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A Person-Centered Approach to Commitment Research: Theory, Research, and Methodology

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Abstract

There has been a recent increase in the application of person-centered research strategies in the investigation of workplace commitments. To date, research has focused primarily on the identification, within a population, of subgroups presenting different cross-sectional or longitudinal configurations of commitment mindsets (affective, normative, continuance) and/or targets (e.g., organization, occupation, supervisor), but other applications are possible. In an effort to promote a substantive-methodological synergy, we begin by explaining why some aspects of commitment theory are best tested using a person-centered approach. We then summarize the result of existing research and suggest applications to other research questions. Next, we turn our attention to methodological issues, including strategies for identifying the best profile structure, testing for invariance across samples, time, culture, etc., and incorporating other variables in the models to test theory regarding profile development, consequences, and change trajectories. We conclude with a discussion of the practical implications of taking a person-centered approach to the study of commitment as a complement to the more traditional variable-centered approach.

Key words. Commitment, Mindsets, Targets, Person-Centered, Profiles, Mixture Models

There has been a recent increase in the use of *person-centered* research strategies in the study of workplace commitments (Meyer, Stanley, & Vandenberg, 2013), and in organizational research more generally (Wang & Hanges, 2011; Zyphur, 2009). The person-centered approach differs from the more traditional *variable-centered* approach in several ways (Meyer et al., 2013; Morin, Morizot, Boudrias & Madore, 2011). Notably, the variable-centered approach assumes that all individuals from a sample are drawn from a single population and that a single set of averaged parameters can be estimated. The person-centered approach relaxes this assumption and considers the possibility that the sample might in fact reflect multiple subpopulations characterized by different sets of parameters. The objective, therefore, is to identify potential subpopulations presenting differentiated configurations (or profiles) with regard to a system of variables. Additional benefits of the person-centered approach are that (a) individuals are treated in a more holistic fashion by focusing on a system of variables taken in combination rather than in isolation, and (b) it allows for the detection of complex interactions among variables that would be difficult to detect or interpret using a variable-centered approach. Thus, although not a replacement for the variable-centered approach, the person-centered approach takes a complementary perspective that appears well-suited to testing some aspects of commitment theory.

To date, the person-centered approach has been used most often to examine how the commitment mindsets identified in Meyer and Allen's (1991) three-component model (TCM) – affective, normative, and continuance – combine to form profiles (e.g., Gellatly, Cummings & Cowden, 2014; Meyer, Stanley & Parfyonova, 2012; Stanley, Vandenberg, Vandenberghe & Bentein, 2013; Wasti, 2005). It has also been used to investigate how commitments to different targets (e.g., organization, occupation, supervisor) combine (e.g., Becker & Billings, 1993; Morin, Morizot et al., 2011). Most recently, research has been conducted to identify mindset profiles to dual targets, including the organization and occupation (Morin, Meyer, McInerney, Marsh & Ganotice, 2015; Tsoumbris & Xenikou, 2010) and organization and supervisor (Meyer, Morin & Vandenberghe, 2015). There is now sufficient research, particularly as it pertains to mindset profiles of organizational commitment, to take stock of how well it supports theory and/or suggests needs for revision. However, it also provides an opportunity to evaluate how well the strategy is being applied, how it might be improved, and key areas for future research. Thus, our objective is to work toward a substantive-methodological synergy (Marsh & Hau, 2007) by drawing attention to the ways important substantive (and practical) issues pertaining to workplace commitments can be addressed using the most recent advances in person-centered analytic strategies. In doing so, we advance previous reviews and critiques of the person-centered approach to commitment research (Meyer et al., 2012, 2013) in several ways.

From a substantive perspective, we provide an updated review of person-centered commitment studies, including new mindset studies exploring profile consistency across samples (Meyer, Kam, Bremner, & Goldenberg, 2013) and over time (Kam et al., 2016) as well as profile studies involving multiple mindsets to dual targets (Meyer et al., 2015; Morin et al., 2015; Tsoumbris & Xenikou, 2010). We also introduce a new labeling scheme to aid in the interpretation and comparison of mindset profile studies and to facilitate integration of findings and advancement of theory. Unlike the labeling schemes currently being used, our scheme acknowledges variation not only in profile shape but also in elevation and scatter (Cronbach & Glesser, 1953). Finally, we discuss how the person-centered approach can be used similarly to test and advance theory pertaining to multiple workplace 'bonds,' including commitment, as described by Klein, Molloy and Brinsfield (2012), and commitments to multiple targets (e.g., Johnson, Chang & Wang, 2010; Meyer & Allen, 1997).

On the methodological side, we advance the previous treatment by Meyer, Stanley et al. (2013) to include a broader discussion of the Generalized Structural Equation Modeling framework (Muthén, 2002; Skrondal & Rabe-Hesketh, 2004) as it applies to person-centered research, including advanced analytic procedures that can be applied to longitudinal data to address the nature, prediction, and implications of profile changes. Finally, in addition to providing guidelines for person-centered analyses, we articulate a novel strategy for evaluating the consistency of profile solutions across samples and/or over time. We conclude with a discussion of the practical implications of taking a person-centered approach to the study of commitment.

Substantive Issues in Person-Centered Research

Commitment Mindsets

As noted earlier, the person-centered approach has been applied most widely in the investigation of the organizational commitment mindsets identified in the TCM (Meyer & Allen, 1991). According to the TCM, employee commitment to an organization can be experienced as an emotional attachment to, and involvement in, the organization (affective commitment: AC), a sense of obligation to the organization (normative commitment: NC), or an awareness of the costs associated with leaving the organization (continuance commitment: CC). Although most tests of the TCM focused on the development and/or consequences of individual 'commitment mindsets,' implicit in the theory is the notion that each mindset can be experienced to varying degrees. Meyer and Herscovitch (2001) elaborated on this notion by identifying eight potential profiles reflecting varying combinations of high and low scores on AC, NC and CC and offering propositions concerning the development and consequences of these profiles.

Meyer and Herscovitch (2001) stated their propositions concerning the combined influence of the commitment mindsets on behavior in such a way that they could be tested using both variable- and person-centered approaches. However, using a variable-centered approach requires the detection of three-way interactions among AC, NC, and CC. Such interactions are difficult to detect and assume that the effects are linear (Marsh, Hau, Wen, Nagengast, & Morin, 2013; McClelland & Judd, 1993). To our knowledge, only one published study has reported a significant three-way interaction (Gellatly, Meyer & Luchak, 2006). In contrast, a person-centered approach is specifically designed to identify subgroups with differing AC, NC, and CC profiles, and to test propositions involving profile comparisons.

Several early person-centered studies used a mid-point split approach to create commitment profiles (e.g., Gellatly et al., 2006; Markovits, Davis, & Van Dick, 2007). Although this approach creates the eight profiles required to test Meyer and Herscovitch's (2001) propositions, it leaves unanswered the question of whether these profiles occur naturally and are an adequate representation of the heterogeneity that exists within a sample (Meyer et al., 2013; Vandenberg & Stanley, 2009). An alternative approach has been to use analytic procedures such as cluster analysis or latent profile analysis (LPA) to identify naturally occurring profiles (e.g., Gellatly et al. 2014; Meyer, Stanley et al., 2012; Somers et al., 2009; Stanley et al., 2013). These studies consistently identify five to seven profile groups, many of which (but not all) correspond to those proposed by Meyer and Herscovitch.

The existence of multiple profile groups is consistent with the notion that the basic TCM mindsets combine to form more complex mindsets, but little attention has been paid to what these mindsets represent. Moreover, cross-study comparisons of profiles and their relations with other variables are complicated by the fact that researchers often use different labeling schemes, and the most common schemes do not always capture the full essence of the profiles. Therefore, before summarizing what has been learned about the nature and implications of mindset profiles, we address the labeling issue.

Profile labeling. Profiles of any kind can vary in terms of *shape* (pattern of high and low mean scores on various indicators, such as the three TCM mindsets), *elevation* (average mean score across indicators), and *scatter* (degree of differentiation of the mean scores on the various indicators). For the most part, commitment researchers have focused on profile shape in their labels. The most common labeling scheme involves identifying the mindset(s) with the highest scores as 'dominant'. For example, 'AC-dominant' is used to describe a profile where AC is considerably higher than NC and CC, whereas the label 'AC/NC-dominant' is used when AC and NC are both stronger than CC. These profiles are considered to be *qualitatively* distinct from one another – that is, there is at least one score higher than the others in each profile, and the specific configuration of dominant mindsets differs across profiles. When all three mindsets are at approximately the same level, labels such as 'uncommitted,' 'moderately committed,' or 'fully committed' have been used. The distinctions between these profiles are considered to be *quantitative* in nature. This labeling scheme, which was used by Meyer, L. Stanley et al. (2012) in an earlier review of profile studies, has the potential to mask differences in elevation or scatter. That is, profiles with a similar shape can vary in terms of average level on the indicators (elevation) and/or degree of dispersion between the mean scores on the indicators (scatter). For example, in an AC-dominant profile, AC is stronger than NC and CC, but all three scores can be below or above the sample mean (low vs. high elevation). Moreover, AC scores can be moderately or much higher than NC and CC scores (low vs. high scatter). Therefore, we propose an alternative scheme.

Although introducing elevation and scatter into the labeling scheme increases accuracy, it also adds complexity. To keep this complexity to a minimum, we retain the current shape labels under conditions where elevation is moderate and scatter shows a clear differentiation between profile indictors within a profile. To illustrate, consider the graphical representation of three quantitatively distinct profiles in Figure 1a and six qualitatively distinct profiles in Figure 1b. With the exception of the moderately committed profile in Figure 1a, these profiles correspond to the eight theoretical profiles discussed by Herscovitch and Meyer (2001). To add further precision to the description of the profiles, we use qualifiers to describe profiles where the level of elevation is either high or low, and profiles show a weak level of differentiation (scatter) across mindsets. Figure 2 introduces the profiles reflecting variations in elevation and scatter. To reflect elevation, we use the qualifier ‘high’ when all three mindset scores are above some midpoint (e.g., scale midpoint; sample average) within a single profile (Figure 2a), and ‘low’ when all three mindset scores are below the midpoint (Figure 2b). To reflect scatter, we use the term ‘weak’ when there is relatively small differences in mindset scores within a profile (Figure 2c). Note that in cases where elevation is high or low, scatter is naturally restricted (weakened). For simplicity, we do not use the label ‘weak’ in this situation.

Mindset profiles. In Table 1 we provide a summary of the profiles identified to date in published research. This table includes only studies involving all three commitment mindsets and using cluster analysis or LPA to identify naturally occurring profiles. Along the top right-hand side of the table, we identify the nine basic quantitative and qualitative shape distinctions from Figure 1. An X indicates that the profile identified in the column label was detected, and that elevation and scatter were at what we judged to be moderate levels. The qualifiers ‘high’ or ‘low’ are used to indicate deviations from a moderate elevation, whereas the qualifier ‘weak’ is used to reflect a low level of within-profile differentiation between mindsets. Because these labels sometimes differ from those used by the original authors, we provide the original and modified labels on the left hand side of the table.

From Table 1 it can be seen that some profiles emerge quite regularly across studies, most notably the CC-dominant, AC-dominant, and AC/NC-dominant profiles. Others are found quite often, albeit less frequently, including weakly committed, fully committed, and AC/CC-dominant. Note that we use the term ‘weakly committed’ rather than ‘uncommitted’ as some authors do because, as noted by Sinclair et al. (2005), it is rarely the case that employees available to be surveyed have no commitment at all. Overall, we identify fewer studies reporting a weakly-committed or fully-committed profile than would be apparent from the original labels reported in Table 1. This is because, in reviewing these studies, we judged that it was often the case that one or two of the mindsets were slightly elevated in relation to the other mindsets. That is, the profile had a qualitatively distinct shape that was not reflected in the label, probably due to the exclusion of elevation and scatter in the labeling scheme. It is unclear at this point how important it will be to make distinctions based on elevation and scatter. To investigate their importance, it will be necessary to quantify these characteristics in future research. We describe how and in which circumstance this can be done in the Methodological Issues section.

One noteworthy observation from Table 1 is that most studies report between five and seven profiles. This is consistent with the assumption underlying the person-centered approach that a sample can reflect multiple subpopulations. It is also consistent with the notion that the TCM mindsets can combine in different ways (Meyer & Allen, 1991) and presumably reflect more complex mindsets. The fact that a fairly common set of profiles tends to emerge suggests that these reflect meaningful psychological states pertaining to employees’ relationship with the organization. However, with few exceptions (e.g., Gellatly et al., 2006), little attention has been paid to how employees with these profiles actually experience their commitment. We offer suggestions for some of the more common profiles to emerge, and also use these psychological states as alternate profile descriptors in Figure 1b.

It is not uncommon to find a profile dominated by AC or CC. In these cases we expect that the employees feel *emotionally committed* or *trapped* in the organization, respectively. A profile dominated by NC is less common but employees with such a profile likely feel *obligated* to the organization. We can only speculate on how the combination of two or more mindsets are experienced, but consistent with Gellatly et al. (2006), we propose that employees with an AC/NC-dominant profile experience something akin to a *moral commitment* – a desire (AC) to do the right thing (NC). By contrast, those with a CC/NC-dominant commitment may feel *indebted* to the organization and would find it costly (CC) to fail to live up to their obligations (NC). Following the same logic, those with an AC/CC-dominant profile may feel *invested* in that they are experiencing personal benefits (AC) from a relationship that would be costly to lose (CC). Finally, those with strong AC, NC, and CC are fully committed, possibly because they see costs (CC) associated with failure to follow through on their moral commitment (AC/NC); those who are moderately committed may be experiencing the same state but to a lesser degree.

Whether the foregoing descriptions truly reflect how employees with varying profiles experience their commitment remains to be determined. For example, it might be possible to develop measures that tap into these 'compound mindsets' more directly and to use them to compare profile groups. Alternatively, as more profile studies are conducted, we can look for patterns in relationships with theoretical antecedents or consequences to see if they are consistent with these interpretations. For example, are employees with a moral commitment (AC/NC-dominant) more resistant to setbacks in the relationship (cost-cutting measures by the organization) and willing to make personal sacrifices for the organization than those who are emotionally attached (AC-dominant) or invested (AC/CC-dominant)? If our interpretations are supported, these more descriptive labels might be more appealing to managers and others with a practitioner focus (Morin, Morizot et al., 2011; Zyphur, 2009).

It is also noteworthy that the most common profiles found in North American studies (e.g., Kam et al., 2016; Meyer, L. Stanley et al., 2012; Stanley et al., 2013) were also found in Turkey (Wasti, 2005, Studies 1 and 2) and Hong Kong (Morin et al., 2015). Indeed, there are no obvious geographic or cultural differences reflected in the pattern of findings in Table 1. However, the number of studies, especially of studies conducted in non-Western countries, is limited. There is a need for more studies comparing the profile structure across cultures. Finally, in one study (Meyer, Kam et al., 2013) analyses were conducted on two samples drawn from the same military organization and yielded nearly identical profiles. This, combined with evidence from Kam et al. (2016) who found a similar profile structure within a sample (exposed to organizational change) over time, suggests a considerable degree of consistency in profile structure. We discuss the importance of consistency, and strategies for evaluating invariance, in the Methodological Issues section.

Implications of mindset profiles. In addition to identifying profiles, researchers have attempted to test Meyer and Herscovitch's (2001) propositions concerning the behavioral implications of those profiles. In one of the earliest studies, Gellatly et al. (2006) observed that, in contrast to the proposition that the AC-dominant profile would be optimal with regard to behavior, they found the highest levels of intention to remain and discretionary effort among those with AC/NC-dominant and fully-committed profiles. Similarly, Somers (2010) and Wasti (2005, Study 1) found that turnover intentions were lower among employees with fully committed and AC/NC-dominant profiles than for those with an AC-dominant profile. Thus, rather than mitigating the effects of AC, strong NC and CC appear to have a synergistic effect in predicting behavioral outcomes. Gellatly et al. also found that NC was associated with greater intention to stay and OCB when combined with strong AC than when combined with strong CC and weak AC. Somers (2009, 2010) found similar results, but Wasti (2005) found no differences between the two profiles.

Another noteworthy comparison is between the CC-dominant profile and the fully-committed profile. In both cases, CC is strong. However, the behavioral consequences have generally been found to be more positive for employees with a fully-committed profile than for those with a CC-dominant profile (Meyer, L. Stanley et al., 2012; Stanley et al., 2013; Wasti, 2005). The same is true for well-being: employees with a CC-dominant profile have been found to report lower levels of well-being than those with any other profile, with the possible exception of the weakly committed. Together, these observations suggest that the findings from variable-centered research linking the individual mindsets to other variables (e.g., Meyer L. Stanley et al., 2002; Riketta, 2002) may be somewhat misleading. Rather, as noted above, the combination of the basic TCM mindsets may create more nuanced mindsets that can have implications for behavior and well-being. This is an important observation that derives from taking a person-centered approach.

Beyond mindsets. There is disagreement in the literature about the utility of differentiating among commitment mindsets. Notably, Klein et al. (2012, p. 137) proposed a unidimensioinal target-free conceptualization of commitment as "*a volitional psychological bond reflecting dedication to and responsibility for a particular target*" (emphasis in original). They argue, however, that commitment is only one type of bond with a target that can form and influence behavior. Other bonds include *acquiescence* (perceived absence of alternatives), *instrumental* (high cost or loss at stake), and *identification* (merging of oneself with the target). Klein et al. suggest that different bond types might emerge under different conditions and will relate differently to behavior. They also acknowledge that different bond types might combine and potentially interact. In this case, there may be advantages to taking a person-centered approach to determining whether, and how, the bonds actually combine and are experienced. For example, a combination of identification with commitment might be experienced as what Rousseau (1998) described as "deep structure identity" where the individual alters his/her self-concept to include characteristics of the collective. In contrast, when combined with an instrumental bond, identification might be experienced as what Rousseau described as "situated identity" – a more superficial identity based on common self-interest. These distinct 'bond profiles' would be expected to have quite different implications for behavior. Other combinations might also be found, such as a strong instrumental bond combined with commitment. An employee with this combination might feel 'invested' much like the employee with the AC/CC-dominant profile described earlier, and would be expected to do more in support of the well-being of the target than one purely instrumental bond. According to Klein et al., commitment is positioned between instrumental and identification bonds on a continuum, and adjacent bonds are expected to correlate most strongly. If this is the case, certain bond profiles might be more common, and this too can be tested using a person-centered strategy. Such an approach has been used recently to test similar hypotheses based on the self-determination theory motivational continuum (e.g., Moran, Diefendorff, Kim, & Liu, 2012; Van den Broeck, Lens, Witte, & Coillie, 2013) with some intriguing results.

Commitment Targets

Although most commitment research focuses on commitment to their organization, it has long been recognized that employees can develop commitments to multiple constituencies (Becker, 1992; Cohen, 2003; Klein et al., 2012; Morrow, 1993; Reichers, 1985). Commitments to many of these constituencies, including occupation, union, supervisor, work team, customers, projects, or goals, have been studied in their own right (see Becker, 2009; Neubert & Wu, 2009; Vandenberghe, 2009). Our focus here is on theory and research involving commitments to two or more of these targets. Much of the research on dual (two-target) commitment has been conducted using a variable-centered approach (e.g., Meyer, Allen & Smith, 1993; Stinglhamber & Vandenberghe, 2003). However, as the number of targets increases (e.g., Morin, Morizot et al., 2011), or multiple mindsets pertaining to each target are considered (e.g., Meyer et al., 2015; Morin et al., 2015; Tsoumbris & Xenikou, 2010), a person-centered approach is well-suited to detecting heterogeneity in the ways the commitment components (mindsets and targets) combine.

Theory. Theory pertaining to how commitments to distinct targets combine and influence outcome variables is sparse, particularly when different mindsets pertaining to each target is also considered. Considering targets alone, some theorists have proposed that multiple targets create the potential for conflicts among commitments (Gouldner, 1957; Reichers, 1985). For example, Gouldner proposed that some employees would be more committed to their organizations than to their occupations (locals), and others would be more committed to their occupation (cosmopolitans). Using cluster analysis, Becker and Billings (1993) were able to demonstrate that this was indeed the case, but that there were also employees who were committed to both or neither of these targets. Others have developed models to explain the relative strength of association between commitments to different targets (e.g., Morrow, 1993). Most research conduct to test these models has been variable-centered and has revealed moderate to strong correlations between commitments (typically affective) to multiple targets (Cooper-Hakim & Viswesvaran, 2005; Lee, Carswell & Allen, 2000). We focus here on two theoretical approaches that are well-suited to person-centered investigations, one pertaining to competition, compatibility, and synergy among multiple commitments (Johnson et al., 2010), and the other to dependencies among targets (Lawler, 1992; Meyer & Allen, 1997).

Drawing on identity theory (Brewer & Gardner, 1986; Lord & Brown, 1996) and regulatory focus theory (Higgins, 1997, 1998), Johnson et al. (2010) argued that employees can form individual, relational, or collective identities, and that these identities can have implications for commitment targets. For example, employees prone to developing relational identities might commit to their supervisor or work team, those inclined to form collective identities might commit to the organization, and those with strong individual identities might commit to their personal careers. At the same time, employees' regulatory focus can influence the *nature* of these commitments. Those with a *promotion focus* (concern with gains, ideals, and accomplishment) are more likely to develop AC, whereas those with a *prevention focus* (concern with duties, obligations, and security) are more likely to develop NC or CC. Importantly, types of self-identity and regulatory focus are assumed to be orthogonal, raising the possibility that employees can commit to one, both, or neither targets, and experience different mindsets toward each target. These propositions are consistent with, and help to explain, the notion that a sample can be heterogeneous with regard to both the nature and target of commitment. They also raise the possibility that commitments can be similar or in conflict across targets.

Lawler (1992) noted that, of the constituencies to which employees can commit, some are nested within others. Building on this notion, Meyer and Allen (1997) argued that such nesting can create dependencies that have implications for the nature of their commitment. For instance, in the absence of strong AC to the organization, an employee with strong AC to a supervisor or work group might experience strong CC to the organization (i.e., loss of opportunity to work for the supervisor is a potential cost of leaving the organization). Although not nested to the same degree, commitment to external targets (e.g., profession) can also combine with commitment to the organization to create dependencies. For example, individuals with strong commitment to a profession may develop a strong commitment to an organization if they believe that there are few other organizations where they could practice. If the organization is not a particularly attractive place to work, the desire to remain in the profession might contribute to the perceived cost (CC) of leaving the organization. Reframing these examples in terms of bonds (Klein et al., 2012) rather than mindsets, strong commitment to one's supervisor or profession in the absence of commitment to the organization could make salient the employee's acquiescence and/or instrumental bond with the organization.

Relatively few multi-target person-centered studies have been conducted to date and, although some were guided in part by the theories described here, none addressed the psychological mechanisms (e.g., identity, regulatory focus) that might explain the emergence of different profiles. Therefore, for present purposes, we briefly summarize existing research and interpret findings in the context of theory with the objective of stimulating more theory-driven research in the future.

Multi-target research. Morin, Morizot et al. (2011) conducted what is arguably the most ambitious multi-target profile study to date, considering seven distinct targets of commitment: organization, workgroup, supervisor, customer, occupation, work in general, and career. However, they measured only AC to each target. Using factor mixture analysis, they identified five profiles: (a) highly committed to all targets, (b) weakly committed to all targets, (c) highly committed to the supervisor and moderately committed to other targets, (d) committed to career advancement but weakly committed to all other targets (i.e., careerists), and (e) committed to the proximal work environment (i.e., organization, workgroup, customers) but uncommitted to their supervisor. Importantly, the profiles also differed in meaningful ways with regard to behaviors (e.g., those with a strong commitment to the supervisor reported more citizenship behaviors directed at the supervisor; those with a dominant commitment to their career had stronger intentions to leave).

Morin, Morizot et al.'s (2011) findings clearly illustrate the benefits of a person-centered approach and provided evidence for heterogeneity with regard to targets of commitment as well as evidence for both compatibility (e.g., occupation and organization) and conflicts (e.g., workgroup and supervisors) among commitments to various targets. An important next step might be to determine whether profile membership and its consequences can be predicted on the basis of theory. For example, according to Johnson et al. (2010), those employees prone to forming an individual identity might be more likely to have a career-focused profile whereas those predisposed to form relational identities might be more likely to have a supervisor-dominant profile. Given the differential implications for behavior, being able to identify and predict target profiles could have practical advantages. Morin, Morizot et al. (2011) used the Workplace Affective Commitment Multidimensional Questionnaire (Morin, Madore, Morizot, Boudrias, & Tremblay, 2009), but a similar approach could be applied using Klein's unidimensional target-free (KUT) measures (Klein et al., 2013).

Multi-target multi-mindset studies. Tsoumbris and Xenikou (2010) were the first to investigate mindset profiles pertaining to two targets, the organization and occupation. Applying cluster analysis to data from a small sample of Greek employees, they identified four profiles: non-committed, CC-dominant, AC/NC-dominant, and highly committed. Interestingly, these profiles varied primarily with regard to mindset, showing a similar mindset pattern within profiles across targets. More recently, Morin et al. (2015) also measured AC, NC, and CC to the organization and occupation in a sample of Hong Kong teachers and found seven profiles. In contrast to Tsoumbris and Xenikou, they found both similarity and differences in mindset pattern across targets. The differences were more indicative of the target dependencies discussed by Meyer and Allen (1997) than of conflicting commitments. For example, in one case, teachers were fully committed to the occupation and had an NC-dominant commitment to the organization, perhaps suggesting a sense of obligation to the organization for the opportunity to practice their desired profession. Meyer and Allen (1997) proposed that such a dependency might result in the elevation of CC to the organization, so the observed elevation in NC might reflect a collectivist orientation (Wasti & Őnder, 2009).

Importantly, both Tsoumbris and Xenikou (2010) and Morin et al. (2015) found that profile membership was associated with intentions to remain in the organization and occupation. Not surprisingly, given that the mindset profiles were similar for both targets, Tsoumbris and Xenikou (2010) also found a similar pattern across profiles with regard to intentions to remain in the organization and occupation. Both were greatest among the highly committed and weakest among the non-committed. The opposite was observed for organizational citizenship behaviors. The findings reported by Morin et al. (2015) were more nuanced, particularly for profiles where the mindset configuration differed across targets. For example, in one case, profiles differed with regard to intention to leave the organization but not the occupation. Morin et al. (2015) also found that the profiles differed with regard to well-being, with the lowest scores observed for employees who were weakly committed to both targets, and for those who had a CC-dominant profile to both targets. As found by Meyer, L. Stanley et al. (2012) for organizational commitment, strong CC was only associated with reduced well-being when it dominated the profile. In contrast, well-being scores were highest among teachers who were fully-committed (including strong CC) to the teaching profession.

In the only other multiple-mindset dual-commitment study of which we are aware, Meyer et al. (2015) measured AC, NC, and CC to the organization and supervisor. Like Morin et al. (2015), they found multiple profiles (five) reflecting both similarities and differences in profile pattern across targets. Where differences existed, they again appeared to reflect dependencies as proposed by Meyer and Allen (1997). For example, for one profile, AC, NC and CC to the supervisor were well-above average, whereas CC and NC dominated the profile for commitment to the organization. This suggests that severing the relationship with the supervisor could have been perceived as a cost of leaving the organization and/or that some employees may have felt an obligation to the organization for providing the opportunity to work with a supervisor that they liked. In another profile, CC to the organization dominated the profile and was accompanied by weaker CC to the supervisor, perhaps suggesting that seeking an alternative supervisory relationship might be costly if it involves having to leave the organization. In the remaining profiles, the mindset pattern was very similar for commitment to the organization and supervisor, possibly suggesting that the supervisor was viewed as the embodiment of the organization (Eisenberger et al., 2010).

Summary. So far, person-centered studies involving multiple mindsets, targets, or both provide evidence for population heterogeneity. Interestingly, TCM mindset studies reveal a relatively consistent set of profiles across studies, samples, cultures and time. The optimal profiles from the standpoint of behavior and well-being tend to be the AC-dominant, AC/NC-dominant, and fully-committed; the least desirable profiles are the weakly committed and CC-dominant. However, additional research is needed to systematically test the invariance of profile solutions across samples, time, and cultures. In contrast, there are too few studies to draw any firm conclusions about the nature of the dual- or multi-target profiles that are most likely to emerge, or to reach conclusion regarding the expected generalizability of these profiles across samples, cultures, or time points. Going forward, it would be helpful to use theory a priori to predict the nature of the expected profiles, the factors that might predict profile membership (e.g., identity; culture), and the outcomes of profiles (e.g., retention; in- and extra-role performance; well-being). With this in mind, we turn now to discussion of methodological issues likely to be encountered in conducting this research.

Methodological Issues in Person-Centered Research

Among the various person-centered methodologies that have been used in commitment research, latent profile analysis (LPA) is arguably the most flexible and the one that can be used to address the widest array of research questions. However, LPA is part of a greater family of statistical models, called mixture models (e.g., Muthén, 2002), including factor mixture models, latent transition analyses, growth mixture models, and mixture regression. It is on this wider range of models that we focus in the following sections.

Mixture Models

As the name implies, mixture modeling is a model-based approach to clustering data, based on the assumption that a sample includes a mixture of subpopulations. More precisely, mixture models are part of the Generalized Structural Equation Modeling (GSEM) framework (e.g., Muthén, 2002;

Skrondal & Rabe-Hesketh, 2004) that allows for the estimation of relations between any type of continuous or categorical observed and latent variables. SEM, as a *variable-centered* framework, yields results reflecting a synthesis of relations observed in the total sample and assumes that all individuals are drawn from a single population. GSEM relaxes this assumption by considering the possibility that all or part of any SEM model can differ across subgroups of participants. These subgroups are referred to as *latent profiles*, and are represented in the model as the various categories of an underlying categorical latent variable. These profiles are called latent because they are represented by an unmeasured categorical variable where each category represents an inferred subpopulation. Latent profile analysis (LPA) is one form of mixture model that aims to describe subgroups of participants differing from one another on their configuration on a series of indicators (e.g., commitment mindsets and/or targets). LPA is similar to a factor analytic model, except that the latent variable is categorical (reflecting profiles that represent groupings of persons) rather than continuous (reflecting factors that represent groupings of variables) (Lubke & Muthén, 2005). Being model-based, LPA allows for the direct specification of alternative models that can be compared with fit statistics. In particular, LPA allows for the estimation of models in which some of the rigid assumptions inherent in alternative modeling approaches (e.g., cluster analysis) can be progressively relaxed (e.g., variances can be freely estimated across profiles; correlated uniquenesses and latent factors can be added to the model). It also allows for the application of a multilevel structure to the data, and for the simultaneous consideration of continuous, ordinal and categorical measures in the same model (Muthén, 2002; Vermunt & Madgidson, 2002). Finally, LPA allows for the direct inclusion of covariates (or predictors) in the models, helping to limit Type 1 errors by combining analyses (i.e., the profiles and all of the relationships are estimated in a single step). This direct inclusion of covariates has been shown to reduce biases in the estimation of the relationships between covariates and the latent profiles (Bolck, Croon, & Hagenaars, 2004; Lubke & Muthén, 2007).

GSEM combines SEM with mixture modeling person-centered analyses to identify relatively homogeneous latent profiles of participants, differing qualitatively and quantitatively from one another in relation to (a) their configuration of a set of observed and/or latent variable(s) and/or (b) relations among observed and/or latent variables. Person-centered analyses conducted within this framework have three key characteristics that must be kept in mind when interpreting results. First, they are *typological*, providing a classification system to guide the categorization of individuals into qualitatively and quantitatively distinct profiles (e.g., Bergman, 2000). Second, they are *prototypical*. Thus, in contrast to cluster analysis, all participants have a probability of membership in all profiles based on their similarity with each prototypical *latent* profile (McLachlan & Peel, 2010). Third, mixture models are typically *exploratory*, at least from an analytical perspective. That is, conventional goodness-of-fit indices (e.g., CFI, RMSEA) indicating the absolute degree to which the model represents the data are not available for mixture models. Rather, solutions including differing numbers of latent profiles are typically contrasted to select the final solution in a mainly exploratory manner. However, this does not preclude the possibility of generating theory-based hypotheses concerning the expected structure and confirming or disconfirming this hypothesis based on the solutions that are generated. It is also possible to devise confirmatory applications of mixture models where the adequacy of an a priori model is assessed through a comparison with unconstrained models to show that their degree of fit to the data remains comparatively acceptable (Finch & Bronk, 2011).

In practice, several solutions varying from one profile to some number of profiles exceeding expectations are typically estimated and contrasted. Selection of the optimal number of profiles (i.e. the class enumeration procedure) is then determined by inspection of (a) the substantive meaning and theoretical conformity of the solution (Marsh, Lüdtke, Trautwein, & Morin, 2009), (b) the statistical adequacy of the solution (e.g., convergence, absence of negative variance estimates), and (c) statistical indicators (e.g., Marsh et al., 2009; Morin, Morizot et al., 2010). For a complete overview of how to select the optimal number of profiles using statistical indicators and theory, we refer the reader to Vandenberg and Stanley (2009). However, it must be kept in mind that these statistical indicators are heavily influenced by sample size (Marsh et al., 2009) meaning that, with a sufficiently large sample, they may continue to suggest the addition of profiles without converging on a preferable solution. In such cases, it is recommended that these indicators (i.e., the information criteria) be presented graphically in the form of "elbow plots" (Morin, Maïano et al., 2011; Petras & Masyn, 2010). These plots illustrate the gains in fit associated with the addition of profiles, and the point after which the slope flattens typically indicates the optimal number of profiles.

Another key consideration is to demonstrate that the extracted profiles are meaningful in their own right. In this regard, it is important to keep in mind that it is technically impossible to empirically distinguish a LPA model including *k* profiles from a common factor model including *k* – 1 factors (e.g., Steinley & McDonald, 2007) because both have identical covariance implications and can be considered 'equivalent' models (e.g., Cudeck & Henly, 2003) – so that both end up explaining equivalent variance. Similarly, it is hard to rule out the possibility that spurious profiles might emerge due to violations of the model's distributional assumptions (Bauer, 2007; Bauer & Curran, 2004). Therefore, the best way to support a substantive interpretation is to embark on a process of construct validation to demonstrate that the profiles: (a) have heuristic value, (b) have theoretical conformity or value, (c) are meaningfully relate to key covariates, and (d) generalize to new samples (Marsh et al., 2009; Morin, Morizot et al., 2011; Muthén, 2003). We argue that LPA studies should address the first two criteria (heuristic and theoretical) and at least one of the others (relations and generalizability).

Reporting Results

Raw vs. standard score plots. Previous studies have typically reported results using either raw scores on the commitment components (e.g., Meyer, L. Stanley et al., 2012) or standardized scores (e.g., Morin, Morizot et al., 2011). Each has advantages and limitations. Raw score plots reflect actual scores on the components within profiles and are arguably more transparent than standardized scores. However, the scores on the various indicators might use different scales or reflect different units of measurement that make comparisons within profile, across profiles, and across studies quite difficult. Standard scores provide a common scale for the indicators and arguably generate profile plots that are more easily interpreted (i.e., scores are interpreted in standard deviation units, with scores above zero reflecting results that are above average and score below zero reflecting results that are below average). However, the selection of the standard for comparison can be limiting. If the sample mean and standard deviation are used, comparison across subscales within profiles and across profiles can remain constant in relation to the characteristics of the specific sample under study. However, it then becomes difficult to make comparison across studies with a different grand mean. Using population norms eliminates this problem but such norms are not often available. Even in the case of AC, NC, and CC where norms are available (Meyer, Stanley, Jackson, McInnis, Maltin & Sheppard, 2012), one would have to decide whether to use the overall or country-specific norms, and this could have implications for cross-national comparison. Given this state of affairs, the option we recommend is that authors present the more interpretable standard score plots but also make available raw score means and standard deviations on the indicators for purpose of transparency.

Shape, elevation and scatter. The profile labeling scheme presented earlier considers the shape of the extracted profiles, the global level of commitment that characterizes each profile, and the dispersion among the various commitment indicators within each profile. To date, most commitment profile researchers have focused on shape, with little concern for elevation or scatter. As we noted earlier, using profile labels that reflect only shape can lead to confusion in within- and across-study comparison. Although there are no methods currently available to incorporate estimates of elevation or scatter directly within LPA, they can be calculated by hand or using the MODEL CONSTRAINT function available in Mplus (Muthén, & Muthén, 2014). This last function also makes it possible to calculate between-profile differences in elevation of scatter. *Elevation* can be calculated as the mean of the various indicators in each profile, and *scatter* as the standard deviation of the indicators within each profile. One potential use of such scores might be in making decisions about whether to select a solution including two profiles with similar shape over another that combines these into a single profile. If the two profiles are found to differ in elevation and/or scatter, it might be best to retain the solution including both. Comparison of these profiles with regard to theoretical antecedent or outcome variables could help to evaluate the potential meaningfulness of elevation and scatter. Again, decisions about whether to compute elevation and scatter on the basis of raw, standard or normed scores should be made with due consideration of the issues raised above.

Technical Considerations in the Estimation of Mixture Models

Although LPA is not new (e.g., Gibson, 1959), the emergence of user friendly statistical packages (e.g., Muthén & Muthén, 2014; Vermunt & Magidson, 2005) has made them increasingly popular in recent years. However, as is the case with any advanced statistical methodologies, there is often a gap between best practices and research applications (Boorsboom, 2006; Marsh & Hau, 2007). Therefore, we provide a series of suggestions for users of these methods.

Mixture indicators. Typically, mixture models have been estimated using scale scores on the various commitment components as indicators (e.g., taking the sum or average on a series of items used to asses AC and using this aggregated score as a profile indicator). It is well known that manifest scale scores incorporate measurement errors that may lead to biased results, and that fully latent models with an explicit control for measurement error (i.e., models where items are used to estimate latent factors) provides a much stronger approach (e.g., Bollen, 1989). However, applications of mixture models where items are used to estimate latent factors, which are then used as indicators of the latent profiles within a single model, are rare (e.g., Morin, Scalas & Marsh, 2015). Although this fully-latent approach may seem ideal in terms of providing an optimal control for measurement errors, it is often impossible to implement in practice. Indeed, given the complexity of mixture models, fully latent models generally tend to converge on statistically improper solutions, or not to converge at all. An alternative approach is to rely on factor scores saved as part of preliminary measurement models (e.g., Kam et al., 2016). Although factors scores do not explicitly control for measurement errors the way latent variables do, they do provide at least some degree of control for measurement error by giving more weight to items presenting lower levels of measurement errors. An added advantage of factors scores is that, when longitudinal or group-based comparisons of profile solutions are conducted, it becomes possible to systematically assess the invariance of the factor analytic measurement model across time or groups (e.g., Vandenberg & Lance, 2000). Factor scores can then be saved from the most invariant measurement model to ensure comparability of the results over time or groups. Factors scores can also be estimated in standardized units (with a mean of zero and a variance of one; allowing all loadings and intercepts to be freely identified: Little, Slegers, & Card, 2006). This provides a standardization of the data in line with our prior recommendation.

Random starts. Mixture models are estimated using an iterative process that carries a high risk of converging on a local solution rather than on a true maximum likelihood (Hipp & Bauer, 2006). To control this risk, models need to be estimated with multiple sets of random start values (Hipp & Bauer, 2006; McLachlan & Peel, 2000). Researchers typically have their own interpretation of how many random starts are enough, and no clear guideline has been published so far. Based on experience with the estimation of a wide range of mixture models, our recommendation is to use at least 3000 sets of random starts, 100 iterations of reach of these sets of starts values, and to retain at least the 100 best sets of start values for final stage optimisation. These values can be increased to 5000, 200, and 200 when the final solution is not sufficiently replicated. We see these values as a minimum that can be increased as needed pending the availability of properly powerful computers.

Relaxing assumptions. A key limitation of cluster analyses in comparison with LPA is their reliance on rigid assumptions that often fail to hold with field data (Morin, Morizot et al., 2011; Vermunt & Magidson, 2002)[1]. However, classical LPA models also rely on some of these assumptions, or have been implemented in some statistical packages as a function of these assumptions. Fortunately, the GSEM framework provides alternative ways to relax these constraints. Here, we address two of these constraints: (a) the class-invariance of the indicators' variances (i.e., the variances of the indicators are the same across profiles), and (b) the conditional independence of the indicators (i.e., the indicators are uncorrelated conditional on the classification).

In contrast to cluster analyses, LPA does not assume that the variance of the profile indicators is the same (invariant) across subgroups. However, the default parameterization of LPA in some statistical packages (e.g., Mplus) imposes invariance constraints on the variance of the indicators across profiles. Relaxing this default has been shown to result in less biased parameter estimates (Peugh & Fan, 2013) and a more realistic representation of the complexity of human nature (Morin, Maïano et al., 2011).

The conditional independence assumption, however, applies equally to classical LPA and cluster analyses. According to this assumption, all observed indicators are expected to be unrelated to one another, conditional on the latent profiles. Fortunately, the GSEM framework provides two alternative ways to relax this assumption, either through the inclusion of correlations among the uniquenesses of the LPA indicators, or through the reliance on factor mixture models. Despite some evidence from simulation studies suggesting that there might be benefits associated with the inclusion of correlated uniquenesses (Uebersax, 1999; Peugh & Fan, 2013), this inclusion should only be done with caution and based on strong a priori expectations of relations among the indicators beyond those reflected in the profiles (e.g., similar wording or keying). Indeed, correlated uniquenesses change the meaning of any model, which typically aims to explain associations among items with a finite number of latent factors or profiles (Marsh et al., 2009). Even when there is a need to explicitly control for some residual source of covariance among the indicators, method factors provide a much more explicit form of control and should generally be preferred. Interestingly, factor mixture models make possible the inclusion of method factors, so that the latent profiles can be estimated controlling for the effects of explicitly modeled residual associations among items (e.g., Lubke & Muthén, 2005).

More generally, GSEM allows for the inclusion of continuous (factors) and categorical (profiles) latent variables into the same model as a more generic and meaningful way to relax the conditional independence assumption of classical LPA. When these two types of latent variables are estimated from the same set of indicators, the resulting model is called a factor mixture model. For example, it may be important to control a generic tendency (e.g., global level of competencies, global tendency to commit) across all indicators before identifying patterns reflecting relative strength. For example, in a study of university teachers, Morin and Marsh (2015) sought to estimate profiles of specific strengths and weaknesses on a wide array of teaching competencies while also taking into account teachers' global level of effectiveness. They observed that controlling for this global level of overall competencies was necessary for the estimation of clearly differentiated profiles of teachers presenting specific areas of teaching effectiveness over and above this global level of effectiveness. In other words, they observed that teachers differed from one another on their overall level of competencies (i.e., there are generally good and poor teachers), while still having specific profiles of strength and weaknesses. For example, good and poor teachers could both be weaker in their relational competencies, or in their marking ability, than in other facets of their teaching. This approach could have relevance in commitment research, particularly in cases where there might be strong individual differences in the propensity to commit that could mask differences in the relative strength of commitment to multiple targets (Morin, Morizot et al., 2011). It is less applicable in the investigation of mindset profiles because AC, NC and CC scores are unlikely to be subject to the same underlying propensity. Although a complete review of factor mixtures analyses is beyond the scope of this manuscript, these analyses form a broad framework that can be used advantageously to investigate the underlying continuous or categorical nature of psychological constructs (Clark, Muthén, Kaprio, D'Onofrio, Viken & Rose, 2013; Masyn, Henderson & Greenbaum, 2010), or to test the invariance of measures across unobserved subpopulations (Tay, Newman & Vermunt, 2011).

Whenever class-varying variances or correlated uniqueness are added to a mixture model, or whenever a factor mixture representation of the data is explored, the statistical indicators of model fit can be contrasted to directly assess the added value of these more flexible models in comparison to classical LPA models. However, it may not always be possible to implement all or even a subset of these modifications. Mixture models are complex and frequently converge on improper solutions, or fail to converge at all. When this occurs, it suggests that the model may have been overparameterized (e.g., too many profiles, too many parameters freely estimated across profiles: e.g., Bauer & Curran, 2003) and thus that a more parsimonious model should be selected. Our recommendation is to always start with theoretically "optimal" models, and then to reduce model complexity when necessary.

At this stage, it is important to note that applications of mixture models are best suited to large samples, which not only contribute to the ease with which these models are able to converge on proper solutions, but also to the ability to identify rare but potentially meaningful profiles. Unfortunately, no clear statistical guideline has yet been published regarding sample size requirements for mixture models under various conditions. Thus, when researchers have the luxury of access to potentially large (500) or very large (>1000) samples, they may want to take advantage of this to test the more complex mixture models described above. However, they also need to be aware that, with large samples, they may detect statistically significant differences across models or identify smaller profiles that lack practical significance. In contrast, when only small samples (e.g., <300) are available to researchers, they will have to make appropriate adjustments to the complexity of the models they attempt to test.

Integrating covariates. A critical advantage of mixture models is the ability to include covariates (predictors, correlates or outcomes) directly in the model rather than relying on suboptimal two-steps strategies. A typical two-step strategy involves exporting the information about the most likely class membership to an external data file, and then relating this newly created categorical variable to a variety of covariates using traditional logistic regressions or ANOVAs approaches. The critical disadvantage of this approach is that it ignores the prototypical nature of the latent profiles and the fact that each individual has a probability of membership in each profile (Marsh et al., 2009).

Before including covariates, a critical question is whether these covariates are logically and theoretically conceptualized as having an impact on profile membership (predictors), as being impacted by profile membership (outcomes), or are simply being used to get a richer description of the nature of the profiles (correlates). Predictors are typically included in the model using a multinomial logistic regression where they are used to predict the likelihood of membership into the various profiles. In multinomial logistic regressions, each predictor has k-1 (with k being the number of profiles) effects for each possible pairwise comparison of profiles. It is important to include predictors after the class enumeration procedure has been completed, as this method allows for the verification of the stability of the model following inclusion of the covariates (Marsh et al., 2009; Tofighi & Enders, 2008). More importantly, the inclusion or exclusion of predictors should not change the nature of the profiles. Such a change would indicate a violation of the assumption that covariates predict profile membership, and would instead show that the nature of the profiles is dependent on the choice of the predictors (Marsh et al., 2009; Morin, Morizot et al., 2011). When this happens, alternative strategies need to be used to estimate these relations without allowing covariates to influence the nature of the profiles. A first strategy involves the estimation of the model with covariates using the start values taken from the final unconditional model (rather than random starts). When this strategy also fails, auxiliary approaches, where the associations between profiles and covariates are estimated while keeping the covariates inactive, are available (see Asparouhov & Muthén, 2014; Vermunt, 2010).

The situation is more complex for outcomes. The typical way of including outcomes directly in the model involves including them as additional profile indicators. However, when multiple outcomes are considered, this method will almost always result in a change in the nature of the profiles (Morin, Morizot et al., 2011; Petras & Masyn, 2010). Whenever this is the case, associations between inactive outcomes and the profiles can also be easily tested using a variety of auxiliary approaches (e.g., Asparouhov & Muthén, 2014; Lanza, Tan & Bray, 2013; Vermunt, 2010)

Finally, correlates used for purely descriptive purposes should clearly not impact on the nature of the estimated profiles, and should not even be included directly in the model. This suggests the use of auxiliary approaches, such as the AUXILIARY *(e)* implemented in Mplus (also see Magidson & Vermunt, 2001). This approach relies on the Wald chi-square test of significance based on pseudo-class draws and tests the equality of means across profiles (Asparouhov & Muthén, 2007; Bolck et al., 2004) and does not assume directionality in the associations between profiles and correlates.

Shared method variance. Although multiple attempts have been made over the years to debunk the myth that shared method variance introduces bias in the estimation of key relationships among variables (Conway & Lance, 2010; Lance, Dawson, Birkelbach & Hoffman, 2010; Spector, 2006), this myth still seems well anchored in organizational research. It even seems to have resisted a formal equation-based demonstration (Siemsen, Roth & Oliveira, 2010) that multivariate analyses, where effects are estimated from predictors' unique (i.e., not shared) contribution, are naturally protected against biases related to shared method variance. Unfortunately, no such demonstration has yet been published for mixture models. However, for similar reasons, mixture models are unlikely to be biased by shared method variance because they aim to explain covariances among a set of indicators through the extraction of profiles that are distinct from one another. As such, any uncontrolled source of shared influence is only likely to result in a slightly lower level of dispersion in the profile. We note here that, even though the factor mixture models described above also control for shared method variance as part of the global factor, it should not be used simply to control for shared method variance given that such latent factors are known to absorb a substantial level of meaningful covariance from the constructs (e.g., Marsh et al., 2010; Richardson, Simmering, & Sturman, 2009). Finally, analyses of relations between covariates (predictors, correlates or outcomes) and latent profiles are inherently multivariate and thus also unlikely to be biased by shared method variance (e.g., Siemsen et al., 2010).

Future Applications

Consistency of profile solutions across samples and cultures. As noted earlier, the bulk of research on commitment profiles has been conducted in Western countries, more specifically in North America. Even though a few studies have been conducted in non-Western countries (e.g., Morin, Meyer et al., 2015), there has yet to be a true quantitative cross-national comparison of commitment profiles, their development, or their consequences. Even within Western countries, there has yet to be a systematic investigation of the extent to which profiles generalize across subgroups of participants defined on the basis of age, gender, cultural group, or profession. Although it is true that some person-centered studies have used some of these variables to predict profile membership (Morin, Morizot et al., 2011; Morin, Meyer et al., 2015), no study has yet investigated the possibility that profile structure may change across subpopulations. Finally, although it is recognized that tests of the generalizability of a profile solution is a key consideration if one wants to support a substantive interpretation of the profiles, very few studies have tested the extent to which extracted profiles replicate across samples (e.g., Meyer, Kam et al., 2013; Meyer, Morin et al., 2015), and these have done so relying on visual comparisons. Thus, the systematic testing of the invariance of profile solutions across samples, cultures, and subpopulations is a key direction for future commitment research.

In variable-centered studies (Vandenberg, 2002; Vandenberg & Lance, 2000), comparison of results across subpopulations typically starts with the investigation of the equivalence of the measurement model underlying the constructs (in terms of number of factors, type of model, and global patterns of associations between items and factors) is the same across subpopulations, namely *configural invariance*. From a model of configural invariance, additional levels of invariance can be tested, typically in sequence. Tests of weak invariance determine whether the factor loadings are the same across subpopulations. Tests of strong invariance determine whether the factor loadings and item intercepts are the same across subpopulations. Tests of strict invariance determine whether the factor loadings, item intercepts, and item uniquenesses are the same across subpopulations. These tests can be extended to assess the invariance of the latent variances, covariances and means, as well as of the relations among various constructs. Although a more extensive review of these variable-centered methods is beyond the scope of this article (see Vandenberg, 2002; Vandenberg & Lance, 2000), comparisons of profile solutions should also start with a variable-centered verification that the measurement model underlying the profile indicators is invariant across subpopulations.

Morin, Meyer, Creusier, and Biétry (2016) recently proposed a comparable approach for the investigation of the *similarity* of LPA solutions across subgroups of participants. They retained the term *similarity* to help differentiate this person-centered framework from the more commonly used variable-centered measurement invariance framework described above. The first test for *configural similarity* involves determining whether the same number of latent profiles can be identified in all subpopulations. As in variable-centered studies, this step tests whether the same number of profiles can be identified in all groups, using the same overarching model (i.e., based on the same indicators, with or without correlated uniquenesses, with or without the inclusion of method factors, etc.). Failure to support the configural similarity of a profile solution means that the latent profiles differ across subpopulations and need to be contrasted using a more qualitative process. The second test for *structural similarity* determines whether the profiles are characterized by similar levels on the profile indicators – the commitment components – across subpopulations. The profile labeling scheme presented earlier focused on three characteristics of profiles (shape, elevation, and scatter) to determine the nature of the latent profiles. Because each of these three characteristics is defined based on the within-profile average level on each indicator, evidence of structural similarity is sufficient to argue that the nature of the profiles is the same across subpopulations. If the number and/or structure of the profiles differ across subpopulations, all subsequent analyses must be conducted separately across subpopulations, and further tests of similarity are neither possible nor relevant. This might indicate problems with the operationalization of the constructs, perhaps suggesting the need to revisit preliminary variable-centered tests of measurement invariance to ensure that the indicators provide an unbiased reflection of the same construct across groups. Alternatively, a lack of configural similarity might also reflect true differences in the ways the variables combine as a function of groups.

Assuming structural similarity, the third step tests the *dispersion similarity* of the profiles and determines whether the within-profile variability of the indicators is similar across subpopulations. Testing for dispersion similarity thus involves assessing whether the profiles are more or less homogenous across samples or whether some subpopulations present higher levels of within-profile variability than others. Regardless of whether dispersion similarity is supported, the fourth test assesses the *distributional similarity* of the profiles – that is, whether the relative size of the profiles is similar or different across subpopulations. Support for distributional similarity shows that the relative frequency of the various profiles is similar across groups, while a lack of distributional similarity suggests that some profiles are more or less prevalent in some groups than others. Distributional similarity is also not a pre-requisite to the next steps.

Once the similarity of the profiles has been determined (i.e., configural, structural, dispersion, distributional), predictors and outcomes (when relevant) can be added to the most similar model from the foregoing sequence, starting minimally with structurally similar profiles. The fifth test of *predictive similarity* assesses whether the relations between predictors and profiles are equivalent across subpopulations. Failure to support predictive similarity suggests that the group moderates these relations. Finally, the sixth test of *explanatory similarity* assesses whether the relations between the profiles and the outcomes replicate across subpopulations, or if the group moderates these relations.

Interestingly, Morin et al. (2016) illustrated the application of this approach using ratings of AC, NC, and CC to the organizations obtained among French and North American employees. Their results revealed that five common profiles (see Table 1) could be identified in both countries. They further found evidence of configural, structural, and dispersion similarity across countries, but noted the presence of distributional differences suggesting that the *Low CC-Dominant* and *AC-Dominant* profiles were more prevalent in France, while the *High AC/NC-Dominant* and *High NC-Dominant* profiles were more prevalent in North America. They further evidence of predictive similarity in the relations between demographic predictors and employees' perceptions of managerial practices in the prediction of profile membership, as well as of explanatory similarity in the way the profiles predicted employees' levels of turnover intentions and work exhaustion.

Consistency of profile solutions across time. To date, the bulk of research on commitment profiles has been cross-sectional (Meyer et al., 2013; Vandenberg & Stanley, 2009). Latent Transition Analyses (LTA) estimate LPA solutions at multiple time points (typically two or three, after which these models become too demanding for modern computers). Broadly, LTA involves the estimation of LPA solutions at multiple time points, as well as the connections between the profiles estimated at these multiple time points (i.e., the transitions; e.g. Collins & Lanza, 2009; Nylund, 2007). LTA typically involves the estimation of LPA solutions based on the same set of indicators across time points, but can be extended to test connections between any types of mixture models, whether or not they are based on the same indicators (Nylund-Gibson, Grimm, Quirk, & Furlong, 2014).

Kam et al. (2016) argued that LTA allows for the investigation of two types of stability in latent profile solutions over time. A first involves the stability of the profile structure within a sample, over time (i.e., *within-sample stability*), and can be assessed using the same set of procedures described previously for the assessment of profile similarity (Morin et al., 2016). Kam et al. (2016) argue that the demonstration of within-sample profile stability (in particular configural and structural invariance) supports the idea that person-centered research on commitment can be used to guide organization strategies designed to select, promote, or differentially manage employees with specific profiles. A second form of stability pertains to the consistency of individual employees' profiles over time (i.e., *within-person stability*).

So far, we were able to locate only a single application of LTA in commitment research. In this study, Kam et al. (2016) showed that profiles of organizational commitment presented a very high level of within-sample and within-person stability over an eight month period characterized by organizational changes. Based on these promising preliminary results, the investigation of the temporal stability of latent profiles among more diverse groups of employees at different career-stages and exposed to different contexts, as well as considering other targets of commitment and a richer set of predictors, should be seen as a future priority for person-centered commitment research.

Commitment trajectories. Growth mixture models (GMM) extract subgroups of participants presenting distinct longitudinal trajectories on one – or many – commitment component(s) over multiple time points (three or more; Meyer et al., 2013; Vandenberg & Stanley, 2009). GMM are built from latent curve models (LCM; Bollen & Curran, 2006). In LCM, trajectories at the sample level are estimated through intercept and slope(s) factors that are allowed to differ between individuals. LCM thus estimates person-specific longitudinal trajectories, and allows for the integration of predictors and outcomes of these trajectories. For instance, Bentein, Vandenberghe, Vandenberg, and Stinglhamber (2005) applied LCM analyses to a sample of 330 employees who completed TCM measures of commitment to the organization three times at three-month intervals. Their results revealed that, on average, AC and NC decreased over time, intentions to leave the organization increased, and CC remained relatively stable. Interestingly, they found that steeper decreases in AC and NC were significantly associated with steeper increases in intentions to leave the organization, which in turn predicted higher rates of turnover over the next nine months.

In contrast to LCM, GMM extracts latent profiles differing at the level of these growth factors, or even following distinct functional forms (linear, quadratic, etc.; e.g., Morin, Maïano et al., 2011, 2013; Ram & Grimm, 2009). For example, in a study of employees' trajectories of organizational AC following an organizational change, one might observe one trajectory profile showing a linear increase in commitment levels over the next year (suggesting that they are pleased with the change), a second showing a steady decline (suggesting that the change may have negative consequences for them) and a third group showing an initial increase in commitment level, followed by a decline (suggesting an initial interest in the change followed by disappointment).

As for LPA, more flexible GMM may provide a much richer perspective (see Morin, Maïano et al., 2011, 2013; Ram & Grimm, 2009), although the ability to estimate these models is likely to be limited with smaller samples, or fewer time points. We recommend starting with theoretically 'optimal' models and slowly imposing constraints when less restricted models fail to converge on proper solutions. Importantly, with LCM/GMM, sample size is not limited to the number of participants, but also takes into account the number of measurement points so that more measurement occasions can offset sample size limitations (Diallo & Morin, 2015; Diallo, Morin, & Parker, 2014).

Another critical issue is that LCM/GMM rely on the assumption that the chosen time interval is meaningful (Metha & West, 2000). Thus, typical organizational studies where a sample of employees presenting a variety of age and tenure levels is recruited and followed over time are not suitable for LCM/GMM. Suitable applications require trajectories to be explicitly modelled as a function of age or tenure levels, or as a function of key transition points (intervention or experiment, organizational change, retirement, change of employment, etc.). Otherwise, time effects will be confounded with a multiplicity of other, unmodelled, effects of age, tenure, etc. that vary across employees.

Arguably, examining longitudinal trajectories of commitment components represents another key area for future commitment research, and is well suited to investigations of the effects of experimental interventions, organizational changes, or job transitions (e.g., allowing for the identification of subgroups showing differential reactivity to the intervention or change). So far, we are aware of only a single study that has applied a restricted form of GMM (due to limited sample size of n = 72) to the study of newcomers' organizational AC starting four weeks prior to the commencement of the new employment and extending to 25 weeks into the new employment. In this study, Solinger et al. (2013) extracted five distinct longitudinal profiles of employees, characterized by a "high match", "moderate match", or "low match" with the organization (i.e., persistently high, moderate, or low AC, respectively), by a "learning to love" profile (increasing AC level), or by a "Honeymoon hangover" profile (increasing AC level, followed by a decrease). Clearly, these results beg replication and additional investigation of possible interventions to favor the emergence of the most desirable profiles.

Consistency of predictions involving commitment. A final, and potentially very interesting, application of mixture modeling is mixture regression (MRM). There are relatively few published examples of MRM in the psychological or organizational literature at large (e.g., Morin, Scalas et al., 2014), and none in the commitment area. This is surprising given the potential of MRM to identify subgroups of participants differing at the levels of estimated relations between constructs. In other words, rather than profiling participants on the basis of their cross-sectional configuration on a series of commitment components, or on the basis of their longitudinal trajectories of commitment, MRM extracts subgroups of participants for whom estimated relationships among constructs differ. For example, although it is reasonably well-documented that AC predicts higher levels of well-being (e.g., Meyer & Maltin, 2010) and lower levels of turnover (Meyer et al., 2002), MRM could be used to extract profiles of employees presenting different patterns of relations between these constructs. In this example, a dominant profile would likely show that AC relates as expected to turnover and well-being, while another profile may show a significant negative relation between AC and turnover, but a non-significant relation between AC and well-being. Yet a third profile may reveal one or both relation in the opposite direction, perhaps demonstrating that there can be risks to extreme levels of AC (Morin, Vandenberghe, Turmel, Madore, & Maïano, 2013). In essence, when compared to classical latent profile models with outcomes included directly in the models (which essentially tests mean differences on the outcomes between profiles), MRM models estimate regressive relations between the profile indicators and the outcomes, and allow these regressions to differ from one profile to the other.

Practical Implications

Although it is important to emphasize that variable-centered and person-centered approaches are complementary and contribute meaningfully to our understanding of workplace commitments, we focus here on what we consider to be some of the unique contributions of the person-centered approach from a practical perspective. First, as noted previously (Morin, Morizot et al, 2011; Zyphur, 2009), identifying subgroups of individuals who differ in meaningful and predictable ways is likely to have a natural appeal to managers. In this regard, the findings will be most helpful when it can be demonstrated that similar subgroups can be identified across samples, and possibly even cultures. This has been demonstrated to some extent for the TCM mindset profiles, and future research may well demonstrate cross-sample consistency in bond and/or target profiles. However, even if differences in profile structure are observed across samples, the person-centered approach continues to have value as long as the emergence of different profile can be explained empirically and theoretically. One obvious example would be if different profile structures are detected in different countries and the differences can be explained in terms of cultural values, economic conditions, or other national differences.

A second contribution is the more holistic treatment of the key targets of this research – people. Rather than focusing on individual differences on specific variables and/or the relationships among variables at a sample level, the person-centered approach focuses on the persons and on how they can be characterized on a system of variables (e.g., commitment mindsets or targets, bond types). It is perhaps this more holistic focus that makes the findings of person-centered research particularly appealing to managers. For example, they might be better able to relate to findings indicating that employees who are *morally committed* to the organization are more likely to remain and perform effectively compared to those who feel *indebted*, than to the finding that the relation between NC and performance varies as a function of the relative levels of AC and CC (Gellatly et al., 2006).

Third, because person-centered studies are better suited than variable-centered studies to the detection of complex interactions, they sometimes provide more accurate information to guide practice. For example, accumulated variable-centered research suggests that CC is unrelated, or even negatively related, to job performance (Meyer et al., 2002; Riketta, 2002) and employee well-being (Maltin & Meyer, 2010). This might lead to concerns about elevated CC scores on employment surveys. However, person-centered research suggests that employees with strong CC can be happy, healthy and perform effectively when they have a fully committed profile (i.e., strong CC is accompanied by strong AC and NC; Meyer, L. Stanley et al., 2012). Future research focusing on targets of commitment might produce similar insights with practical implications. For example strong union commitment might inhibit employees from going beyond minimum performance requirements when organizational commitment is weak. However, when combined, strong organizational and union commitment might produce a powerful synergy (Johnson et al., 2010), leading to even higher performance than organizational commitment alone. The implications of these two scenarios for management efforts to promote (or suppress) union commitment would be dramatically different.

Finally, once profiles are identified, it is possible to use the probability of membership in the profile groups as dependent variables in investigations of profile development. Developmental studies are rare at this point, and most studies focus on situational variables. For example, Kam et al. (2016) investigated whether profile membership, and shifts in profile membership during organizational change, could be predicted from perceptions of management trustworthiness. The advantage of focusing on situational determinants is that they can guide interventions to increase the proportion of individuals with more desirable profiles within the workforce. It should be noted, however, that Kam et al. found little movement across profiles even under conditions of fairly radical change, suggesting that profile membership might also be due, at least in part, to stable individual differences. Although yet to be investigated, Johnson et al. (2010) suggested that differences in identity predisposition (individual, relational, collective) and regulatory focus (promotion or prevention) might predict profile development. If future research supports these propositions, the findings might have important implications for the selection of employees who are more likely to have the desired commitment profile. In all likelihood, some combination of selection and effective management will be required.

Note that the foregoing discussion was restricted to applications of the more basic forms of person-centered analyses. More advanced techniques introduced in the Methodological Issues section have the potential to answer more complex questions and to guide practice pertaining to the management of commitment under more dynamic situations (e.g., organizational change).

Conclusion

Person-centered methodologies are well-suited to testing aspects of commitment theory not easily addressed using the more traditional variable-centered techniques, particularly those involving complex interactions among variables. We hope that by demonstrating how the person-centered approach has been applied to date, and by introducing the various basic and advanced analytic strategies that are currently available, we will stimulate researchers to think creatively about how these strategies can be applied to address a wide range of new questions.

Footnotes

[1] Cluster analyses rely on rigid assumptions that often fail to hold with field data and can easily be relaxed in the context of mixture models (Muthén, 2002; Vermunt & Magidson, 2002). These assumptions include conditional independence (i.e., the indicators are uncorrelated conditional on the classification; Uebersax, 1999), class-invariant variances (the variances of the indicators are the same across profiles; Morin, Maïano et al., 2011; Peugh & Fan, 2013), and exact class assignment whereby each individual is assumed to correspond entirely to a single profile. Furthermore, cluster analyses do not provide clear guidelines to help in the identification of the correct number of profiles present in the data, and are highly sensitive to the distribution of the indicators. However, recent and emerging clustering methods (e.g., fuzzy clustering) provide ways to circumvent at least some of these limitations (for a review of these methods, see Brusco, Steinley, Cradit, & Singh, 2012).

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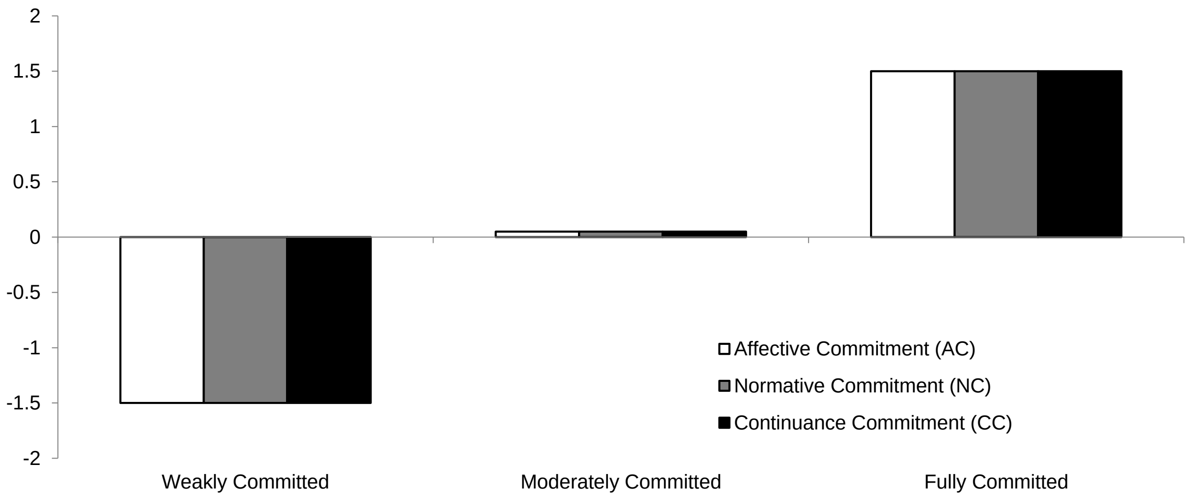

Figure 1a. Prototypical Profiles: Quantitative Distinctions

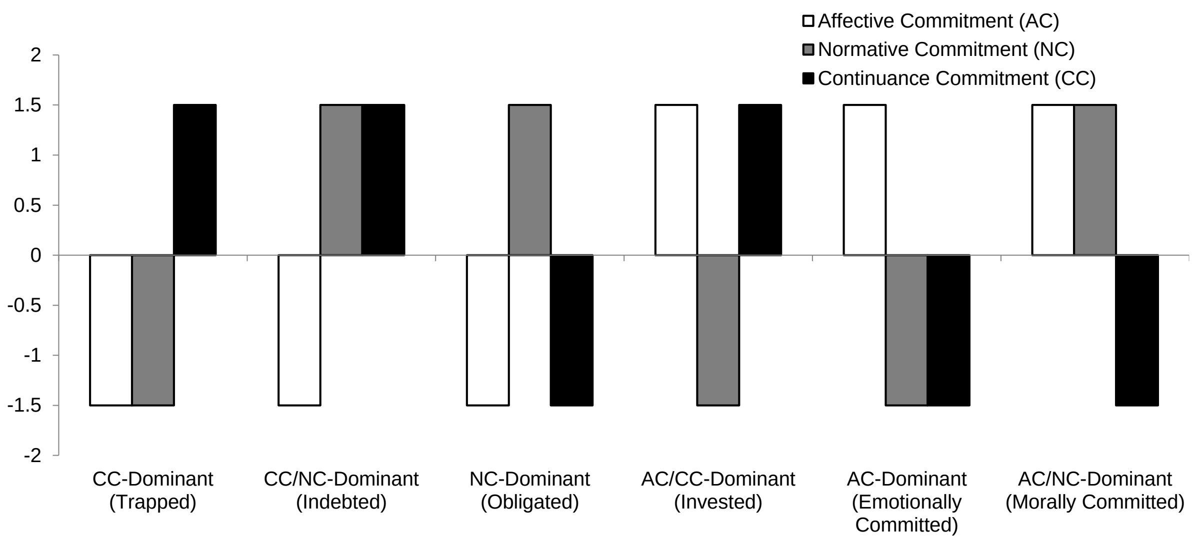

Figure 1b. Prototypical Profiles: Qualitative Distinctions

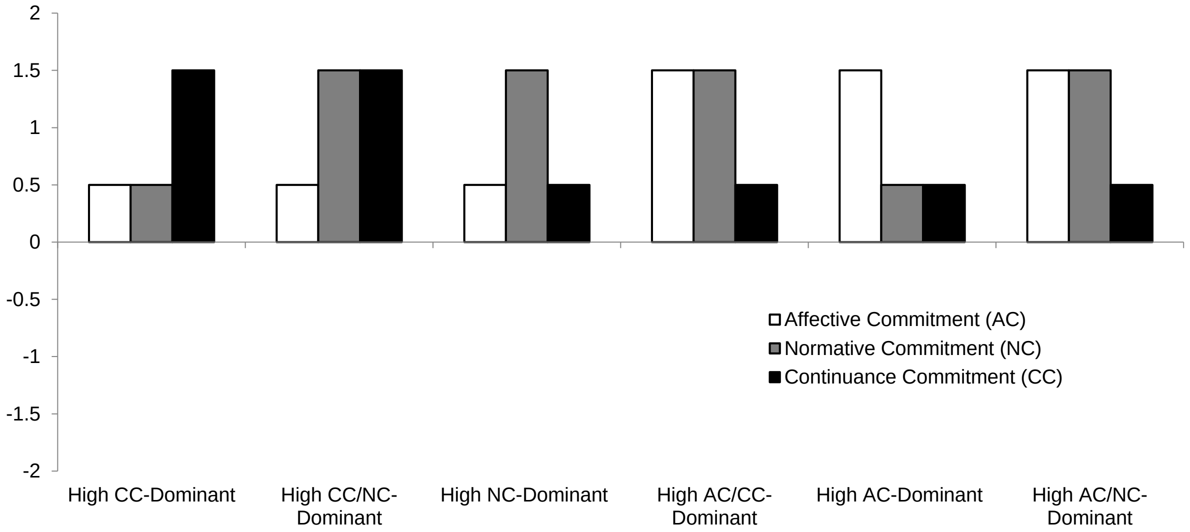

Figure 2a. Prototypical Profiles: High Qualitative Distinctions

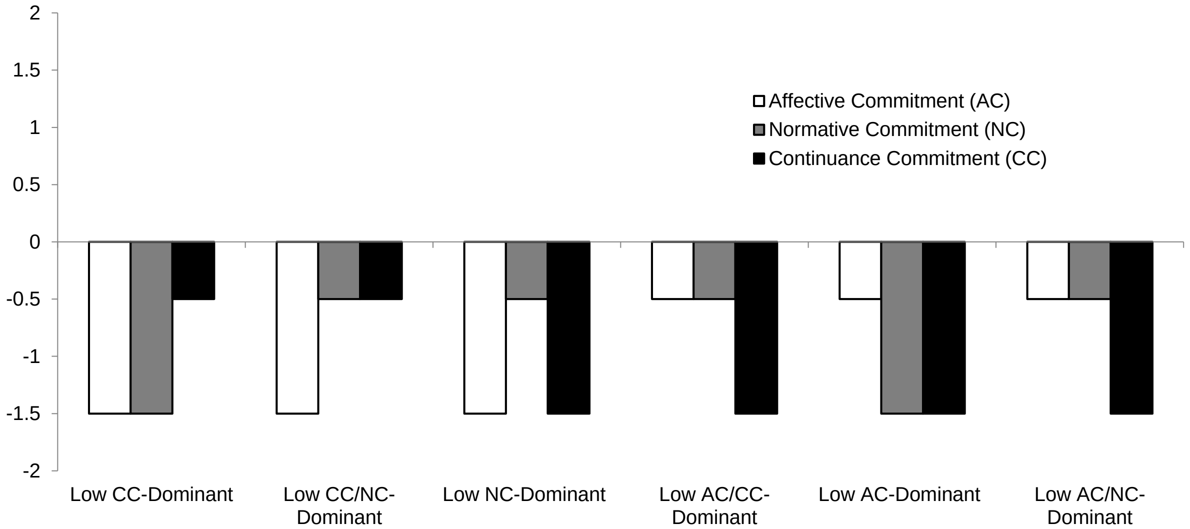

Figure 2b. Prototypical Profiles: Low Qualitative Distinctions

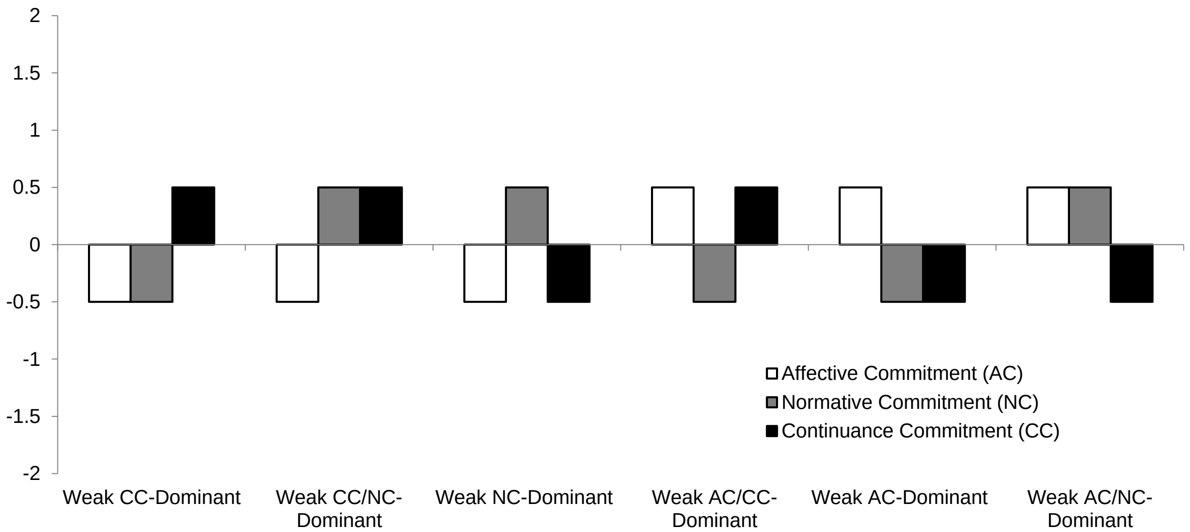

Figure 2c. Prototypical Profiles: Weak Qualitative Distinctions

Table 1.
Summary of Person-Centered Studies of Mindsets of Commitment to the Organization

Article	Original Label	Revised Label	Weakly Committed	Moderately Committed	Fully Committed	CC-Dominant (Trapped)	CC/NC-Dominant (Indebted)	AC-CC-Dominant (Invested)	NC-Dominant (Obligated)	AC-Dominant (Emotional)	AC/NC-Dominant (Moral)
Wasti (2005, Study 1)	AC-dominant	AC-dominant								X	
Cluster Analyses	Neutrals	Low NC-dominant							Low		
Standardized Scores	Non-committed	Low CC-dominant				Low					
	CC-dominant	CC-dominant				X					
	Highly committed	Fully committed			X						
	AC/NC-dominant	AC/NC-dominant									X
Wasti (2005, Study 2)	Highly committed	Fully committed			X						
Cluster Analyses	Non-committed	Weakly committed	X								
Standardized Scores	NC/CC-dominant	NC/CC-dominant					X				
	AC-dominant	AC-dominant								X	
	CC-dominant	Weak CC-dominant				Weak					
	AC/NC-dominant	AC/NC-dominant									X
Somers (2009)	Highly committed	High AC/NC-dominant									High
Cluster Analyses	CC-dominant	High CC-dominant				High					
Raw Scores	AC/NC-dominant	Weak AC/NC-dominant									Weak
	CC/NC-dominant	High CC/NC-dominant					High				
	Low commitment	Weak CC-dominant				Weak					
Somers (2010)	Highly committed	High AC-dominant								High	
Cluster Analyses	AC/NC-dominant	High AC/NC-dominant									High
Raw Scores	AC-dominant	Weak AC-dominant								Weak	
	AC/NC-dominant	High AC/CC-dominant						High			
	CC/NC-dominant	High CC/NC-dominant					High				
	CC-dominant	CC-dominant				X					
	Low commitment	Low CC/NC-dominant					Low				
Meyer, L. Stanley et al.	Uncommitted	Low CC-dominant				Low					
(2012)	CC-dominant	CC-dominant				X					
Latent Profile Analyses	Moderate commitment	High CC-dominant				High					
Standardized Scores	Low-moderate commitment	Weakly committed								X	
	Fully committed	Fully committed			X						
	AC/NC-dominant	AC/NC-dominant									X
Meyer, Kam et al (2013,	AC/NC-dominant	High AC/NC-dominant									High
Sample 1)	AC-dominant	AC-dominant								X	
Latent Profile Analyses	All mid	Weak AC/CC-dominant						Weak			
Raw Scores	All low mid	Low AC-dominant								Low	
	CC-dominant	CC-dominant					X				
	Uncommitted	Weakly committed	X								

Article	Original Label	Revised Label	Weakly Committed	Moderately Committed	Fully Committed	CC-Dominant (Trapped)	CC/NC-Dominant (Indebted)	AC-CC-Dominant (Invested)	NC-Dominant (Obligated)	AC-Dominant (Emotional)	AC/NC-Dominant (Moral)
Meyer, Kam et al (2013,	AC/NC-dominant	High AC/NC-dominant									High
Sample 2)	AC-dominant	AC-dominant								X	
Latent Profile Analyses	All mid	Weak AC/CC-dominant						Weak			
Raw Scores	All low mid	Low AC-dominant								Low	
	CC-dominant	CC-dominant					X				
	Uncommitted	Weakly committed	X								
Stanley et al. (2013)	Not-committed	Low AC-dominant								Low	
Latent Profile Analyses	Committed	Fully committed			X						
Raw Scores	AC/NC-dominant	AC/NC-dominant									X
	CC-dominant	CC-dominant				X					
	Moderately committed	Low AC/CC-dominant						Low			
	AC-dominant	Weak AC/CC-dominant						Weak			
Gellatly et al. (2014)	Uncommitted	Very weakly committed	X								
Latent Profile Analyses	All low	Weakly committed	X								
Standardized Scores	All moderate	Moderately committed		X							
	All high	High AC/NC-dominant									High
	AC-dominant	AC-dominant								X	
	CC-dominant	CC-dominant				X					
Kam et al. (2016)	AC/NC-dominant	AC/NC-dominant									X
Latent Profile Analyses	AC-dominant	AC-dominant								X	
Raw and Normed Scores	All mid with AC-dominant	Low AC-dominant								Low	
	All mid with CC-dominant	Low AC/CC-dominant						Low			
	CC-dominant	Low CC-dominant				Low					
Morin et al. (2015)	Weak CC-dominant	Low CC-dominant				Low					
Latent Profile Analyses	Weakly committed	Weakly committed	X								
Standardized Scores	Strong CC-dominant	CC-dominant				X					
	Moderately committed	Moderately committed		X							
	AC-dominant	AC-dominant								X	
	AC/NC-dominant	High AC/NC-dominant									High
Morin et al. (2016)	CC-dominant	Low CC-dominant				Low					
Latent Profile Analyses	Moderately committed	Moderately committed	X								
Standardized Scores	AC/NC-dominant	High AC/NC-dominant									High
	NC-dominant	High committed		X					High		
	AC-dominant	Weak AC-dominant								Weak	