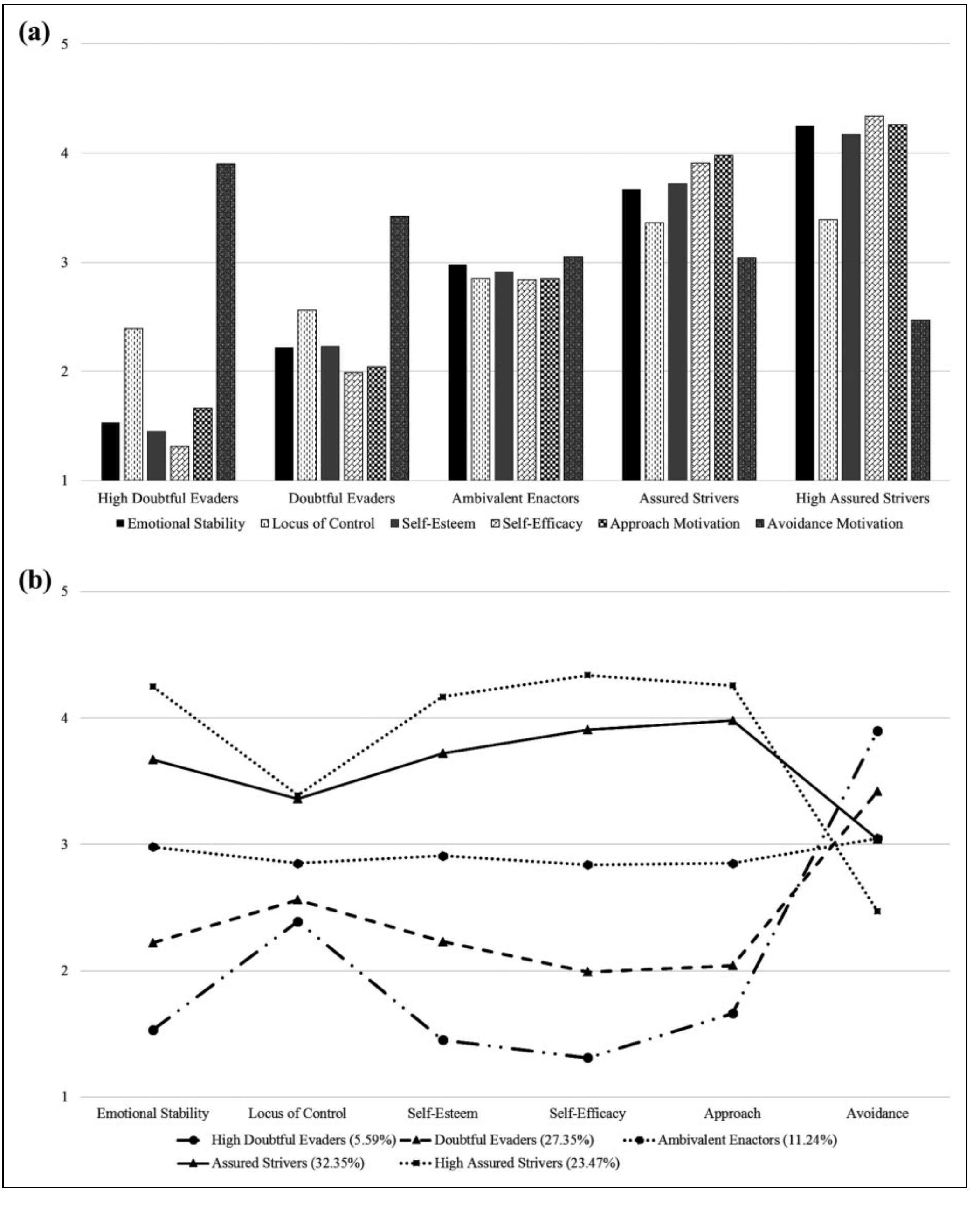

Figure 2. (a) Histogram of latent profiles of core self-evaluations (CSE) and approach/avoidance motivation from LPA. (b) Plot of latent profiles of core self-evaluations (CSE) and approach/avoidance motivation from LPA.
Note: All CSE and approach/avoidance motivation constructs were assessed on a 5-point scale (1 = *strongly disagree*, 5 = *strongly agree*) that is represented on the y-axis.

3.39, respectively) compared to the other CSE traits and approach motivation. However, *high assured strivers* exhibited higher emotional stability (M = 4.25), self-esteem (M = 4.17), self-efficacy (M = 4.34), and approach motivation (M = 4.26), and lower avoidance motivation

($M = 2.47$) compared to *assured strivers* (emotional stability $M = 3.67$; self-esteem $M = 3.72$; self-efficacy $M = 3.91$; approach motivation $M = 3.98$; avoidance motivation $M = 3.04$).

The other pair of profiles were classified as having lower positive self-evaluations and higher avoidance motivation. Specifically, our *high doubtful evaders* exhibited low emotional stability ($M = 1.53$), self-esteem ($M = 1.45$), self-efficacy ($M = 1.31$), and approach motivation ($M = 1.66$), along with slightly higher locus of control ($M = 2.39$) and the highest avoidance motivation ($M = 3.90$). *Doubtful evaders* (27.35%) exhibited similar trends, albeit with higher CSE traits (emotional stability $M = 2.22$; locus of control $M = 2.56$; self-esteem $M = 2.23$; self-efficacy $M = 1.99$) and approach motivation ($M = 2.04$), and lower avoidance motivation ($M = 3.42$). The final profile of employees we labeled as *ambivalent enactors* (11.24%) due to their moderate self-views (emotional stability $M = 2.98$; locus of control $M = 2.95$; self-esteem $M = 2.91$; self-efficacy $M = 2.84$) and mixed levels of approach ($M = 2.85$) and avoidance ($M = 3.05$) motivation. In sum, the presence of these profiles provides a clear answer to Research Question 1: latent profiles comprised of CSE and motivational traits do exist.

In regard to the profiles relating to job satisfaction, *high assured strivers* had the highest levels of job satisfaction ($M = 4.15$) compared to *assured strivers* ($M = 3.68$), as well as *ambivalent enactors* ($M = 2.81$), *doubtful evaders* ($M = 1.97$), and *high doubtful evaders* ($M = 1.84$). Interestingly, all of the job satisfaction means per profile were statistically significantly different from each other ($p < .001$) except for the *doubtful evaders* and the *high doubtful evaders*; these two profiles were not significantly different ($p > .05$). Moreover, the overall chi-square test for DCON analysis was significant, $\chi^2(4) = 680.81$, $p < .001$. Thus, in regard to Research Question 2—Do profiles of CSE and motivational traits differentiate employees' ratings of their job satisfaction?—we concluded that there are significant mean differences in job satisfaction across our latent profiles, with profiles exhibiting higher levels of emotional stability, self-esteem, self-efficacy, and approach motivation, relatively lower locus of control, and the lowest level of avoidance motivation yielding the highest levels of satisfaction with one's job.

Fuzzy Set Qualitative Comparative Analysis: Analytic Approach

We conducted fsQCA analyses with fsQCA 2.5 (Ragin & Davey, 2014), using the truth table algorithm for fuzzy sets (see the Supplemental Material 2 online for a step-by-step guide to conducting fsQCA). Because we already selected our outcome, attributes of interest, and cases, the first step involved calibrating our measures of interest to enable analyses. Calibration is tied to theory regarding set membership, where final values of each measure range from 0 to 1 with multiple in-between values, and reflect belonging in a given class or set (Zadeh, 1965). In this framework, 0 represents "fully out" of the set, 1 represents "fully in," and the values in between represent the degree to which a given observation is in the set, such as the set of employees with high job satisfaction. Values above 0.50 are considered more in than out, while those below 0.50 are more out than in; as such, this threshold represents an important qualitative breakpoint. Following prior work (e.g., Campbell et al., 2016; Fiss, 2011; Greckhamer, 2016; Misangyi & Acharya, 2014), we used the direct method of calibration (see Ragin, 2008), where the researcher specifies the "fully out" and "fully in" values, as well as the so-called point of maximum ambiguity or "neither in nor out" (0.50), and the software performs the calibration.

The selection of these three points should be theoretically driven or based on substantive knowledge to reflect meaningful values. In our case, we specified the raw aggregate value of 1 as "fully out," 5 as "fully in," and 3 as "neither" since the scales on which these measures are based are tied to psychometric theory and nicely correspond to the aforementioned thresholds.[5] Once the three points were specified for each raw measure, the software performed the transformation of all variable values into fuzzy set scores based on the log odds of full membership (Ragin, 2006). Following the aforementioned prior research,

Table 3. QCA Necessity Analyses for the Outcome of Job Satisfaction and Its Negation (Absence of Job Satisfaction).

	Outcome: Job Satisfaction		Outcome: ∼Job Satisfaction	
Attribute	Consistency	Coverage	Consistency	Coverage
Emotional stability	0.868	0.821	0.551	0.458
∼Emotional stability	0.427	0.520	0.784	0.839
Locus of control	0.775	0.799	0.611	0.554
∼Locus of control	0.568	0.624	0.779	0.752
Self-esteem	0.872	0.824	0.549	0.455
∼Self-esteem	0.424	0.517	0.788	0.844
Self-efficacy	0.884	0.828	0.518	0.426
∼Self-efficacy	0.387	0.478	0.791	0.857
Approach motivation	0.911[a]	0.847	0.509	0.416
∼Approach motivation	0.372	0.463	0.813	0.889
Avoidance motivation	0.608	0.625	0.782	0.707
∼Avoidance motivation	0.715	0.789	0.586	0.567

Note: ∼indicates a logical NOT (the absence of a condition).
[a]Exceeds the suggested consistency threshold for necessary conditions

we also added a small constant of 0.001 to all membership scores equal to exactly 0.50 to ensure these observations did not get dropped from the analyses for technical reasons.

Following past recommendations (e.g., Rihoux & Ragin, 2009; Schneider & Wagemann, 2012), we conducted necessity analyses first (see Table 3). Upon applying the recommended consistency benchmark of 0.90 (Schneider & Wagemann, 2012), and evaluating the conditions' coverage to ensure that any potentially necessary conditions were also empirically nontrivial, we have identified one necessary condition for job satisfaction. Specifically, we found that approach motivation was necessary for the outcome of (high) job satisfaction (consistency = 0.911; coverage = 0.847). This has implications for the sufficiency analysis, as discussed below, and provides insight into Research Question 3 proposed for fsQCA, in that approach motivation represents a necessary condition for job satisfaction to occur.

After analyses of necessity, we moved onto sufficiency analysis. In this step, we created a "truth table," which is a data matrix summarizing the property space occupied by our attributes of interest (Fiss, 2011). The analyses performed on this Boolean property space are comprised of 2^k logically possible combinations, where k is the number of attributes under consideration (Greckhamer et al., 2013). In our study, the truth table includes 64 rows (2^6). As shown in Table 4, our data exhibit "limited diversity" (Ragin & Sonnett, 2005), such that not all logically possible combinations are represented in our data or exist empirically (Fiss, 2007). Truth table rows without any cases in them with a membership score of 0.50 or higher are referred to as "logical remainders." For instance, we have no individuals in our sample that are high on self-esteem but low on all other attributes (the last row of the truth table). Similarly, our dataset does not include individuals low on self-esteem but high all other attributes. Importantly, limited diversity is common in many social science settings (Gilbert & Campbell, 2015) because not all theoretically possible combinations are likely to occur due to "attributes' tendency to fall into coherent patterns" (A. D. Meyer et al., 1993, p. 1176).[6]

Next, the truth table was consolidated in four stages. First, following recommendations in the literature, we employed a frequency threshold for the number of cases that fall within a given configuration for the solution to be considered. In small-N situations, this threshold number can be as low as 1 or 2; however, in larger N situations (i.e., hundreds of cases) a higher threshold is generally chosen (Rihoux & Ragin, 2009), with the requirement that at least 80% of the cases are retained after the frequency threshold is imposed (Bell et al., 2014; Ragin, 2008). This ensures that

Table 4. QCA Truth Table for the Outcome of Job Satisfaction.

Emotional Stability	Locus of Control	Self-Esteem	Self-Efficacy	Approach	Avoidance	Number of Cases	Percentage of Sample	Raw Consist.	PRI Consist.
1	1	1	1	1	0	126	29.03	0.931	0.869
0	0	0	0	0	1	102	23.50	0.571	0.090
1	1	1	1	1	1	91	20.97	0.914	0.808
0	0	0	0	0	0	21	4.84	0.712	0.143
0	1	0	0	0	1	14	3.23	0.712	0.126
0	1	1	1	1	1	11	2.53	0.918	0.686
1	0	1	1	1	0	10	2.30	0.934	0.835
0	0	0	0	1	1	8	1.84	0.873	0.444
1	0	1	1	1	1	5	1.15	0.925	0.786
1	1	1	1	0	0	4	0.92	0.886	0.480
1	0	0	0	0	1	4	0.92	0.820	0.237
1	0	0	0	0	0	4	0.92	0.839	0.273
0	1	1	1	1	0	4	0.92	0.934	0.726
1	0	1	0	1	1	3	0.69	0.926	0.639
1	0	1	0	0	0	3	0.69	0.859	0.305
0	1	0	1	1	1	3	0.69	0.924	0.663
0	1	0	0	0	0	2	0.46	0.793	0.178
1	1	1	1	0	1	1	0.23	0.892	0.482
1	1	1	0	1	1	1	0.23	0.929	0.636
1	1	1	0	1	0	1	0.23	0.935	0.676
1	1	1	0	0	1	1	0.23	0.872	0.310
1	1	1	0	0	0	1	0.23	0.877	0.322
1	1	0	1	0	0	1	0.23	0.899	0.391
1	1	0	0	1	1	1	0.23	0.919	0.565
1	0	1	1	0	1	1	0.23	0.893	0.476
1	0	1	1	0	0	1	0.23	0.889	0.479
1	0	1	0	0	1	1	0.23	0.852	0.289
1	0	0	1	1	1	1	0.23	0.930	0.696
1	0	0	1	1	0	1	0.23	0.935	0.712
1	0	0	1	0	0	1	0.23	0.890	0.379
0	1	1	0	1	0	1	0.23	0.926	0.578
0	1	0	1	0	1	1	0.23	0.878	0.321
0	0	1	0	1	1	1	0.23	0.913	0.544
0	0	1	0	0	0	1	0.23	0.845	0.246
0	0	0	1	0	1	1	0.23	0.866	0.294
0	0	0	0	1	0	1	0.23	0.901	0.499
1	1	0	1	1	1	0			
1	1	0	1	1	0	0			
1	1	0	1	0	1	0			
1	1	0	0	1	0	0			
1	1	0	0	0	1	0			
1	1	0	0	0	0	0			
1	0	1	0	1	0	0			
1	0	0	1	0	1	0			
1	0	0	0	1	1	0			
1	0	0	0	1	0	0			
0	1	1	1	0	1	0			
0	1	1	1	0	0	0			
0	1	1	0	1	1	0			

(continued)

Table 4. (continued)

Emotional Stability	Locus of Control	Self-Esteem	Self-Efficacy	Approach	Avoidance	Number of Cases	Percentage of Sample	Raw Consist.	PRI Consist.
0	1	1	0	0	1	0			
0	1	1	0	0	0	0			
0	1	0	1	1	0	0			
0	1	0	1	0	0	0			
0	1	0	0	1	1	0			
0	1	0	0	1	0	0			
0	0	1	1	1	1	0			
0	0	1	1	1	0	0			
0	0	1	1	0	1	0			
0	0	1	1	0	0	0			
0	0	1	0	1	0	0			
0	0	1	0	0	1	0			
0	0	0	1	1	1	0			
0	0	0	1	1	0	0			
0	0	0	1	0	0	0			

that solution is not driven by empirically rare configurations. We chose 5 cases (i.e., 5 individuals) as the threshold, which encompassed 89% of our sample.

Second, we evaluated consistency, or “the degree to which cases that share a combination of attributes ‘agree,’ or, in other words, consistently produce the key outcome” (Campbell et al., 2016, p. 173). Since 0.80 is considered satisfactory for a consistent subset relation (Misangyi & Acharya, 2014), this is the commonly employed threshold, although higher thresholds are also appropriate depending on the setting (Crilly, 2011; Ragin, 2008). High consistency—with perfect consistency being 1—signifies that a given configuration is almost always sufficient for the outcome of interest (i.e., job satisfaction), while low consistency means that the configuration is not reliably linked to the outcome. We initially employed 0.80 as the consistency threshold, ensuring that there were no other natural breaks in consistency scores right above the threshold. We then evaluated a more stringent measure of consistency known as PRI or “proportional reduction in inconsistency,” which aims to minimize empirical paradoxes that sometimes result in fuzzy set relations “where a case is consistent for both the presence and the absence of an outcome (Y and $\sim$Y)” (Gilbert & Campbell, 2015, p. 321). In line with Greckhamer (2016), we set 0.65 as the PRI consistency threshold. This resulted in effective 0.89 standard consistency threshold (0.68 for PRI) for job satisfaction, and—later on—0.94 (0.67 for PRI) for the absence of job satisfaction.

In the third step of the analysis, because we identified approach motivation as a necessary condition, we followed recent empirical research (Greckhamer, 2016) and updated recommendations in the literature (Schneider & Wagemann, 2012) and ensured that we did not allow any counterfactuals that included the absence of this necessary condition. In practice, this meant that for any truth table rows that did *not* include any cases but included the absence of approach motivation, we coded the outcome as 0 for the purposes of analysis.

In the final step, the truth table configurations were logically reduced using the software’s Boolean algorithm based on counterfactual analysis. The analysis produces three solutions: complex, intermediate, and parsimonious. The intermediate solution, which lies in the middle of the complexity–parsimony continuum, differs from the complex solution in that causal conditions that are inconsistent with existing knowledge are removed (Ragin & Sonnett, 2005). The parsimonious solution, which represents the most reduced form, employs all simplifying assumptions (i.e., those that may be

Table 5. Results of Fuzzy Set Sufficiency Analyses for Job Satisfaction and Job Dissatisfaction.

Outcome	Job Satisfaction		Lack of Job Satisfaction	
Configuration #	1a	1b	2a	2b
Attribute				
Emotional stability	•		⊗	⊗
Locus of control		•	⊗	
Self-esteem	•	•	⊗	⊗
Self-efficacy	●	●	⊗	⊗
Approach	■	■	⨂	⨂
Avoidance		•		•
Consistency	0.89	0.90	0.95	0.95
Raw coverage	0.79	0.51	0.62	0.60
Unique coverage	0.29	0.01	0.05	0.04
Overall solution consistency	0.89		0.95	
Overall solution coverage	0.80		0.66	

Note: Black circles ("•") indicate the presence of a condition, and open circles ("⨂") indicate its absence. Squares ("■") indicate the presence of a necessary condition. Blank spaces indicate "don't care"—i.e., the condition is not relevant to that particular configuration in regard to the outcome (it can be either present or absent). Large circles suggest "core" or central conditions, while small circles indicate "contributing" or peripheral conditions.

consistent with empirical evidence but inconsistent with theoretical knowledge [Schneider & Wagemann, 2012]; for a more extended discussion of counterfactual analysis, see Fiss, 2011).[7] Regardless of the assumptions made, none of the solutions "ever contradicts the empirical evidence at hand" (Schneider & Wagemann, 2012, p. 164). It has become a convention in management research to incorporate the intermediate and parsimonious solutions (Misangyi et al., 2017), which allows one to differentiate which conditions are "core" to a given configuration and which ones play a "contributing" or peripheral role. Core conditions are part of both solutions, while the latter are absent from the most simplified, parsimonious solution. This is represented graphically (see Table 5).

Fuzzy Set Qualitative Comparative Analysis: Results

With job satisfaction as the outcome, our analyses revealed two "sister" permutations of a profile that consistently led to high job satisfaction; that is, we uncovered two configurations of attributes that are sufficient to produce high job satisfaction (see Table 5), which provides an answer to Research Question 4a. They share the core attributes and only differ on contributing conditions. The core characteristics of the underlying configuration were approach motivation (a necessary condition) and high self-efficacy (a core condition), supported by high emotional stability and high self-esteem (Configuration 1a), and high locus of control and high self-esteem with high avoidance motivation (Configuration 1b). Interestingly, while both profiles exhibit high consistency, Configuration 1a had a significantly larger unique coverage, indicating that it is more empirically prevalent in our data compared to Configuration 1b. We labeled the former configuration as *steady confident* employees, and the latter as *cautious confident* employees.

Because fsQCA allows for causal asymmetry, in examining Research Question 4b, we explored what profiles consistently led to the absence of job satisfaction. At a conceptual level, this examines what predicts the other end of the continuum of job satisfaction (i.e., employees that score very low on job satisfaction). To test this, the original outcome measure was negated (i.e., reverse-coded). An important feature of fsQCA is that the recipes for negated outcomes need not be the mirror opposites of those predicting the original outcome of interest. For instance, what predicts the intent to leave the organization may be very different from what predicts the intent to stay, and vice versa; in other words, the underlying configurations of "quitters" are perhaps very different from the configurations of "stayers." In the current study, we can therefore test whether the configurations of those fully in the set of highly satisfied employees and fully out of the set are inherently different. This is possible since fsQCA is grounded in set theory and based on set relations, which need not be symmetric.

Again, two permutations of a general underlying profile emerged as consistently tied to the lack of job satisfaction. While the absence of approach motivation failed to meet the currently accepted necessity threshold (consistency $= 0.813$) as it did for job satisfaction, it did emerge as a core condition for its inverse. The combinations of contributing conditions to job dissatisfaction were also different when compared to job satisfaction, and included a combination of low levels of all four CSE traits (emotional stability, locus of control, self-esteem, and self-efficacy; Configuration 2a), and low emotional stability, self-esteem, and self-efficacy with high avoidance motivation (Configuration 2b). We labeled these constellations as containing *powerless diffident* and *anxious diffident* employees, respectively. Based on unique coverage, Configuration 2a was only marginally more empirically common than Configuration 2b. This illustrates that job satisfaction is causally asymmetric: what contributes to job satisfaction is not simply the reverse of what contributes to its absence.

Discussion

In examining CSE and approach and avoidance motivation, we provided an illustration of how LPA and fsQCA can be used to garner insight into how CSE traits and theoretically relevant motivations combine to predict job satisfaction. In a complementary sense, across both analytic approaches, the "best" configurations or recipes included high self-esteem, self-efficacy, and approach motivation; for our LPA results, our *high assured strivers* exhibited the highest job satisfaction, whereas for our fsQCA results, our *steady confident* configuration, which also included high emotional stability, displayed the highest unique coverage among consistent configurations in predicting employees' levels of job satisfaction.[8] Based on our LPA results, *high doubtful evaders* had the lowest job satisfaction—these employees were characterized by the lowest levels of emotional stability, self-esteem, self-efficacy, and approach motivation, as well as slightly higher levels of locus of control, and the highest level of avoidance motivation.

When comparing *high doubtful evaders* to the results from fsQCA, one must consider configurations predicting the absence of job satisfaction (i.e., the negated outcome), which perhaps represents the largest difference between LPA and fsQCA, and a point we discuss below. Nonetheless, when considering configurations that led to the absence of job satisfaction, the configuration with the highest coverage pointed to a lack of approach motivation, as well as low CSE traits (emotional stability, locus of control, self-esteem, and self-efficacy) in a contributing role. Notably, avoidance motivation was not empirically relevant to this particular configuration (although it operates as a contributing condition in its sister permutation), which highlights another difference between LPA and fsQCA (i.e., not all constructs are retained in fsQCA configurations, whereas all constructs are retained in profiles captured via LPA). As such, our *powerless diffident* configuration did share some overlap with our *high doubtful evader* profile, though the interpretation is slightly different.

Although there were similarities across the two analytic approaches, we were able to delineate how the conclusions reached via each approach may be slightly different. The most telling difference between the two strategies is how the profile indicators, or variables included in the configurations, are handled analytically: In LPA, all profile indicators are included at some level, whereas in fsQCA, a condition can be absent from a configuration. For instance, the *steady confident* configuration from fsQCA was represented by high self-efficacy and approach motivation, with emotional stability and self-esteem further contributing to this configuration's prediction of job satisfaction; locus of control and avoidance motivation were not relevant. Conversely, the best performing profile from LPA—*high assured strivers*—had all indicators represented, including fairly high levels of locus of control and low levels of avoidance motivation. Thus, fsQCA allowed us to isolate the key conditions in predicting job satisfaction, meaning some characteristics were no longer represented because they were deemed not causally relevant. Conversely, LPA had all constructs present in each profile within the final solution, albeit with some constructs having lower levels (locus of control, avoidance motivation).

Moreover, fsQCA allows researchers to distinguish between necessary and/or sufficient "causes" of outcomes. Indeed, we found one necessary condition in the form of approach motivation in predicting job satisfaction. This indicates that high approach motivation is a subset of the set of employees with high job satisfaction; as a result, approach motivation must be present for job satisfaction to occur. Yet, approach motivation alone is not sufficient (in other words, it is insufficient but necessary for job satisfaction). The slightly simpler of the two recipes (Configuration 1a) included three other conditions, while the other (Configuration 1b) included four additional conditions. The two aforementioned sister configurations are considered equally sufficient for job satisfaction, and highlight the principle of equifinality in fsQCA.

An additional difference between the two analytic approaches is the ability in fsQCA to "negate" outcomes to examine so-called causal asymmetry; in the current study, negating job satisfaction allowed us to examine the combinations of attributes predicting the absence of job satisfaction. From a mathematical standpoint, the negated outcome was obtained by reverse-scoring the original job satisfaction scores. This procedure could be applied to LPA, such that a reverse-scored job satisfaction composite could be treated as a distal outcome. However, as previously articulated, in LPA, the profiles are selected without consideration and/or influence of the criteria. Thus, the same exact profiles used to predict job satisfaction would be used to predict its inverse. In fsQCA, on the other hand, different configurations can emerge for the absence of a criterion variable, which fits the results of the current CSE exploration: the configurations that led to job satisfaction and its absence had similarities, but there were also distinct differences. This focus on the presence and absence of criteria relates to how research questions are derived for fsQCA versus LPA: Whereas LPA first focuses on how profile indicators (i.e., CSE traits, motivation) uniquely combine, fsQCA first focuses on identifying an outcome of interest, and then identifies the constructs that may or may not combine in predicting the outcome.

Finally, although we did not include tests of antecedents in our study, this raises another distinction between LPA and fsQCA: In LPA, auxiliary variables—such as antecedents—are frequently modeled. Several studies (e.g., Bennett et al., 2016; Dahling, Gabriel, & MacGowan, 2017; Gabriel et al., 2015; Morin et al., 2011) have identified how increases in an antecedent—which can include demographics, as well as broader contextual or environmental factors (e.g., personality traits, dispositional affect, job demands)—can make individuals more or less likely to belong to one profile over another. Although a conceptually analogous analysis is possible in principle in fsQCA (i.e., the outcome could be a measure of membership in a particular configuration/recipe and one could run a QCA analysis on recipe membership, assuming there were theoretical or substantive reasons for doing so), this is not typically done in practice.

Theoretical Implications for CSE Theory

Although the primary purpose of the current paper was to highlight the similarities and differences between LPA and fsQCA, the results from each analytic approach have implications for CSE theory. Prior research has, for example, raised questions about the structural validity of the higher-order CSE construct. In particular, researchers (e.g., Chang et al., 2012; Johnson et al., 2015; Johnson, Rosen, Chang, & Lin, 2016) have expressed doubt about locus of control's status as an indicator of CSE, given that this trait reflects evaluations of the responsiveness of the environment as opposed to evaluations of the self. Results of the current study support this idea, indicating that locus of control (a) does little in terms of differentiating profiles in LPA and (b) is only causally relevant in two of the four configurations in the fuzzy set analyses, and within those configurations, always appears in a supporting role. Therefore, these results corroborate and extend initial findings suggesting that locus of control differs from the other CSE traits.

Researchers have also sought to better understand the overall meaning of CSE, with some suggesting that it may simply reflect a broader conceptualization of emotional stability (Bono & Judge, 2003), self-esteem (Johnson et al., 2008), or approach/avoidance motivation (Ferris et al., 2011; Ferris et al., 2013). Our results offer insight into what might reflect the "true core" of CSE. Based on the fsQCA results, approach motivation, self-efficacy, and self-esteem emerged as more central conditions for each outcome, whereas avoidance motivation, emotional stability, and locus of control were not included in all the paths. The LPA results similarly indicated that the same three constructs—self-esteem, generalized self-efficacy, and approach motivation—were critical for differentiating the profiles. Across analyses, the status of emotional stability is also somewhat ambiguous. Although the appropriateness of emotional stability as an indicator of CSE has not been broached, our results suggest that this issue deserves theoretical and empirical attention.

Finally, the relevance of approach/avoidance motivation for CSE and what role it might play has been debated (e.g., Ferris et al., 2011; Johnson et al., 2008). For example, Johnson et al. (2008) suggested that approach and avoidance dispositions warrant inclusion among the set of CSE trait indicators. In fact, emotional stability, which may be a marker of (low) avoidance motivation (Elliot & Thrash, 2002), is already included. Other researchers (e.g., Ferris et al., 2011) have suggested that approach and avoidance motivations may instead be proximal outcomes of CSE. Our results provide a starting point for thinking about this issue, albeit they paint a complex picture. Although approach motivation was revealed to be central to the CSE construct (based on the fsQCA results) and critical for distinguishing between CSE profiles (based on the LPA results), avoidance motivation was neither central nor a distinguishing factor. Thus, our results indicate that avoidance motivation should not be included as a CSE indicator (which also raises questions about the status of emotional stability), and we call for further research to understand the unique role that approach motivation might play with respect to CSE.

Choosing Between Latent Profile Analysis and Fuzzy Set Analysis

Importantly, our central aim was to not make LPA and fsQCA "compete," but rather to focus on how the two methods can be combined, and how researchers can choose between the two approaches. Thus, to aid researchers in determining whether LPA or fuzzy set analysis is more or less appropriate for their research question(s), we generated "typical" research questions addressed by each analytic approach in Table 6, as well as common features of each analysis in Table 7. Of note, we are not recommending that these are the only two approaches to address person-centered research questions. For instance, a newer alternative to both LPA and fsQCA has recently emerged in the form of mixture structural equation modeling (mixture SEM; e.g., Morin, Scalas, & Marsh, 2015; Morin & Wang, 2016). Within this approach, scholars are not only able to test for the presence of latent profiles, but can also examine how the subgroups differ in regard to specific relationships amongst the variables of interest (Henson, Reise, & Kim, 2007; Morin et al., 2015). Thus, if a broader theoretical model exists, particularly one that implies mediation, scholars can use mixture SEM to simultaneously extract profiles, while also seeing if a similar pattern of direct relations occurs amongst the profile indicators. In the context of the current empirical example, we focused on a series of direct effects of our four CSE constructs and two motivation variables on job satisfaction, with no larger model being considered. In addition, we recognize that, in some simulation studies, traditional cluster analysis has been able to more effectively uncover the underlying profile solution in the data compared to LPA (for further reading, see Shireman, Steinley, & Brusco, 2016; Steinley

Table 6. Questions Suited to Latent Profile Analysis Versus Fuzzy Set Analysis.

Questions that latent profile analysis (LPA) can help answer
1. Do latent profiles exist related to the indicators of interest? How are they characterized?
2. Are there quantitatively and qualitatively distinct profiles of the indicators of interest?
3. Do certain antecedents predict profile membership? That is, do certain antecedents increase the likelihood of belonging to a particular latent profile?
4. Do latent profiles exhibit different levels of distal outcomes of interest?
Questions that fuzzy set analysis (fsQCA) can help answer
1. Which theoretically possible configurations of characteristics of interest (attributes or conditions) exist in our data, and which are absent?
2. Which combinations are most frequently populated by cases from our data (i.e., numbers of individuals attached to a given configuration), and which combinations are less frequent?
3. Are any conditions causally necessary to produce the outcome (or lack/reverse thereof)?
4a. Which conditions or configurations of conditions are sufficient for the outcome(s) of interest to occur?
4b. Which conditions or configurations of conditions are sufficient for the absence of outcome(s) of interest to occur?

Note: We view the aforementioned research questions as distinct in the sense that they more closely tie to the analytic capabilities of LPA or fsQCA. However, we also note that these questions can be used in a complementary manner within the same study.

Table 7. Key Differences Between Latent Profile Analysis and Fuzzy Set Analysis.

	LPA	fsQCA
Focus	Profile indicators	Outcomes
Type of method	Mixture modeling	Set-theoretic
Analysis based in	Maximum likelihood	Boolean algebra
Features		
Ability to examine configurations of constructs?	Yes	Yes
Ability to conduct a counterfactual analysis of unobserved configurations?	No	Yes
Ability to include antecedents as predictors of profiles/configurations?	Yes, common in practice	Yes, in theory, but not used in practice
Ability to exclude some constructs from the final configuration?	No	Yes

& Brusco, 2011). However, given that both LPA and fsQCA are gaining increased popularity in the micro and macro literatures above and beyond these alternative approaches, we only discuss considerations for each approach below.

As illustrated in our empirical example, the primary question researchers must ask prior to conducting analyses is the following: are we more interested in examining whether sets of indicators combine, or are we more focused on identifying a key outcome and then determining constructs that may combine in configurations to produce that outcome? The former question tends to be more suited for LPA, whereas the latter question is more suitable for fsQCA. That said, whether the focus is on combinations of indicators or the outcome(s) of interest, scholars must ask themselves whether it is *theoretically* possible for constructs to combine meaningfully. For example, in Gabriel et al. (2015), the researchers created an a priori framework in an LPA study that outlined possible quantitatively and qualitatively distinct profiles of emotional labor that were used to guide their theorizing. Alternatively, Campbell et al. (2016) created a theoretical framework in a study using fsQCA that built on the premise that investors react to combinations of opportunity, motivation, and ability signals embedded in an acquisition announcement. Critically, if it is not theoretically meaningful for constructs to combine (i.e., there is not a theoretical rationale for why the constructs would form profiles or configurations), then we strongly recommend that researchers use variable-centered methods (e.g., regression, ANOVA, SEM, confirmatory factor analysis, etc.).

If there is theoretical rationale for constructs to combine into profiles/configurations, researchers must also ask themselves whether they are interested in identifying antecedents of the profiles. For instance, do scholars wish to know whether demographics, individual differences, or broader contextual/environmental factors determine profile and/or configuration membership (e.g., Kinnunen et al., 2014)? If so, then LPA may be a more likely choice given the prevalence of antecedent tests using this approach compared to the current use of fuzzy set analysis. If antecedents are not indispensable to the research question, however, scholars must ask themselves whether they want all constructs represented at some level in their profiles, or if it is acceptable or even desirable to have certain variables not contribute to the final solution. If researchers desire all variables to be represented, LPA should be used. Yet, if researchers are instead interested in which select constructs are causally relevant when considering the contribution to a criterion variable, then fsQCA becomes more appropriate. Similarly, if researchers are interested in potential causal asymmetry in the outcome variable (whereby the combinations leading to the outcome and the absence of it are qualitatively, and not just quantitatively, different), then fsQCA is a suitable methodological tool, as such an analytic approach is not possible with LPA.

Of course, we recognize that there are still unknowns surrounding LPA and fsQCA. For example, it is unclear how nonnormal distributions affect profile enumeration for LPA (for recent work, see B. Muthén & Asparouhov, 2015). Likewise, although it is clear that larger sample sizes increase the ability to detect more complex profile solutions in LPA, there is limited evidence surrounding optimal sample size (Marsh, Lüdtke, Trautwein, & Morin, 2009; Morin et al., 2016). In addition, with LPA and fsQCA, scholars are continuing to run simulations and other analyses to determine optimal decision rules, meaning the criteria for solutions are constantly changing (e.g., the optimal threshold for PRI consistency in fsQCA). Finally, a big unresolved challenge in fsQCA lies in how to best treat cross-sectional time-series or panel data. Thus, although there is much to be gleaned using these two analytic techniques, there is also much to be learned about the application of either analytic approach.

Conclusion

Our study demonstrates that both LPA and fsQCA are powerful tools for addressing person-centered research questions and can offer many advantages over variable-centered approaches. Although these techniques are rooted in different methodological traditions, have divergent assumptions, and offer somewhat different utility, our hope is that organizational scholars continue to examine and apply them in tandem. Doing so can not only help unpack important theoretical nuance in organizational constructs of interest, but also further our understanding of the distinctions between LPA and fsQCA.

Authors' Note

The authors wish to thank the editorial team—particularly Aleksandra Bujacz—and reviewers for the Person-Centered Research Methods in the Organizational Sciences feature topic for their feedback and support during the review process. Additionally, the authors wish to thank Marcus Butts and Peer Fiss, who were helpful resources in discussing issues pertaining to LPA and fsQCA, respectively.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

ORCID iD

Allison S. Gabriel http://orcid.org/0000-0002-3755-8863

Supplemental Material

Supplemental material for this article is available online.

Notes

1. The "causal" terminology stems from the fact that in set-theoretic methods the attributes are theoretically and empirically tied to an outcome. The underlying premise of these methods is that different conditions combine to create—or cause—an outcome (Fiss, 2007), and the two are examined in tandem. This is in stark contrast to LPA, where profile indicators are examined in isolation from an outcome. Moreover, all profile indicators in LPA are included in the resulting configuration, regardless of their individual empirical contribution to the outcome; in fsQCA, after the Boolean logical reduction procedure is accomplished via dedicated software programs, only variables deemed "causally relevant" in relation to the outcome remain. Therefore, the use of causal language is not to suggest that set-theoretic methods are intrinsically better at establishing causality than other research methods.
2. We note that we used only one sample in the current investigation. However, it is recommended to replicate and extend latent profiles, such that profiles are first established in one study, and then replicated in a second study and examined in relation to antecedent and/or outcome variables (e.g., Bennett, Gabriel, Calderwood, Dahling, & Trougakos, 2016; Gabriel, Daniels, Diefendorff, & Greguras, 2015; Wang & Hanges, 2011). This can help increase confidence that the profiles extracted are generalizable.
3. The number of response options plays an important role in regard to whether scholars wanting to use a person-centered methodology should use LPA or shift to latent class analysis (LCA), which is appropriate to use when the profile indicators are ordinal in nature. Following recommendations from Finney and DiStefano (2013), scholars assessing items with four or fewer response options can treat each option as an ordinal category and use LCA; scholars assessing items with five or more response options may use LPA and treat the scale as continuous in nature.
4. In the event that allowing the residuals to vary creates issues with model convergence, scholars can also model residuals as fixed (Bauer & Curran, 2003; Chen, Bollen, Paxton, Curran, & Kirby, 2001; Morin, Meyer, Creusier, & Biétry, 2016).
5. We adjusted these points for two of the measures (i.e., locus of control and self-efficacy) where both 1 and 5 were above the minimum and maximum in our sample to 1.4 and 4.6.
6. For a detailed discussion of limited diversity and logical remainders, please refer to chapter 6 in Schneider and Wagemann (2012).
7. The assumptions regarding "counterfactuals" in our analyses are that the four constructs composing CSE should positively contribute to job satisfaction given the wealth of extant theory and empirical evidence; we did not make a directional assumption regarding approach or avoidance motivation. These assumptions do not affect actual cases.
8. Of note, higher coverage does not necessarily imply a better performing recipe in terms of producing job satisfaction—only a more common or prevalent one.

References

Asparouhov, T., & Muthén, B. (2014). Auxiliary variables in mixture modeling: Three-step approaches using Mplus. *Structural Equation Modeling*, *21*, 329-341. doi:10.1080/10705511.2014.915181

Aversa, P., Furnari, S., & Haefliger, S. (2015). Business model configurations and performance: A qualitative comparative analysis in Formula One racing, 2005-2013. *Industrial and Corporate Change*, *24*, 655-676. doi:10.1093/icc/dtv012

Barney, J. B., & Hoskisson, R. E. (1990). Strategic groups: Untested assertions and research proposals. *Managerial and Decision Economics*, *11*(3), 187-198. doi: 10.1002/mde.4090110306

Bauer, D. J., & Curran, P. J. (2003). Distributional assumptions of growth mixture models: Implications for over-extraction of latent trajectory classes. *Psychological Methods*, *8*(3), 338-363. doi: 10.1037/1082-989X.8.3.338

Bell, R. G., Filatotchev, I., & Aguilera, R. V. (2014). Corporate governance and investors' perceptions of foreign IPO value: An institutional perspective. *Academy of Management Journal*, *57*, 301-320. doi:10.5465/amj.2011.0146

Bennett, A. A., Gabriel, A. S., Calderwood, C., Dahling, J. J., & Trougakos, J. P. (2016). Better together? Examining profiles of employee recovery experiences. *Journal of Applied Psychology*, *101*, 1635-1654. doi:10.1037/apl0000157

Bono, J. E., & Judge, T. A. (2003). Core self-evaluations: A review of the trait and its role in job satisfaction and performance. *European Journal of Personality*, *17*, S5-S18. doi:10.1002/per.481

Campbell, J. T., Sirmon, D. G., & Schijven, M. (2016). Fuzzy logic and the market: A configurational approach to investor perceptions of acquisition announcements. *Academy of Management Journal*, *59*, 163-187. doi: 10.5465/amj.2013.0663

Chang, C.-H., Ferris, D. L., Johnson, R. E., Rosen, C. C., & Tan, J. A. (2012). Core self-evaluations a review and evaluation of the literature. *Journal of Management*, *38*, 81-128. doi:10.1177/0149206311419661

Chen, F., Bollen, K. A., Paxton, P., Curran, P. J., & Kirby, J. B. (2001). Improper solutions in structural equation models: Causes, consequences, and strategies. *Sociological Methods & Research*, *29*(4), 468-508. doi: 10.1177/0049124101029004003

Cohen, J. (1992). Quantitative methods in psychology. *Nature*, *112*, 155-159. doi:10.1038/141613a0

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple correlation/regression analysis for the behavioral sciences*. London, UK: Taylor & Francis.

Cool, K. O., & Schendel, D. (1987). Strategic group formation and performance: The case of the U.S. pharmaceutical industry, 1963-1982. *Management Science*, *33*, 1102-1124. doi:10.1287/mnsc.33.9.1102

Crilly, D. (2011). Predicting stakeholder orientation in the multinational enterprise: A mid-range theory. *Journal of International Business Studies*, *42*, 694-717. doi:10.1057/jibs.2010.57

Crilly, D., Zollo, M., & Hansen, M. T. (2012). Faking it or muddling through? Understanding decoupling in response to stakeholder pressures. *Academy of Management Journal*, *55*, 1429-1448. doi:10.5465/amj.2010.0697

Dahling, J. J., Gabriel, A. S., & MacGowan, R. L. (2017). Understanding typologies of feedback environment perceptions: A latent profile investigation. *Journal of Vocational Behavior*, *101*, 133-148. doi:10.1016/j.jvb.2017.05.007

Deci, E. L., & Ryan, R. M. (1985). The general causality orientation scale: Self-determination in personality. *Journal of Research in Personality*, *19*, 109-134. doi:10.1016/0092-6566(85)90023-6

Dess, G. G., & Davis, P. S. (1984). Porter's (1980) generic strategies as determinants of strategic group membership and organizational performance. *Academy of Management Journal*, *27*(3), 467-488. doi: 10.2307/256040

De Fruyt, F. (2002). A person-centered approach to P-E fit questions using a multiple-trait model. *Journal of Vocational Behavior*, *60*, 73-90. doi:10.1006/jvbe.2001.1816

Diallo, T. M. O., Morin, A. J. S., & Lu, H. (2016). Impact of misspecifications of the latent variance-covariance and residual matrices on the class enumeration accuracy of growth mixture models. *Structural Equation Modeling*, *23*, 507-531. doi:10.1080/10705511.2016.1169188

Diallo, T. M. O., Morin, A. J. S., & Lu, H. (2017). The impact of total and partial inclusion or exclusion of active and inactive time invariant covariates in growth mixture models. *Psychological Methods*, *22*, 166-190. doi:10.1037/met0000084

Dormann, C., Fay, D., Zapf, D., & Frese, M. (2006). A state-trait analysis of job satisfaction: On the effect of core self-evaluations. *Applied Psychology: An International Review*, *55*, 27-51. doi:10.1111/j.1464-0597.2006.00227.x

Elliot, A. J., & Thrash, T. M. (2002). Approach-avoidance motivation in personality: Approach and avoidance temperaments and goals. *Journal of Personality and Social Psychology*, *82*, 804-818. doi:10.1037/0022-3514.82.5.804

Erez, A., & Judge, T. A. (2001). Relationship of core self-evaluations to goal setting, motivation, and performance. *Journal of Applied Psychology*, *86*, 1270-1279. doi:10.1037/0021-9010.86.6.1270

Ferris, D. L., Johnson, R. E., Rosen, C. C., Djurdjevic, E., Chang, C. H. D., & Tan, J. A. (2013). When is success not satisfying? Integrating regulatory focus and approach/avoidance motivation theories to explain the relation between core self-evaluation and job satisfaction. *Journal of Applied Psychology*, *98*, 342-353. doi:10.1037/a0029776

Ferris, D. L., Rosen, C. R., Johnson, R. E., Brown, D. J., Risavy, S. D., & Heller, D. (2011). Approach or avoidance (or both?): Integrating core self-evaluations within an approach/avoidance framework. *Personnel Psychology*, *64*, 137-161. doi:10.1111/j.1744-6570.2010.01204.x

Fiegenbaum, A., & Thomas, H. (1995). Strategic groups as reference groups: Theory, modeling and empirical examination of industry and competitive strategy. *Strategic Management Journal*, *16*(6), 461-476. doi: 10.1002/smj.4250110303

Finney, S. J., & DiStefano, C. (2013). Non-normal and categorical data in structural equation modeling. In G. R. Hancock & R. O. Mueller (Eds.), *Structural equation modeling: A second course* (2nd ed., pp. 439-492). Greenwich, CT: Information Age.

Fiss, P. C. (2007). A set-theoretic approach to organizational configurations. *Academy of Management Review*, *32*, 1180-1198. doi:10.5465/AMR.2007.26586092

Fiss, P. C. (2011). Building better causal theories: A fuzzy set approach to typologies in organization research. *Academy of Management Journal*, *54*, 393-420. doi:10.5465/AMJ.2011.60263120

Foti, R. J., Bray, B. C., Thompson, N. J., & Allgood, S. F. (2012). Know thy self, know thy leader: Contributions of a pattern-oriented approach to examining leader perceptions. *Leadership Quarterly*, *23*, 702-717. doi:10.1016/j.leaqua.2012.03.007

Frambach, R. T., Fiss, P. C., & Ingenbleek, P. T. (2016). How important is customer orientation for firm performance? A fuzzy set analysis of orientations, strategies, and environments. *Journal of Business Research*, *69*, 1428-1436. doi:10.1016/j.jbusres.2015.10.120

Gabriel, A. S., Daniels, M. A., Diefendorff, J. M., & Greguras, G. J. (2015). Emotional labor actors: A latent profile analysis of emotional labor strategies. *Journal of Applied Psychology*, *100*, 863-879. doi:10.1037/a0037408

García-Castro, R., Aguilera, R. V., & Ariño, M. A. (2013). Bundles of firm corporate governance practices: A fuzzy set analysis. *Corporate Governance: An International Review*, *21*, 390-407. doi:10.1111/corg.12024

García-Castro, R., & Francoeur, C. (2014). When more is not better: Complementarities, costs and contingencies in stakeholder management. *Strategic Management Journal*, *37*, 406-424. doi:10.1002/smj.2341

Gilbert, B. A., & Campbell, J. T. (2015). The geographic origins of radical technological paradigms: A configurational study. *Research Policy*, *44*, 311-327. doi:10.1016/j.respol.2014.08.006

Goldberg, L. R. (1999). A broad-bandwidth, public domain, personality inventory measuring the lower-level facets of several five-factor models. In I. Mervielde, I. Deary, F. De Fruyt, & F. Ostendorf (Eds.), *Personality psychology in Europe* (Vol. 7, pp. 7-28). Tilburg, the Netherlands: Tilburg University Press.

Graves, L. M., Cullen, K. L., Lester, H. F., Ruderman, M. N., & Gentry, W. A. (2015). Managerial motivational profiles: Composition, antecedents, and consequences. *Journal of Vocational Behavior*, *87*, 32-42. doi:10.1016/j.jvb.2014.12.002

Greckhamer, T. (2011). Cross-cultural differences in compensation level and inequality across occupations: A set-theoretic analysis. *Organization Studies*, *32*(1), 85-115. doi:10.1177/0170840610380806

Greckhamer, T. (2016). CEO compensation in relation to worker compensation across countries: The configurational impact of country-level institutions. *Strategic Management Journal*, *37*, 793-815. doi:10.1002/smj.2370

Greckhamer, T., Misangyi, V., & Fiss, P. C. (2013). The two QCAs: From a small-N to a large-N set theoretic approach. *Research in the Sociology of Organizations*, *38*, 49-75. doi:10.1108/S0733-558X(2013)0000038007

Henson, J. M., Reise, S. P., & Kim, K. H. (2007). Detecting mixtures from structural model differences using latent variable mixture modeling: A comparison of relative model fit statistics. *Structural Equation Modeling*, *14*, 202-226. doi:10.1080/10705510709336744

Howard, J., Gagné, M., Morin, A. J., & Van den Broeck, A. (2016). Motivation profiles at work: A self-determination theory approach. *Journal of Vocational Behavior*, *95*, 74-89. doi:10.1016/j.jvb.2016.07.004

Johnson, R. E., Chang, C.-H., Meyer, T., Lanaj, K., & Way, J. D. (2013). Approaching success or avoiding failure? Approach and avoidance motives in the work domain. *European Journal of Personality*, *27*, 424-441. doi:10.1002/per.1883

Johnson, R. E., Rosen, C. C., Chang, C.-H., & Lin, S.-H. (2015). Getting to the core of locus of control: Is it an evaluation of the self or the environment? *Journal of Applied Psychology*, *100*, 1568-1578. doi:10.1037/apl0000011

Johnson, R. E., Rosen, C. C., Chang, C.-H., & Lin, S.-H. (2016). Assessing the status of locus of control as an indicator of core self-evaluations. *Personality and Individual Differences*, *90*, 155-162. doi:10.1016/j.paid.2015.11.002

Johnson, R. E., Rosen, C. C., & Djurdjevic, E. (2011). Assessing the impact of common method variance on higher order multidimensional constructs. *Journal of Applied Psychology*, *96*, 744-761. doi:10.1037/a0021504

Johnson, R. E., Rosen, C. C., & Levy, P. E. (2008). Getting to the core of core self-evaluation: A review and recommendations. *Journal of Organizational Behavior*, *29*, 391-413. doi:10.1002/job.514

Judge, T. A., & Bono, J. E. (2001). Relationship of core self-evaluations traits—self-esteem, generalized self-efficacy, locus of control, and emotional stability—with job satisfaction and job performance: A meta-analysis. *Journal of Applied Psychology*, *86*, 80-92. doi:10.1037/0021-9010.86.1.80

Judge, T. A., Bono, J. E., Erez, A., & Locke, E. A. (2005). Core self-evaluations and job and life satisfaction: The role of self-concordance and goal attainment. *Journal of Applied Psychology*, *90*, 257-268. doi:10.1037/0021-9010.90.2.257

Judge, T. A., Bono, J. E., & Locke, E. A. (2000). Personality and job satisfaction: The mediating role of job characteristics. *Journal of Applied Psychology*, *85*, 237-249. doi:10.1037/0021-9010.85.2.237

Judge, T. A., Locke, E. A., & Durham, C. C. (1997). The dispositional causes of job satisfaction: A core evaluations approach. *Research in Organizational Behavior*, *19*, 151-188.

Judge, T. A., Locke, E. A., Durham, C. C., & Kluger, A. N. (1998). Dispositional effects on job and life satisfaction: The role of core evaluations. *Journal of Applied Psychology*, *83*, 17-34. doi:10.1037/0021-9010.83.1.17

Jung, T., & Wickrama, K. (2008). An introduction to latent class growth analysis and growth mixture modeling. *Social and Personality Psychology Compass*, *2*, 302-317. doi:10.1111/j.1751-9004.2007.00054.x

Kabins, A. H., Xu, X., Bergman, M. E., Berry, C. M., & Willson, V. L. (2016). A profile of profiles: A meta-analysis of the nomological net of commitment profiles. *Journal of Applied Psychology*, *101*, 881-904. doi:10.1037/apl0000091

Ketchen, D. J., Jr., & Shook, C. L. (1996). The application of cluster analysis in strategic management research: An analysis and critique. *Strategic Management Journal*, 441-458. doi: 10.1002/(SICI)1097-0266(199606)17:6<441::AID-SMJ819>3.0.CO;2-G

Kinnunen, U., Mäkikangas, A., Mauno, S., De Cuyper, N., & De Witte, H. (2014). Development of perceived job insecurity across two years: Associations with antecedents and employee outcomes. *Journal of Occupational Health Psychology*, *19*, 243-258. doi:10.1037/a0035835

Lanza, S. T., Tan, X., & Bray, B. C. (2013). Latent class analysis with distal outcomes: A flexible model-based approach. *Structural Equation Modeling*, *20*, 1-26. doi:10.1080/10705511.2013.742377

Lawrence, B. S., & Zyphur, M. J. (2011). Identifying organizational faultlines with latent class cluster analysis. *Organizational Research Methods*, *14*, 32-57. doi:10.1177/1094428110376838

Lewis, P., & Thomas, H. (1990). The linkage between strategy, strategic groups, and performance in the UK retail grocery industry. *Strategic Management Journal*, *11*(5), 385-397. doi: 10.1002/smj.4250110505

Lo, Y., Mendell, N. R., & Rubin, D. B. (2001). Testing the number of components in a normal mixture. *Biometrika*, *88*, 767-778. doi:10.1093/biomet/90.4.991

Marsh, H. W., Lüdtke, O., Trautwein, U., & Morin, A. J. (2009). Classical latent profile analysis of academic self-concept dimensions: Synergy of person-and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling*, *16*, 191-225. doi:10.1080/10705510902751010

Meuer, J. (2014). Archetypes of inter-firm relations in the implementation of management innovation: A set-theoretic study in China's biopharmaceutical industry. *Organization Studies*, *35*, 121-145. doi:10.1177/0170840613495339

Meyer, A. D., Tsui, A. S., & Hinings, C. R. (1993). Configurational approaches to organizational analysis. *Academy of Management Journal*, *36*, 1175-1195. doi:10.2307/256809

Meyer, J. P., & Morin, A. J. (2016). A person-centered approach to commitment research: Theory, research, and methodology. *Journal of Organizational Behavior*, *37*, 584-612. doi:10.1002/job.2085

Miles, R. E., & Snow, C. C. (1978). *Organizational strategy, structure, and process*. New York, NY: McGraw-Hill.

Misangyi, V. F., & Acharya, A. G. (2014). Substitutes or complements? A configurational examination of corporate governance mechanisms. *Academy of Management Journal*, *57*, 1681-1705. doi:10.5465/amj.2012.0728

Misangyi, V. F., Greckhamer, T., Furnari, S., Fiss, P. C., Crilly, D., & Aguilera, R. (2017). Embracing causal complexity: The emergence of a neo-configurational perspective. *Journal of Management*, *43*, 255-282. doi:10.1177/0149206316679252

Moran, C. M., Diefendorff, J. M., Kim, T.-Y., & Liu, Z.-Q. (2012). A profile approach to self-determination theory motivations at work. *Journal of Vocational Behavior*, *81*, 354-363. doi:10.1016/j.jvb.2012.09.002

Morin, A. J., Boudrias, J. S., Marsh, H. W., McInerney, D. M., Dagenais-Desmarais, V., Madore, I., & Litalien, D. (2017). Complementary variable-and person-centered approaches to the dimensionality of psychometric constructs: Application to psychological wellbeing at work. *Journal of Business and Psychology*, *32*, 395-419. doi:10.1007/s10869-016-9448-7

Morin, A. J., & Marsh, H. W. (2015). Disentangling shape from level effects in person-centered analyses: An illustration based on university teachers' multidimensional profiles of effectiveness. *Structural Equation Modeling*, *22*, 39-59. doi:10.1080/10705511.2014.919825

Morin, A. J., Meyer, J. P., Creusier, J., & Biétry, F. (2016). Multiple-group analysis of similarity in latent profile solutions. *Organizational Research Methods*, *19*, 231-254. doi:10.1177/1094428115621148

Morin, A. J. S., Morizot, J., Boudrias, J., & Madore, I. (2011). A multifoci person-centered perspective on workplace affective commitment: A latent profile/factor mixture analysis. *Organizational Research Methods*, *14*, 58-90. doi:10.1177/1094428109356476

Morin, A. J. S., Scalas, L. F., & Marsh, H. W. (2015). Tracking the elusive actual-ideal discrepancy model within latent subpopulations. *Journal of Individual Differences*, *36*, 65-72. doi:10.1027/1614-0001/a000157

Morin, A. J. S., & Wang, J. C. K. (2016). A gentle introduction to mixture modeling using physical fitness data. In N. Ntoumanis & N. Myers (Eds.), *An introduction to intermediate and advanced statistical analyses for sport and exercise scientists* (pp. 183-210). London, UK: Wiley.

Muthén, B., & Asparouhov, T. (2015). Growth mixture modeling with non-normal distributions. *Statistics in Medicine*, *34*, 1041-1058. doi:10.1002/sim.6388

Muthén, L. K., & Muthén, B. O. (1998-2013). *Mplus user's guide* (6th ed.). Los Angeles, CA: Muthén & Muthén.

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling*, *14*, 535-569. doi:10.1080/10705510701575396

Pajunen, K. (2008). Institutions and inflows of foreign direct investment: A fuzzy-set analysis. *Journal of International Business Studies*, *39*(4), 652-669. doi:10.1057/palgrave.jibs.8400371

Pastor, D. A., Barron, K. E., Miller, B. J., & Davis, S. L. (2007). A latent profile analysis of college students' achievement goal orientation. *Contemporary Educational Psychology*, *32*, 8-47. doi:10.1016/j.cedpsych.2006.10.003

Perry-Smith, J. E., & Blum, T. C. (2000). Work-family human resource bundles and perceived organizational performance. *Academy of Management Journal*, *43*, 1107-1117. doi:10.2307/1556339

Peugh, J., & Fan, X. (2013). Modeling unobserved heterogeneity using latent profile analysis: A Monte Carlo simulation. *Structural Equation Modeling*, *20*, 616-639. doi:10.1080/10705511.2013.824780

Peugh, J., & Fan, X. (2015). Enumeration index performance in generalized growth mixture models: A Monte Carlo test of Muthén's (2003) hypothesis. *Structural Equation Modeling*, *22*, 115-131. doi:10.1080/10705511.2014.919823

Ragin, C. C. (2000). *Fuzzy-set social science*. Chicago, IL: University of Chicago Press.

Ragin, C. C. (2006). Set relations in social research: Evaluating their consistency and coverage. *Political Analysis*, *14*(3), 291-310. doi: 10.1017/pan.2017.31

Ragin, C. C. (2008). *Redesigning social inquiry: Fuzzy sets and beyond*. Chicago, IL: University of Chicago Press.

Ragin, C. C., & Davey, S. (2014). fs/QCA (Version 2.5/3.0) [Computer software]. Irvine: University of California, Irvine.

Ragin, C. C., & Sonnett, J. (2005). Between complexity and parsimony: Limited diversity, counterfactual cases, and comparative analysis. In S. Kropp & M. Minkenberg (Eds.), *Vergleichen in der Politikwissenschaft* (pp. 180-197). Wiesbaden, Germany: VS Verlag fur Sozialwissenschaften.

Reger, R. K., & Huff, A. S. (1993). Strategic groups: A cognitive perspective. *Strategic Management Journal*, *14*(2), 103-123. doi: 10.1002/smj.4250140203

Rihoux, B., & Ragin, C. C. (2009). *Configurational comparative methods: Qualitative comparative analysis and related techniques*. Thousand Oaks, CA: Sage.

Rosenberg, M. (1989). *Society and the adolescent self-image*. Middletown, CT: Wesleyan University Press.

Schmitt, N., Oswald, F. L., Kim, B. H., Imus, A., Merritt, S., Friede, A., & Shivpuri, S. (2007). The use of background and ability profiles to predict college student outcomes. *Journal of Applied Psychology*, *92*, 165-179. doi:10.1037/0021-9010.92.1.165

Schneider, M. R., Schulze-Bentrop, C., & Paunescu, M. (2010). Mapping the institutional capital of high-tech firms: A fuzzy-set analysis of capitalist variety and export performance. *Journal of International Business Studies*, *41*, 246-266. doi:10.1057/jibs.2009.36

Schneider, C., & Wagemann, C. (2012). *Set-theoretic methods for the social sciences*. Cambridge, UK: Cambridge University Press.

Schwarzer, R., & Jerusalem, M. (1995). Generalized Self-Efficacy Scale. In J. Weinman, S. Wright, & M. Johnston (Eds.), *Measures in health psychology: A user's portfolio. Causal and control beliefs* (pp. 35-37). Windsor, UK: NFER-NELSON.

Seashore, S. E., Lawler, E. E., Mirvis, P., & Cammann, C. (1982). *Observing and measuring organizational change: A guide to field practice*. New York, NY: John Wiley.

Shireman, E. M., Steinley, D., & Brusco, M. J. (2016). Local optima in mixture modeling. *Multivariate Research Methods*, *51*, 466-481. doi:10.1080/00273171.2016.1160359

Smithson, M., & Verkuilen, J. (2006). *Fuzzy set theory: Applications in the social sciences*. Thousand Oaks, CA: Sage.

Stanton, J. M., & Weiss, E. M. (2002). *Online panels for social science research: An introduction to the StudyResponse Project* (Tech. Rep. 13001). Syracuse, NY: Syracuse University, School of Information Studies.

Steinley, D., & Brusco, M. J. (2011). Evaluating mixture modeling for clustering: Recommendations and cautions. *Psychological Methods*, *16*, 63-79. doi:10.1037/a0022673

Tofighi, D., & Enders, C. K. (2007). Identifying the correct number of classes in growth mixture models. In G. R. Hancock & K. M. Samuelsen (Eds.), *Advances in latent variable mixture models* (pp. 317-341). Charlotte, NC: Information Age.

Vergne, J.-P., & Depeyre, C. (2016). How do firms adapt? A fuzzy-set analysis of the role of cognition and capabilities in U.S. defense firms' responses to 9/11. *Academy of Management Journal*, *59*, 1653-1680. doi:10.5465/amj.2013.1222

Vermunt, J. K. (2010). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis*, *18*, 450-469. doi:10.1093/pan/mpq025

Wang, M., & Hanges, P. J. (2011). Latent class procedures: Applications to organizational research. *Organizational Research Methods*, *14*, 24-31. doi:10.1177/1094428110383988

Woo, S. E., & Allen, D. G. (2014). Toward an inductive theory of stayers and seekers in the organization. *Journal of Business and Psychology*, *29*, 683-703. doi:10.1007/s10869-013-9303-z

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*, 338-353. doi:10.1016/S0019-9958(65)90241-X

Zyphur, M. J. (2009). When mindsets collide: Switching analytical mindsets to advance organization science. *Academy of Management Review*, *34*, 677-688. doi:10.5465/AMR.2009.44885862

Author Biographies

Allison S. Gabriel is an assistant professor of management and organizations in the Eller College of Management at the University of Arizona. She received her PhD in industrial-organizational psychology from the University of Akron. Her research focuses on emotions and emotional labor, interpersonal stressors at work, employee well-being, and motivation.

Joanna Tochman Campbell is an assistant professor of management at the Carl H. Lindner College of Business at the University of Cincinnati. She holds a PhD in strategic management from Texas A&M University. Her research interests include strategic leadership, corporate governance, stakeholder strategy, and configurational theory and methods.

Emilija Djurdjevic is an assistant professor of management in the College of Business Administration at the University of Rhode Island. She received her PhD in business administration from the University of Arkansas. Her research focuses on interpersonal influence processes at work, measurement and modeling of individual differences, and performance appraisal.

Russell E. Johnson is an associate professor of management in the Broad College of Business at Michigan State University. He received his PhD in industrial and organizational psychology from the University of Akron. His research examines the roles of motivation-, justice-, and leadership-based processes that underlie work attitudes, behaviors, and well-being.

Christopher C. Rosen is a professor of management in the Sam M. Walton College of Business at the University of Arkansas. He received his PhD in industrial-organizational psychology from the University of Akron. His research focuses on employee stress, motivation, and well-being.