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A longitudinal person-centred investigation of commitment in newcomers to the military

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Abstract

Organizational commitment is a force that binds individuals to their company through their desire, obligation, and need to stay. Employees who are committed to the organization are more likely to demonstrate higher engagement, greater satisfaction, and fewer intentions to leave their company. Research has also demonstrated that investigating how each of the three forms of commitment – affective, normative, and continuance – interact allows for better prediction of employee outcomes. Using person-centred approaches, previous research has shown that there are typically five to seven profiles of commitment, and that membership in these profiles has implications for employee behaviours. However, little research has examined how these profiles emerge and develop over time in samples of newcomers.

The current research used archival data collected by the Canadian Armed Forces to investigate the development of commitment over the first year of employment with the military. Two samples were analyzed – one cross-sectional sample of employees at the end of their Basic Training experience (N = 3998) and one longitudinal sample of participants undergoing Occupational Training (N = 636). A person-centred approach to data analysis was adopted.

Latent profile analyses demonstrated a four-profile solution in the Basic Training sample and a six-profile solution in the Occupational Training sample. Further, a latent transition analysis in the longitudinal data showed that membership in commitment profiles was relatively stable over the six-month time lag. These profiles were examined in relation to a number of antecedents and outcomes, with results indicating that value fit and social support were significant predictors of profile membership, and that turnover intentions and levels of well-being differed across profiles.

These results have implications for person-centred commitment research. First, the differences in the profiles extracted in the Basic Training and Occupational Training samples suggest that time may be an important factor in the development of commitment. Further, results for the longitudinal sample suggested that, once profiles form, they become stable. This research validated previous findings on commitment profiles in military samples. Practical implications, limitations, and future directions are discussed.

KEYWORDS: organizational commitment; commitment profiles; newcomers; latent profile analysis; latent transition analysis; Canadian Armed Forces; value fit; social support; training satisfaction; turnover intentions; well-being.

Summary for Lay Audience

Organizational commitment is a force that binds individuals to their company. It can be expressed in different ways, and previous research has shown that individuals can have different mindsets when committing to their organization. Feelings of desire, obligation, or need to stay with the organization can combine within an individual to create a complicated, nuanced expression of commitment that is related to employee behaviors, attitudes, and outcomes. This research sought to investigate those combinations of commitment – called commitment profiles – in newcomers to an organization. Until now, little research has been done to understand how commitment develops in new employees and if this commitment is stable over time.

Participants in this study were new recruits to the Canadian Armed Forces. The first sample was collected at the end of Basic Training, and the second sample was collected at two time points during Occupational Training, which followed Basic Training. All data were gathered within the first year of employment.

This results of this research found four commitment profiles in the Basic Training sample. These profiles were different from those seen in past research on more tenured employees. However, in the Occupational Training sample, six profiles were extracted. These profiles were in line with those found in other studies, suggesting the standard commitment profiles may develop after only a few months with an organization. Further, results showed that these commitment profiles were relatively stable over a six-month period.

These results have implications for our understanding of commitment profiles. The differences in the profiles extracted in the Basic Training and Occupational Training samples suggests that commitment develops quickly, but not immediately, in new personnel. Further, the results demonstrate that once commitment forms, it is fairly stable for military recruits. These findings have implications for future research, and can be used to inform interventions that seek to foster positive forms of commitment in new employees.

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Chapter I: Introduction

Organizational commitment has long been a variable of interest for employers. Research has shown that committed employees are often more satisfied, more engaged, and less likely to leave their organization (e.g., Christian, Garza, & Slaughter, 2011; Meyer, Stanley, Herscovtich, & Topolnytsky, 2002). Investigations have also shown that more nuanced, specific measurement of commitment can better predict employee behaviour (e.g., Gellatly, Meyer, & Luchak, 2006; Meyer, Morin, & Wasti, 2018). However, despite all this interest, there are significant gaps in the literature assessing organizational commitment, its development, and its impact on employee outcomes.

In the current investigation, I sought to contribute to the understanding of organizational commitment by applying a person-centred approach to commitment in Canadian Armed Forces personnel. Commitment to the Forces holds great interest for this organization, given the sensitive and often dangerous nature of the job, and the significant investment in providing training and resources for new employees. The questions addressed here not only add to the academic literature on commitment in a military sample, but also have practical implications for the development and consequences of organizational commitment to the Armed Forces. Previous research has shown that, although the military context differs from that of most workplaces, findings in the military organizational commitment literature are consistent with those found in other occupations and circumstances (e.g., Meyer, Kam, Goldenberg, & Bremner, 2013). Thus, not only does this research add to the literature on commitment in the military but also serves to broaden our understanding of commitment in the workplace in general.

Further, the use of a person-centred approach adds a valuable contribution to the literature. The person-centred approach and associated methodologies (such as latent profile analysis) allows researchers to identify and examine underlying sub-groups in a population based on their scores on interconnected variables (e.g., Morin, Meyer, Creusier, & Biétry, 2016; Morin, Morizot, Boudrias, & Madore, 2011). In contrast, variable-centred approaches use methodologies such as confirmatory factor analyses and regression to examine relations between constructs, assuming that all individuals in a sample come from the same underlying population. For the current investigation, I used a person-centred approach to examine profiles of commitment based on individuals' levels of affective, normative, and continuance commitment. Although research in this area is growing (e.g., Meyer et al., 2013; Morin et al., 2016), few longitudinal studies have been conducted using a person centred-approach. For exceptions, see Kam, Morin, Meyer, and Topolnytsky's (2016) longitudinal investigation of commitment, and Xu and Payne's (2018) study of commitment in a military context.

In the current study, my main objective was to investigate commitment in two stages of employment within a military setting. First, I examined commitment in new recruits, and investigated how factors such as training and satisfaction with various organizational targets relate to the development of commitment, and how this commitment was related to turnover intention and well-being. This investigation included data collected at the completion of Basic Training. The goal of the investigation with this sample was twofold: to better understand the development of commitment profiles, including potential covariates associated commitment profiles; and to make practical recommendations about the factors that may foster positive forms of commitment early in a recruit's military career.

The second stage I examined was Canadian Armed Forces members in their first year in their occupation. These data were obtained from many of the same individuals in the Basic Training sample and were collected three- and nine-months after graduation from Basic Training. This longitudinal investigation addressed how commitment changes over time, and the covariates associated with profiles at each time point. Because of the overlap in samples, I also compared the profiles observed among new recruits with those found among employees in the early stages of occupational placement. Again, practical recommendations were made about the kinds of factors that predicted the development of commitment, and the consequences that were associated with commitment profile membership.

Using the Job Demands-Resources model (Demerouti, Bakker, Nachreiner, & Shaufeli et al., 2001) as a guiding framework, I investigated value fit, social support, and training satisfaction as antecedents of commitment, and turnover intentions and well-being as outcomes. The current study not only addressed the question of commitment stability and evolution of commitment over time, but also provided insight into some possible factors of this development. Given the large scale of the study and the longitudinal nature of the data, this research provides a meaningful contribution to the organizational commitment literature.

Chapter II: Organizational Commitment Theory

The Three Component Model of Organizational Commitment

Early investigations of organizational commitment were popularized by Mowday and colleagues, who considered it a unidimensional construct, evaluating employees' identification and involvement with their organization (Mowday, Steers, & Porter, 1979). Their measure of commitment, the Organizational Commitment Questionnaire (OCQ; Mowday, Steers, & Porter, 1979) focused on the motivations underlying organizational commitment. However, other definitions and conceptualizations of commitment existed (e.g., Becker, 1960; Kanter, 1968; Salancik, 1977; Wiener, 1982), making it difficult to compare early commitment research and findings.

Meta-analyses support the distinction of Mowday's attitudinal commitment from other related constructs, such as job satisfaction, and confirm predicted relationships between organizational commitment and outcomes, including turnover intentions and job performance (e.g., Riketta, 2002; Tett & Meyer, 1993). However, over time it became clear that organizational commitment was a more complicated concept than could be captured with a single dimension. Further, a comprehensive framework was needed to unite the many different conceptualizations of commitment into one cohesive literature. Researchers began to turn their attention toward multidimensional conceptualizations of commitment (e.g., Allen & Meyer, 1990; O'Reilly & Chatman, 1986).

Arguably, the most popular multifaceted theory of organizational commitment is the Allen and Meyer (1990; 1996; Meyer & Allen, 1991) Three-Component Model (TCM). This theory posits that employee commitment binds individuals to their organization, making it less likely they will leave. Further, commitment can be reflected in different "mindsets" that employees can experience which will have implications for their behaviours. These mindsets, or components of commitment, can be characterized as a desire (affective commitment; AC), obligation (normative commitment; NC), or need (continuance commitment; CC) to remain with the organization. Although each form of commitment contributes to persistence in a course of action, including staying with an organization, it is important to note that they are conceptually distinct mindsets that have different relations with and implications for discretionary employee behaviours. Although early TCM theorizing and research focused on commitment to the organization, Meyer and Herscovitch (2001) later defined commitment as a binding force that can tie an individual to any entity (e.g., occupation, team) or course of action (goal attainment; organizational change). This expanded definition allowed for research into commitment to other targets, such as an occupation (see Meyer & Espinoza, 2016), union (see Horsman, Gallagher, & Kelloway, 2016) or action (see Meyer & Anderson, 2016).

Variable-Centred Tests of the TCM

The research investigating the TCM can be divided into two categories based on their underlying statistical approaches. The first, more traditional approach is to study each of these three components and their individual relationships with predictors, correlates, and outcomes. This variable-centred approach assumes that the samples used in research are drawn from one homogenous population. That is, it is presumed that parameters and relationships found within one sample should apply to the population as a whole. Of course, this does not exclude the possibility of testing moderators or covariates, but the general assumption is that a single set of parameters can be derived to describe the population.

Outcomes of Commitment

Decades of research and meta-analyses attest to the predictive power of the three components on employee outcomes (e.g., Meyer, et al., 2002). These investigations have shown that, for some variables, such as turnover intentions, each of the three components predict employee behaviour (e.g., Meyer et al., 2002). In other cases, however, the three components have differential relations. This is especially salient in cases of discretionary behaviour, including citizenship behaviours, engagement, and extra-role performance. For example, meta-analysis has shown that AC was positively related to citizenship behaviours, although the relationship was weaker with NC and negative with CC. The research clearly supported the notion that different components have different implications for behaviour, and therefore are worth investigating.

It should be noted that the variable-centred approach to research has led to an abundance of information on AC, which is commonly thought to be the most desirable and beneficial form of commitment. Researchers have historically chosen to include those components of commitment they believed would show the strongest relations with other study variables and excluded the other components. This has resulted in a gap in our knowledge on NC, and to a lesser degree, on CC. For example, in Meyer and colleagues' (2002) meta-analysis on the TCM, there were many variables for which there were not enough studies to assess relations with NC and CC, but sufficient research to assess their relations with AC. However, using a variable-centred approach with all three forms of commitment included still results in incomplete understanding of commitment as a *whole*, as these approaches do not allow for the study of the complex interplay between components.

In Meyer and Allen's (1991) original TCM study, they noted that the interactions between components may provide interesting and meaningful insights into how commitment is expressed. However, in the above research, each component was viewed in isolation (e.g., one's level of AC was not considered when looking at one's NC). Only a few investigators examined potential interaction effects. Meyer, Paunonen, Gellatly, Goffin, and Jackson (1989) found support for an interaction between AC and CC, such that employees in a high AC, low CC group had higher mean performance than those in any other combination. Somers (1995) found an interaction between AC and CC as well, showing that the relations between CC, workplace absences, and intention to remain were weakest in groups who also demonstrated high AC. Finally, Jaros (1997) investigated the relation between NC and CC, finding that either form of commitment attenuated the relation between the other form and turnover intentions. This research was among the first to suggest the importance of investigating not only all three forms of commitment, but also the interaction between these components and other related constructs.

Gellatly, Meyer, and Luchak (2006) provided the first test of a three-way interaction between the components on employee behaviour. In a variable-centred test of commitment, they used a stepwise regression to investigate the relation of the three components on staying intentions and citizenship behaviours. For each, they added all three individual components in Step 1, the two-way interaction terms in Step 2, and a three-way interaction term in Step 3. For staying intentions, the three individual components were found to be significant predictors but adding the two-way terms did not significantly add to prediction. However, when they added the three-way interaction term into the regression, they found a significant effect. For citizenship behaviours, all three steps of the regression were significant, suggesting that both the two-way interaction terms incrementally added to prediction over the individual components, and the three-way interaction term added to prediction above the two-way terms. Their study found those individuals high on all three forms of commitment experienced the highest levels of performance and the lowest levels of turnover intentions.

Antecedents of Commitment

There has also been an abundance of research on antecedents of the individual components of commitment. Practitioners and researchers alike demonstrate interest in how commitment to the organization can be developed and fostered. A host of variables have been suggested to influence commitment, from employee demographic characteristics, to within-person variables, to situational factors external to the employee. Here, I discuss some examples of antecedents of commitment, but note that other variables, such as personality (e.g., Chan, 2006; Choi, Oh, & Colbert, 2015), self-efficacy (e.g., Bauer, Bodner, Erdogan, Truxillo, & Tucker, 2007), and leader-member exchange (e.g., Liden, Wayne, & Sparrowe, 2000) have been examined as predictors of commitment.

First, demographic variables have been considered potential predictors of the TCM. In North America, greater age and tenure predicted higher levels of all three components of commitment (Meyer et al., 2002). Much of the research on commitment, both from the variable- and person-centred approach, has investigated commitment in samples of employees with mixed tenure, age, and other demographic characteristics. The findings of Meyer and colleagues' (2002) meta-analysis also suggested that some of these age and tenure relationships were subject to cross-cultural differences, with significantly weaker relationships in countries outside of North America. Education, particularly having education that is transferable to other jobs, predicted lower CC but was unrelated to AC or NC (Meyer, et al., 2002).

For within-person variables, self-efficacy has been shown to relate to AC but was largely untested in NC or CC. Satisfaction of an individual's self-determination needs for autonomy, competence, and relatedness (e.g., Deci & Ryan, 1985) have been shown to relate to AC (Greguras & Diefendorff, 2009). Positive affect has also been positively related to AC and NC, with a nonsignificant relation to CC (Meyer, Stanley, & Parfyonova, 2012).

Finally, some of the external variables that have been related to organizational commitment include social support and perceptions of fairness. Good leadership, less role ambiguity, and organizational support all have strong positive relations with AC, moderate relations with NC, and negative relations with CC (e.g., Kurtessis, Eisenberger, Ford, Buffardi, Stewart, & Adis, 2017, Meyer et al., 2002).

In general, the demographic, within-person, and situational variables examined with the three components have been in line with the TCM. They also serve to further reinforce the importance of examining all three components of commitment in a given study. However, much of this research conducted has been cross-sectional. This is problematic for several reasons. First, cross-sectional data do not allow researchers to understand how the relations between commitment and other constructs develop or change over time. Although cross-sectional studies may provide us with preliminary evidence of how commitment is related to other constructs, longitudinal data is required to further develop our understanding of commitment, including the effectiveness of interventions aimed at increasing commitment, or the impact of external and situational factors on long-term commitment. Further, cross-sectional studies often fail to consider the impact of employee tenure on commitment. By combining employees of different tenure lengths into one sample and failing to consider the impact tenure may have on commitment, the possible differences between commitment in newcomers, mid-tenure employees, and long-term employees are masked. To truly understand the development and stability of commitment over time, longitudinal study designs that take into consideration the tenure of the sample are required.

There are many advantages to using longitudinal data. First, it is only with longitudinal data that we can investigate the temporal stability of commitment. Study designs with multiple time points especially allow researchers to track how commitment may develop or change as time passes. It can also be used to effectively monitor the relation between person- or organizational-level interventions and employee commitment. Finally, longitudinal data improves our ability to understand the antecedents and outcomes of commitment.

To assess the development of commitment over time, Meyer and Allen (1987) designed a study using recent university graduates. They assessed participants before entry into the workforce, then one, five, and nine months after beginning employment with the organization. They noted rank-ordered, but not mean-level consistency in commitment. That is, mean levels of commitment tend to universally decline over time, however, individuals remain fairly stable in their rank ordered levels of commitment, in that those who were more committed prior to employment displayed higher commitment at later assessment phases. It is possible that newcomers in general begin with higher commitment, only to experience a lowering of overall commitment as they adjust to the realities of their organization. The authors noted that more stable early-work experiences may result in more stable forms of commitment, although this was not directly tested (Meyer & Allen, 1987).

In a similar study the following year, Meyer and Allen (1988) assessed commitment in employees one, six, and eleven months after beginning a new job. There was, again, a general decline in overall commitment over the first year of employment. The results suggested that the experiences employees face when they first join an organization, such as job challenges, level of satisfaction, and cohesion with peers, influenced level of commitment. Although the measure of commitment used in this study predated the measure currently used to assess the TCM, further research has supported this decline in commitment, adding that some personal characteristics, such as affectivity, may also predict changes in commitment in newcomers (Vandenberghe, Panaccio, Bentein, Mignonac, Roussel, & Ayed, 2018). In a longitudinal study, Irving and Meyer (1994) found that positive work experiences, such as finding respect, intellectual stimulation, and accomplishment at work, are related to AC in newcomers. Thus, it may not be that time itself results in a decline in commitment, but rather the employee’s personal characteristics and the kind of experiences faced in the onboarding period.

Interactions Between Commitment Components

As interaction studies of commitment became more prevalent, interest in understanding how the commitment components related to each other and to other constructs began to grow. Meyer and Herscovitch (2001) examined the existing theory and evidence on commitment and outlined a series of propositions on the ways commitment components may combine to create a “profile” of commitment. That is, these propositions suggested that the “context” set by having certain components of commitment (e.g., high AC) can influence the expression of other forms of commitment (e.g., high CC). Commitment profiles reflect combinations of the three commitment components and have implications for employee behaviour. These propositions were suggested with a variable-centred approach in mind, but true tests of commitment profiles are only possible with more sophisticated, latent-based person-centred statistical analyses.

These propositions fueled further research on the interactions between AC, NC, and CC. For example, Gellatly et al. (2006), discussed earlier, was a direct test of these propositions. Although interaction-focused studies began to provide support for Meyer and Herscovitch’s (2001) propositions, the use of the variable-centred approach limited their generalizability and applicability of results. True tests of these propositions require use of the person-centred approach. Still, these early studies pioneered the examination of commitment components together, and paved the way for the person-centred, latent-variable approaches that followed.

Chapter III: Person-Centred Approach

Person-Centred Methods

In discussing variable- vs. person-centred approaches, it is important to remember that each encapsulates multiple methodologies. Variable-centred approaches use correlations, regressions, and structural equation modeling to investigate relationships among variables. They assume, however, that any given sample is drawn from an underlying population and can be used to estimate parameters that hold for the population as a whole. The variable-centred approach can also be used to analyze the interactions among predictor variables, although this method is often not sensitive or powerful enough to capture all possible interactions (Marsh, Hau, Wen, Nagengast, & Morin, 2013). Further, regression-based approaches do not allow individuals to be assigned to groups based on their levels of each commitment component.

Person-centred methodologies assume that there may be underlying subgroups within a population and seek to estimate the probability that any given individual falls into these subgroups. Person-centred approaches include methodologies like cluster analysis, latent class or profile analysis, and latent transition analysis to detect existing subgroups within a population. They also use statistical indices to assess model fit and allow for the integration of posterior probabilities of profile membership into more complicated models of the antecedents and outcomes of profile membership.

Review of Person-Centred Studies of Organizational Commitment

Initial applications of person-centred approaches to organizational commitment attempted to use a median spilt approach to classify individuals into a priori categories of commitment, based on arbitrary splits of "high" and "low" levels of each commitment component. Then, the relations between commitment and other study variables could be investigated on the basis of group membership.

Gellatly et al (2006) used the median-split approach and found evidence for different relations with outcomes based on profile membership. For example, in AC/NC-dominant profiles, employees may feel both willing and obligated to remain with their organization as it is the right thing to do. In NC/CC-dominant profiles, this sense of obligation is mixed with the perception of being required to remain with an organization. Not surprisingly, the AC/NC-dominant profile showed more favourable relationships with outcomes than the NC/CC-dominant profile, however, the AC/NC-dominant profile also showed more favourable outcomes than a profile dominant in AC alone (Gellatly et al., 2006). These results brought to light the fact that the relations of some commitment components to other variables, like NC, may depend on its pairing with the other two components. This supported theory suggesting that commitment components can interact in meaningful and interesting ways.

There are, however, issues with the median-split approach. First, individuals must be manually classed as either high or low on each component. In the Gellatly et al. (2006) study, these were determined by a cut-off of one standard deviation above or below the mean, respectively. Although other cut-off values could be considered, studies using median-split methodologies always create "profile" groups with arbitrary cut-off values. Rather than extracting the number of profiles that best fits the data, all pairs of commitment components are examined. There is no way to determine the likelihood that any one individual is categorized by these groups, nor how many groups should be considered meaningfully distinct.

In contrast, many researchers have also used a cluster analysis approach to try to understand commitment “profiles”. In cluster analysis, the goal is to identify a possible set of commitment profiles based on commonly seen combinations of the three components. Once a set of profiles is identified, researchers can then examine how individuals in separate profile groups differ on antecedent and outcome variables. Both Wasti (2005) and Somers (2010) found between six and eight profile groups using k-means cluster analysis and found support for the differential relationships between profiles and outcomes such as turnover intentions.

Cluster analysis avoids some of the problems of the median split approach. First, rather than the researcher determining cut off values for creating groups then artificially separating individuals into these groups, cluster analysis creates the groups by minimizing within-cluster variances. Although this research provided some insight into the existence of profiles and their possible consistency and stability, cluster analysis has its own set of inherent issues that restrict our ability to interpret profiles and build their nomological network (e.g., Magidson & Vermunt, 2002). First, it involves statistical assumptions (e.g., equality of variances across clusters) that may not be realistic with real world data. There are also no clear guidelines available to aid in determining the optimal cluster solution. In addition, in cluster analysis, relations with antecedents and outcomes cannot be tested within the same model in which the clusters are formed. That is not to say that we cannot study the relations between commitment clusters and other variables –

it only means we need to manually classify individuals into clusters to test hypothesized relations. As with selecting the number of clusters to extract, classifying individuals into their cluster is arbitrary and there have not been any clear, standardized guidelines established.

Thus, recent focus has been on more sophisticated techniques that allow researchers to model relations between commitment components and their antecedents and outcomes, although relaxing some of the assumptions of cluster analysis. Guidelines for extracting and interpreting profiles have been established (Nylund, Asparouhov, & Muthén, 2007), reducing the ambiguity and researcher-error that can be introduced into cluster analyses. With latent profile analysis (LPA) and latent transition analysis (LTA), we can gain a greater understanding of the predictors and outcomes of commitment, although including various control variables in the model and accounting for important contextual considerations, such as the effect of time. The goal of latent profile analysis is to identify existing groups of individuals within a population, and to understand the meaningful distinctions between these groups. With LTA, we can further assess how membership in these subgroups may change over time. With these methods, I was able not only to identify commitment profiles, but also to assess their stability over time.

Review of Latent-Approach Studies

There is a growing body of research on commitment profiles that use a latent variable approach (e.g., Bremner, McLarnon, Meyer, & Goldenberg, 2015; Meyer et al., 2013; Meyer, Morin, & Vandenberghe, 2015; Meyer et al., 2012; Morin et al., 2016; Stanley, Vandenberghe, Vandenberg, & Bentein, 2013; Xu & Payne, 2018). Typically, research finds support for five to seven profiles that are relatively consistent across samples (Meyer & Morin, 2016). The five most common profiles to emerge are a fully committed profile (high AC, NC, and CC); an affective-dominant profile (high AC, low NC and CC); an affective and normative dominant-profile (high AC and NC, low CC); a continuance-dominant profile (high CC, low AC and NC); and an uncommitted profile (low AC, NC, and CC). Additionally, many studies find support for a normative and continuance-dominant profile (high NC and CC, low AC) and the affective and continuance-dominant profile (high AC and CC, low NC).

As hypothesized, research has further identified meaningful differences across profiles. For example, AC-dominant profiles tend to be associated with better outcomes than CC-dominant or uncommitted profiles. The findings that employees with AC-dominant profiles have better outcomes than those who are uncommitted were not surprising. The more interesting findings were around the relationship between NC and CC with other variables, as these two components are traditionally considered less desirable than AC. For example, CC relates differentially to outcomes depending on whether it is paired with low AC and NC (CC-dominant profile) or paired with high AC and NC (fully committed profile; Meyer et al., 2013; Meyer et al., 2012).

These research findings are counter to the propositions originally outlined by Meyer and Herscovitch (2001), who predicted the best results from the AC-dominant group. Although the results were not always in line with the original predictions, this research has provided insight into the nature of less well-understood components of commitment. It has also highlighted the need for person-centred research to better understand employee commitment to the organization. However, it should be noted that the person-centred commitment literature suffers from one of the same issues with the variable-centred literature: the frequent use of cross-sectional studies. It is only with longitudinal data that we can investigate the temporal stability of commitment. Study designs with multiple time points allow researchers to track how commitment may develop or change as time passes. Longitudinal data can also be used to effectively monitor the impact of person- or organizational-level interventions on employee commitment. Finally, longitudinal data improves our ability to understand the antecedents and outcomes of commitment.

Despite the benefits of longitudinal research, several issues exist within such studies. First, there are issues with data collection inherent in any longitudinal study. It can be difficult to collect and retain participants, especially in workplace samples. Although it is suggested that researchers try to collect a larger sample than needed at Time 1, acknowledging that the average attrition rate for longitudinal samples is around 44% (Roberts, Walton, & Viechtbauer, 2006), it may not always be practical to do so. As a result, many researchers need to use supplemental analyses and corrections to address missing data. Given the variety of options to address missing data, this can make it difficult to directly compare the results of longitudinal studies. Further, there are several decisions involved in designing a longitudinal study that can impact results, including the number of time points to include and the amount of time to allow between data collection periods. It is important to balance both theoretical reasoning and practical implications when choosing the timing of a longitudinal study. Although researchers often state the number of collection periods and time lag between these surveys in their methods, using different timing can make it difficult to compare longitudinal studies.

Profile Consistency

One of the basic criteria for assessing profile validity is profile consistency. Profile consistency, or the degree to which profiles replicate, is used to demonstrate that profiles are not spurious, but rather meaningful classifications of individuals. Consistency can take three forms: cross-sample, within-sample, and within-person consistency (Kam et al., 2016).

Cross-sample consistency is supported when roughly the same profiles are extracted in different samples or studies. As noted above, there are many profile studies that have added to the evidence supporting profile consistency (e.g., Bremner, et al., 2015; Kam et al., 2016; Meyer et al., 2013; Meyer, et al., 2015; Meyer et al., 2018; Morin et al., 2016; Stanley, et al., 2013; Xu & Payne, 2018). However, the evidence for profile consistency across samples extends beyond simply finding a core set of profiles across samples. Profiles with similar patterns of relations to outcomes have been found in widely varying samples. These profiles have been found in studies with healthcare employees (Meyer et al., 2012), energy and service sector employees (Kam et al., 2016) and Canadian Armed Forces personnel (CAF; Meyer et al., 2013). Samples that include a mix of occupations also find a similar profile structure (e.g., Stanley et al., 2013). Further, there has been some preliminary support for the consistency of profile groups across cultures, with studies using samples from Hong Kong (Morin, Meyer, McInerary, Marsh, & Ganotice, 2015) and Turkey (Meyer et al., 2018). More research is needed into the consistency of commitment profiles across samples and cultures before generalizations can be made.

It should be noted that profile consistency can be difficult to determine due to the naming conventions researchers use to classify and interpret their profiles. Profile labels have not been standardized across studies, which has resulted in issues interpreting and comparing results. What may be labelled as an AC/NC-dominant profile in one study could easily be labelled an AC-dominant profile by another researcher.

Kabins, Xu, Bergman, Berry, and Willson (2016) found the typical six-profile solution and classified them into three categories: value-based profiles, exchange-based profiles, and weakly committed profiles. Value-based profiles are those which are based on shared ideology, values, and deep-level characteristics of the employee and the organization (e.g., AC/NC-Dominant). Exchange-based profiles are those that are based on transactional exchanges of goods and services for labour between the employer and employee (e.g., CC-Dominant). Although value-based profiles are based on a bond of shared beliefs, exchange-based profiles are a means to an end of accumulating some resource. Weak commitment profiles, however, are those where no strong bond with the organization exists (e.g., Uncommitted). Employees report low levels of any form of commitment to the organization and often experience negative outcomes, such as turnover and reduced OCB (e.g., Meyer et al., 2012).

These classifications are useful for organizing our thinking around profiles and can help guide prediction when testing new relations between commitment profile membership and other variables. However, it is important to note that using broad classifications is somewhat simplistic and can mask the important differences between profile groups in the same category (e.g., between AC-dominant and AC/NC-dominant profiles). In fact, distinguishing between specific profiles is often made more complicated due to the variability in naming conventions for classes. This is further compounded by the fact that some investigators create and interpret their profiles from raw scores, although others use standard scores. Although studies thus far tend to find a core group of profiles, it is important to gather further validity evidence of profiles using within-sample and within-individual consistency.

Within-sample stability is the consistency of profile structure across two or more sub-groups. Although within-sample consistency can be assessed in a few ways, in the current research, it was used to evaluate the similarity of profile structures across time. Within-person stability is the consistency of profile membership in any given individual over time. If there is within-person stability, this necessarily means within-sample stability; however, within-sample stability could mask the possibility of balanced within-person changes (Kam et al., 2016). Morin and colleagues (2016) suggest a process for examining the within-sample consistency of profiles. Their procedure outlines the steps required to test the similarity of profiles over groups. It is an iterative process that requires the systematic comparison of model fit indices for progressively constrained models. Note, partial similarity can be examined and retained if any of these levels of full similarity are not met.

The first step is to test for configural similarity to determine if the same number of profiles is extracted across the groups being compared. This is established by running the same model independently in the two groups and evaluating if the same number of profiles are extracted. Next, tests of structural similarity assess how consistent the nature of the profiles is across group membership, by constraining the profile means to equality across groups. The model fit of the structural model is compared to the configural model, and if the fit is not decreased, the structural similarity model is retained. Third, dispersion tests of similarity examine the consistency of variability in the indicators across groups. Again, a constrained model is compared to the level of similarity that preceded (in this case, structural) and similar models are retained. Finally, tests of distributional similarity determine whether the relative size of the profiles are consistent across groups. That is, if the proportions of individuals in each profile are stable. Again, a constrained model is contrasted to the dispersion test of similarity above, and similar models are retained, while variant models are rejected. The profile similarity procedures can also be used to determine if two or more groups are similar in their relations with other covariates, but this procedure is outside of the scope of this dissertation. See Morin et al. (2016) for a full explanation of profile similarity and the steps to test for it.

To investigate the similarity of profiles over time, both within-sample and within-person consistency can only be established using longitudinal data. Longitudinal approaches to studying commitment profiles can assess how commitment might change over time in both normal and extenuating circumstances, and which conditions drive these changes. Kam et al. (2016) conducted a thorough test of within-sample and within-person stability. This study investigated both within-sample and within-person consistency using latent transition analyses in employees in the energy sector during a time of organizational change and found strong support for within-sample stability. Moreover, less than 3% of employees changed profile membership over the eight month time lag, suggesting there is little within-person change in commitment over time. Kam's (2016) results found evidence of within-person and within-sample stability.

In a similar vein, although they did not include a longitudinal sample, Meyer and colleagues (2018) were able to compare existing data on Turkish employee commitment to data collected before and after a major economic crisis that hit the country in 2001, part-way through scheduled data collection. This naturalistic quasi-experiment allowed the researchers to assess how the number of profiles extracted, the shape of these profiles, and the proportion of members within each profile compared in samples before and after the crisis. Not only did they find support for the stability of profiles over time and over intense, unexpected change, they also found stability for the predictions and meaningfulness of profiles. That is, the relationships between the antecedents and outcomes of value-based, exchange-based, and weakly committed profiles were similar before and after the crisis. There was some evidence, however, for changes in the distributions of individuals – some profile groups included a greater proportion of individuals relative to the previous sample, suggesting that some within-person change may be expected in response to changing circumstances. For example, this study found a greater proportion of individuals in the CC-dominant profile, and a smaller proportion in the AC-dominant profile, when comparing commitment pre- and post-economic crisis (Meyer et al., 2018).

The most recent examination of commitment profile stability over time was Xu and Payne's (2018) investigation of retention in U.S. military personnel. This study followed Army officers over four years, and tested not only commitment profile stability, but also if profile membership, and changes in profile membership over time, could be used to predict employee retention. To test if the same profiles emerge within an organization (e.g., within sample stability), they used five samples, and found that they extracted the same profiles in all five cases. They then used latent profile analysis within each time point to assess if the same profiles would emerge longitudinally. They generally found support for this hypothesis as well. Once they had tested and found support for within-sample and within-person profile stability, Xu and Payne used latent transition analysis to assess whether profile membership could be used to predict outcomes. They found that individuals with value-based profiles had the lowest rate of turnover over time, and that those with exchange-based profiles had less turnover than those with weak profiles. They also found that changes in profile membership over time (e.g., from an exchange-based profile to a value-based profile), while rare, predicted turnover, in that those who moved to a more value-based membership were less likely to leave than those who remained within an exchange-based or weak profile group.

Not only did this study show profile stability within a military sample, it also demonstrated how commitment profiles over time can be used to predict future employee outcomes. There were, however, some limitations to this study. First, they used archival data, and the authors only had access to employee scores on AC and CC. True tests of TCM profiles could not be conducted with the exclusion of NC. Second, they did not include any antecedents of commitment, and thus, could not account for what might drive the change in some employees’ commitment profiles. This was a preliminary test of commitment profiles, and I sought to expand their work by identifying profiles using the full range of commitment components, and a greater range of antecedents and outcomes.

Overall, commitment profile research has begun to accumulate, and results so far suggest there may be a subset of profiles that can be found across studies and samples. Further, early work suggests that profiles may be stable over time, indicating that employee commitment is an enduring variable. There are still, however, many questions that remain. We have little understanding of commitment profiles among new employees, including whether the stability found in previous studies can be expected in newcomers. There is also little research investigating the antecedents of commitment profiles in either newcomers or most long-tenured employees. This study seeks to address both these gaps in the literature by using a longitudinal sample of newcomers in their first year of employment.

Chapter IV: Outcomes of Commitment Profile Membership

While many variables have been studied in connection with commitment and commitment profiles, I sought to examine a model of commitment guided by theoretical rationale. I suggest the Job Demands-Resource model as a guiding framework to consider the potential antecedents and outcomes of commitment profile membership and highlight some variables to be investigated in this study below.

The Job Demands-Resources Model

Theoretically, the predictors and outcomes of organizational commitment are hypothesized in the Job Demands-Resources (JD-R) model (Demerouti et al., 2001). Originally conceptualized as a model of burnout, the JD-R model hypothesized that different aspects of employee attitudes and behaviours can be explained by two processes – the stress processes that involve job demands, and the motivation processes that include job resources. Job demands are those factors that require an employee to exert significant effort and resources. These demands take a toll on the employee, and, over time, can lead to increased exhaustion and reduced well-being. Traditional examples of job demands include physical stressors, time pressures, and shift work. The original JD-R model proposed that job demands lead to burnout and exhaustion, and further suggested that greater demands would result in increased turnover intentions and reduced well-being.

Job resources, on the other hand, are those components of an individual's job or personal life that lend them the ability to avoid the negative consequences of demands and be more effective and productive in and outside of work. Typical resources include receiving feedback, rewards, job security, and supervisor support. This model states, however, that job resources go beyond only protecting employees from negative events – they are valued motivational tools that allow employees to focus their attention and energy on growth, development, and goal attainment (Bakker & Demerouti, 2007). Early JD-R theory suggested that higher amounts of resources lead to employee engagement, which results in increased commitment to the organization.

As noted, job demands were intended to predict turnover and turnover intentions, although resources were theorized to predict engagement and commitment. On a broader scale, job resources have been thought to predict well-being. I will investigate how commitment profile membership relates to both turnover intentions and well-being in a population of newcomers to the military, thus adding to both the commitment and JD-R literatures.

Turnover Intentions. Turnover intentions are one of the most common outcomes included in commitment research. Countless studies have shown that commitment predicts turnover intentions (e.g., Meyer et al., 2002; Tett & Meyer, 1993), and that this pattern of prediction differs for each component. Some research has also found that the ways commitment predicts turnover intentions are influenced by the time frame involved. In a longitudinal investigation, Culpepper (2011) found that, although AC is negatively related to turnover intentions, this is particularly the case during the few first few months of employment. CC, on the other hand, is more predictive of turnover intentions four to 12 months into employment. The effects of NC on turnover intentions was smaller and more consistent over time. This research suggests that the way commitment predicts turnover intentions may depend on the time with the employer, and a longitudinal design, such as the one in this study, is required for a better understanding of this relationship.

Turnover intentions have also often been included in investigations of commitment profiles. As noted earlier, commonly found commitment profiles have differential relations with outcomes. In their early study, Gellatly et al. (2006) found that those in an uncommitted group reported the highest levels of turnover intentions, although those with both high AC and NC had the lowest levels of turnover intentions. Further, almost all commitment profile studies have examined turnover intentions and found a similar pattern of results. In general, turnover intentions are highest in profiles marked by a lack of commitment. Value-based profiles, such as AC-dominant or AC/NC-dominant, typically display the lowest level of turnover intentions. Numerous studies have supported these findings (e.g., Kam et al., 2016; Meyer et al., 2013; Stanley et al., 2013).

Further, Stanley et al. (2013) measured actual turnover and found a similar pattern of results to investigations using turnover intentions. The highest rates of turnover one year after commitment was measured were seen in uncommitted employees, and the lowest rates of turnover were seen in employees with either the fully committed, the AC/NC-dominant, or the CC-dominant profile.

Stress and Well-Being. Well-being has been defined and examined in many ways. Some studies look at physical health and symptoms (e.g., Merrill et al., 2013), others include mental strain (e.g., Demerouti et al., 2001), and still others look beyond the existence or absence of illness to signs of growth or thriving in individuals (e.g., Ryff, 1989). There is little consistency or agreement on how this variable should be studied, so generalized conclusions about how well-being relates to commitment can be difficult to draw. Much of the work within the JD-R model, however, defines well-being as low on burnout and high on engagement (e.g., Demerouti et al., 2001). Tests of this model have supported the notion that job resources predict increased well-being over time (e.g., Hakanen, Bakker, & Shaufeli, 2006; Hakanen, Schaufeli, & Ahola, 2008).

Well-being has also been related to organizational commitment in previous research. Some studies have found that organizational commitment could help buffer against exhaustion in employees with high job demands (e.g., Öztürk, Karagonlar, & Emirza, 2017), although others have found mixed results of the relation that commitment has with physical and mental health (Donald & Siu, 2001). Schalk (2011) found that organizational commitment is related to several health complaints made by employees, although this did not translate to a difference in later number of employee absences. Thus far, the research on the association between any individual component of commitment and well-being is limited.

Although previous work has focused on the ability of commitment to act as a buffer against stress and strain, Meyer and Maltin (2010) proposed a model where commitment also leads to well-being in a more positive manner, encouraging personal growth and development. Guided by Self-Determination Theory (e.g., Deci & Ryan, 1985), Meyer and Maltin (2010) argued that employees who have their basic needs at work fulfilled are more likely to commit to the organization, and those who do commit experience greater well-being. Further theoretical work by Chris, Maltin, and Meyer (2016) added predictors to this model, suggesting workplace stressors and need-supportive conditions would predict employee commitment and basic need satisfaction.

Some of these hypotheses have been supported by research showing positive relations between need satisfaction and AC and NC, and a negative relation between need satisfaction and CC (e.g., Maltin et al., 2015; Meyer et al., 2012). Although no causal direction has been examined, this research does suggest that organizational commitment components and need satisfaction are connected. The implication for these findings is that commitment may be associated with more than just stress buffering and may be a direct contributor to employee well-being. Although this aspect of the model has remained largely untested, it suggests that an individual’s form of commitment may influence not only the level, but the type of well-being experienced by employees.

Several studies have examined the relations between commitment profiles and well-being. First, Meyer et al. (2012) investigated commitment profiles in professionals across multiple organizations. They assessed well-being with both positive affect and number of general health complaints. They showed that employees with value-based profiles (either fully committed or AC/NC-dominant) demonstrated the highest levels of positivity and reported fewer health complaints than those who were uncommitted or displayed an exchange-based profile. Morin and colleagues (2016) found similar results with reported exhaustion. In Meyer et al.’s (2012) investigation, individuals with value-based profiles such as AC-dominant and AC/NC-dominant profiles reported the lowest levels of job stress, although those who were uncommitted or had CC-dominant profiles reported the highest.

Morin et al. (2015) also investigated commitment profiles and well-being, but defined well-being in a way that was more reflective of eudaimonia, studied in positive psychology. Their definition of well-being was based on psychological growth and development, rather than physical health, and assessed employee thriving, competency, and feelings of recognition at work. They too found that employees with value-based profiles demonstrated greater well-being than those with exchange-based or weakly committed profiles.

The current investigation was guided by this previous research, and will investigate well-being, as defined by mental health; engagement and morale; and negative feelings associated with being away from home and loved ones. These well-being variables are pertinent to the military sample investigated in this study, and, as with previous studies of well-being, may not be applicable in all jobs or contexts.

Chapter V: Predictors of Commitment Profile Membership

In the current research, I sought to not only understand what outcomes are associated with the different profiles, but what variables predicted commitment profile membership. The predictors chosen were in line with the original JD-R theory. There has been little research into the antecedents of commitment and commitment profile membership. One exception is Kam’s (2016) longitudinal investigation of commitment profiles, where trust in management was supported as a predictor of profile membership in a time of organizational change. As we have seen, commitment change over time has been particularly understudied.

Antecedents

In the current research, I included three antecedents of commitment that have been considered job resources. I investigated how social support, value fit, and training satisfaction predicted organizational commitment both during basic training and the onboarding process, and during employment after basic training has been completed.

Perceived Value Fit. Person-organization fit has been cited in the JD-R model as a personal resource (e.g., Yoo, Arnold, & Frankwick, 2014). This variable, assessing the compatibility between people and organizations, has been studied in a variety of ways, from actual fit - comparing the attitudes of the employee and the attitudes of the target, like a supervisor, and determining the discrepancy between the two - to perceived fit - measuring an individual’s perception of the degree of fit between their own values or characteristics and those of their employer. It has also been defined in a variety of ways, including value fit or congruence, skill or competency matching, similarities in goals, congruence between personality variables of members within the organization, etc. (e.g., Kristof, 1996). In each case, however, the theory states that fit between an individual and an organization can increase one's attraction to and identification with an organization, improving trust in the organization and providing employees with resources that enable them to be satisfied and successful in their job (e.g., Edwards & Cable, 2009; Kalliath, Bluedorn, & Strube, 1999; Yang, Yan, Fan, & Luo, 2017). In a direct test of the JD-R model, Yoo et al. (2014) found that value fit positively predicts employee achievement motivation and striving, and negatively predicts emotional exhaustion. Further research has gone on to suggest that misfit between an individual and their organization is a job demand that reduces one's motivation to work and thrive in their job (Petrus, 2017).

There are many studies that have connected fit to organizational commitment in the past. Meta-analyses have shown that both general perceived fit and specific beliefs around value congruence are significant predictors of organizational commitment (Kristof-Brown, Zimmerman, & Johnson, 2005; Verquer, Beehr, & Wagner, 2003). These meta-analyses also suggest that measures of perceived fit, rather than actual fit, are better at predicting employee attitudes. Researchers have suggested that the direct assessment of employee perceptions more closely mirror the cognitive mechanisms that are involved in attitudes and beliefs (e.g., Cable & De Rue, 2002), and perceived fit may be more important for their outcomes than more "objective" assessments. Further research following this meta-analysis has supported the notion that fit is related to outcomes such as turnover intentions (e.g., Boamah & Laschinger, 2017), engagement (e.g., Yang et al., 2017), and organizational commitment (e.g., Greguras & Diefendorff, 2009).

Although some research has only focused on AC, finding positive relationships between AC and value congruence (e.g., Ryu, 2015), and AC and person-organization fit (e.g., Meyer, Hecht, Gill, & Toplonytsky, 2010), others have expanded to include all three components. Amos and Weathington (2008) found that value congruence was positively related to AC and NC, and unrelated to CC, but that the types of values included in the study may influence these relationships. For example, while values around the importance of people are strongly positively correlated with AC and NC, they are unrelated to CC. Some values (e.g., profit orientation) were unrelated to any forms of commitment, and others (e.g., innovation values) demonstrated only weak relationships (Amos & Weathington, 2008). Although an abundance of research exists tying commitment to fit, there was no existing work assessing how fit might influence the formation of commitment profiles or changes in profile membership over time.

Person-organization fit has also been studied specifically within a military context. Given the military's focus on strong ethics and shared values of integrity, loyalty, and excellence (Department of National Defence, 2014), it follows that most of this research focuses on the congruence between individual and employer values. Although much of this work has not been explicitly examined in the context of the JD-R framework, studies have shown that value congruence is associated with both a reduction in turnover and an increase in states like AC (e.g., Ingerick, Diaz, & Putka, 2009). Further research, using a sample of new cadets to the military, has supported the notion that person-organization fit is a resource that leads to positive outcomes for both employees and the organization. Holtom, Smith, Lindsay, and Burton (2014) used a measure of person-organization fit that combined value and goal congruence and found that this measure negatively predicted turnover intentions in newcomers to the U.S. Air Force. They also assessed its relationship with each component of commitment and found that congruence was positively related to AC and NC, and negatively related to CC. Further, regression analyses indicated that congruence added incremental validity to the prediction of turnover intentions over traditional attitudinal variables, such as commitment, job satisfaction, and job embeddedness.

Overall, the research suggests that person-organization fit and value congruence are valuable employee resources that can increase positive attitudes, states, and outcomes, and reduce undesired outcomes, such as turnover intentions. In the current study, I continued the tradition of focusing on value congruence with a military sample and added to the existing literature to assess how perceived value congruence is related to the development of organizational commitment profiles over time.

Social Support. Social support - both internal to the organization (e.g., supervisor, coworkers) and external to work (e.g., family, friends) - has been linked to organizational commitment in the past (e.g., Humphrey, Nahrgang, & Morgeson, 2007; Rodwell & Munro, 2013). The JD-R model treats social support as a resource that employees can draw on to help them improve their outcomes at work and buffer against burnout and disengagement. In an early test of the JD-R model, Bakker et al. (2003a) found that social support was one of the job resources that predicted organizational commitment, which in turn, predicted turnover intentions. Further research in different occupations supported these preliminary findings (e.g., Bakker, Demerouti, De Boer, & Shaufeli, 2003b; Salanova, Agut, & Peiró, 2005).

Social support is an important opportunity for employees to get assistance from others, providing them with positive social interactions. Further, research has suggested that social support aids in the development of commitment via reciprocal social processes (e.g., Eisenberger, Huntington, Hutchinson, & Sowa, 1986). According to social exchange theory, if employees perceive their organization (or supervisors and coworkers) is investing significant time and effort into their development, they will naturally feel inclined to meet these contributions with their own time and effort (Blau, 1964). This sense of support is perceived as commitment on the part of the organization toward the employee and encourages a reciprocal sense of that employee's commitment to the workplace (e.g., Rhoades & Eisenberger, 2002).

Simosi (2012) suggested that this process may be especially salient in newcomers, as socialization processes form the nature and quality of their workplace relationships and attitudes. Although the social exchange model mostly focuses on the importance of organizational, supervisor, and coworker support, research has demonstrated relations between organizational commitment and both internal (e.g., Humphrey, et al., 2007) and external social support (e.g., Rodwell & Munro, 2013).

Research on social support has demonstrated differential relations with the components of commitment, depending on the source of support. For example, meta-analytic research showed that perceived organizational support was positively correlated with both AC ($r = .60$) and NC ($r = .46$), although CC was not included in this study (Kurtessis, et al., 2017). Further meta-analytical work from Meyer et al. (2002) found that organizational support was a strong positive predictor of AC and NC, and a negative predictor of CC.

Further, Simosi (2012) included both AC and NC to the organization in her investigation of different forms of social support, and found that, although perceived organizational, supervisor, and coworker support all predicted AC, only perceived organizational and supervisor support predicted NC. She theorized that, although any form of internal social support might foster feelings of positivity, belonging, and shared values with the organization in employees, only support seeming to come from the employer, whether that be from the organization or supervisor, influenced feelings of indebtedness and obligation to care about the organization's well-being. Although this research does not investigate the effect of social support on CC, it suggests that the form of social support may influence the form of employee commitment.

Previous research has supported the idea that the type of social support is an important determinant in its relationship with commitment. For example, Kurtessis and colleague's (2017) suggested that supervisors, as higher-status agents of the organization, are seen as greater organizational supports than are coworkers or teammates, influencing the way employees perceive and interpret support from these sources. The current study is the first to investigate how different sources of support predict nuanced profiles of commitment.

Training Satisfaction. Finally, I examined satisfaction with training as a third antecedent of commitment. Although training is common in many organizations and industries, the examination of the effect of training has been varied. In general, Human Resource (HR) scientists and researchers have examined the effects of training in terms of transfer and application of the knowledge and skills learned in training to the workplace (Giangreco, Carugati, Sebastiano, & Bella, 2010). Studies in this stream look at improvements in job performance, changes in employee behaviour, and the temporal stability of these changes. Practitioners, however, are often interested in employee reactions to training (e.g., Schmidt, 2007). The perceptions, beliefs, and attitudes toward training can have a large impact on employee behaviour (e.g., Booth-Kewley, Dell'Acqua, & Thomsen, 2017) and may be unnoticed in studies only looking at adoption of new skills from training. Given this study's focus on developing a model of newcomer commitment that can be used in practice in the military and a wider context, I examined the effect of training satisfaction on the formation of commitment over time.

Little to no research has examined training satisfaction in the context of the JD-R model, however, it fits with the other commonly studied job resources. Training is both a tool that employees can use to be successful in their jobs, as well as a sign that their employer is willing to invest in the improvement and well-being of their employees. Previous research has tied training satisfaction to Social Exchange Theory, suggesting that employer investment in employee development may encourage these employees to form positive associations with their organization and their work (e.g., Trinchero, Brunetto, & Borgonovi, 2013). The little work that has examined training in a JD-R manner has suggested that training is a way to reduce the strain that is often associated with job demands, and that HR practices like this can positively predict employee commitment (Teo & Waters, 2002).

Further research has also connected training satisfaction to positive employee outcomes. Trinchero et al. (2013) found that training was related to employee engagement. Matheiu (1988) and Rylander (2003) both found preliminary support for the positive relationship between training satisfaction and organizational commitment. In a military context, Booth-Kewley and colleagues (2017) found that training satisfaction and social support are among the best predictors of organizational commitment in Navy personnel. Although some research has suggested that there may be different components of training satisfaction (e.g., efficacy of training, perceived usefulness of training; Giangreco et al., 2010), the research thus far suggests that employees who are satisfied with their training in general may be more likely to develop commitment to their organization.

In the research examining commitment antecedents, there are differences in the way commitment has been studied. Some include measures of unidimensional commitment, using the OCQ, although others look at each component of the TCM individually. In all cases, however, the research takes a variable-centred approach to their investigations. The person-centred profile approach to organizational commitment is relatively new, and investigations of the antecedents of commitment, especially in specific populations, such as newcomers, are rare. In the current investigation, I examined how satisfaction with Basic Training influenced profile membership in newcomers. As with the antecedents above, training satisfaction has been infrequently studied as a predictor of commitment in newcomers. Given the importance of Basic Training to the experience of new military recruits, this variable in particular has practical implications for military HR personnel. This was the first investigation of social support, value congruence, and training satisfaction together as predictors of organizational commitment.

Chapter VI: Commitment in Context

As noted in earlier chapters, the research on commitment, both from the variable-centred and person-centred approaches, demonstrates a high degree of generalizability across industry samples. Specifically, the profiles extracted across military and civilian samples tend to be stable. This suggests that findings from military samples may have implications for the civilian workforce and vice versa. Given this generalizability, researchers have often focused their attention on testing the nomological network with substantive questions, rather than examining the influence of context on the development, prediction, and consequences of commitment.

However, although the differences between mixed-tenure civilian samples and mixed-tenure military samples may be fairly consistent, what has been given less attention is direct comparisons between different contexts within military populations. In the current research, I examined commitment in two stages of military employment. While the same longitudinal military sample were used to examine these contexts, the data were divided into two time-based samples.

First, I examined commitment to the organization during one of the distinctive components of military employment, Basic Training. This intensive program serves both developmental and onboarding purposes and seeks to immerse newcomers to the military culture. At the same time, Basic Training is used to teach skills and techniques needed for success in the military, while also providing valuable information about the formal and informal rules and norms of the organization (Canadian Armed Forces, 2020). In the current research, I investigated how commitment is formed in this context, and how satisfaction with the training provided influenced the formation of commitment profiles. Finally, I examined the relation between early commitment and turnover intentions and well-being at the end of Basic Training.

Next, I investigated commitment in the first few months of employment post-occupational placement. These data were used to investigate whether the decline in commitment seen in past studies also occurred within a military context. It sought to expand the literature on newcomer commitment by investigating the profiles that emerged early in employment and examined how stable they are over the first year with the organization. Further, the predictors and outcomes discussed in previous chapters were included to better understand the development and consequences of commitment profile membership.

This multi-context approach has two main advantages. First, it furthers our understanding on commitment within specific contexts. It adds to the sparse literature on newcomer commitment and provides more longitudinal data on the development of commitment over time. It also adds to the literature on commitment profiles within a military context, in terms of the number and nature of profiles extracted and the stability of profile classification and membership over time.

Second, there are practical implications to studying the two contexts separately. By independently examining Basic Training and military employment, I can differentiate between those factors that influence commitment, turnover intentions, and well-being in Basic Training, and those factors that influence these constructs in employment. I can test if different antecedents, or different weight given to a similar set of antecedents, impact commitment in the two contexts, suggesting different interventions may be used to increase commitment in either situation. The same can be said for attempting to foster or avoid specific outcomes. Finally, in using a connected sample to investigate these two contexts, I can investigate the potential long-term effects of Basic Training satisfaction and outcomes on commitment and its covariates in the first year of employment.

Chapter VII: The Present Research

The current research sought to add to the literature in several ways. First, I examined the profile structure in a military sample using a person-centred approach. Although the person-centred approach to studying commitment has grown in popularity in the last two decades, there is still a dearth of person-centred research in a military context. Second, I studied commitment within two related but distinct contexts: during Basic Training, and during the first few months of employment following the completion of training. In the first context, I examined commitment with cross-sectional data collected at the end of Basic Training. I also examined covariates of early commitment in this context. In the second context, I used a longitudinal design to investigate commitment profile stability over time during the first six months of Occupational Training. With this sample, I tested both within-person and within-sample stability. This extends the work of Kam et al. (2016) to a military population and expand on Xu and Payne's (2018) research by including all three components of commitment. Finally, I tested a model of organizational commitment profile membership during early employment that includes both antecedents and outcomes in line with the JD-R model. This research builds upon Kam and colleagues' (2016) and Xu and Payne's (2018) work and is the first study to include both antecedents and outcomes in a large, longitudinal sample over multiple time periods.

Profile Development

The development of commitment profiles in Basic Training was the first focus of my research. Previous research would suggest that I might expect to find that AC is more predictive of turnover intentions in this context than is typically seen in mixed-tenure samples (Culpepper, 2001). Given that the sense of obligation felt with NC and the sense of sacrifice that comes with CC take longer to develop, I predicted that they will not be fully formed enough at this time point to be reliable predictors of turnover. However, the study of the formation of commitment and profiles in newcomers is still in its early stages, and more theoretical and empirical work is required before making concrete hypotheses. Rather, I investigated the early commitment profile structure with a research question.

> *Research Question 1:* Will the typical five-to-seven profile structure, including value-based, exchange-based, and weak profiles, be supported in a sample of new recruits to the CAF?

Profile Structure

In the current research, I made a series of predictions for each of my two contexts under investigation. First, my hypotheses for the Basic Training context could be categorized as predictions around the number of profiles and the antecedents and consequences associated with these profiles. In my Occupational Training sample, my expectations around the profiles I extracted were based on organizational commitment theory and prior work in military and non-military samples. Specifically, my predictions were based on the work of Meyer et al. (2013) and Bremner et al. (2015), who found stable sets of six profiles in two Canadian military samples. In stating my predictions, I used Kabin et al.'s (2016) classification system to make distinctions among profile types. This is not to overlook the importance of examining each profile form and making distinctions between them. Rather, at this early stage in the investigation of profile development and change, it can be difficult to make more precise predictions regarding differences across profiles within categories (e.g., AC-dominant versus AC/NC-dominant). Although my hypotheses focused on value- vs. exchange-based profiles, these individual comparisons of profiles within each category were made in actual analyses of the data for exploratory purposes.

> *Hypothesis 1:* Six profiles will be extracted in the Occupational Training sample, including value-based, exchange-based profiles, and weak profiles.

Profile Covariates

Next, I examined a model of organizational commitment profiles that includes three job-resource antecedents and two outcomes. The inclusion of antecedents in commitment profile studies is still new, and there is yet little theory to suggest how each of my variables should relate to each individual profile. In this preliminary stage of model building, I stuck to broad classifications of profile types (e.g., value- vs. exchange-based), rather than delving into predictions on how these antecedents and outcomes will relate to individual profiles in this sample (e.g., AC-dominant vs. AC/NC-dominant).

> *Hypothesis 2:* Value fit will predict the greatest probability of being in a value-based profile over a weak profile, and a smaller, but still significant probability of being in an exchange-based profile over a weak profile.

Hypothesis 3: Social support will predict the greatest probability of being in a value-based profile over a weak profile and a smaller, but still significant probability of being in an exchange-based profile over a weak profile.

Hypothesis 4: Training satisfaction will predict the greatest probability of being in a value-based profile over a weak profile and a smaller, but still significant probability of being in an exchange-based profile over a weak profile.

Hypothesis 5: Turnover intentions will be lowest for those in value-based profiles, higher than the value-based values for those in exchange-based profiles, and strongest for those in weak profiles.

Hypothesis 6: Well-being will be highest for those in value-based profiles, lower than the value-based levels for those in exchange-based profiles, and lowest for those in weak profiles.

Profile Stability

The longitudinal nature of the Occupational Training data allowed me to make predictions about the stability of profile membership over time. Few studies have looked at the early commitment of employees, let alone of specific populations of employees, such as military personnel. Even fewer have been able to compare this early commitment to changes in commitment over the first year of employment. Thus, the longitudinal design and contextual approach both add novel contributions to the commitment literature.

As discussed, profile stability has been demonstrated in several previous commitment studies, including both Kam et al. (2016) and Xu and Payne's (2018) recent investigations using similar procedures and statistical analyses to the ones used in this sample. Commitment theory predicts that commitment profiles will be relatively stable, with little individual movement between categories, and the research thus far has supported this notion in long-tenured employees. The person-centred research on newcomers is less thorough but suggests that there may be individual stability in profiles (e.g., those who are more committed at the beginning of employment will be more committed at a later point in time; Meyer & Allen, 1987), but some sample-wide differences on level of commitment after the first few months of employment. There is no evidence, however, to suggest that any individual component of commitment or profile membership should change over time. However, there is some research in the variable-centred tradition that may have implications for profile research. As discussed previously, AC tends to start relatively high in newcomers and decline over the first year of employment (e.g., Meyer & Allen, 1987). The way this decline impacts profiles is unknown. For example, if AC declines across all profiles, we might conclude that there are mean-level, but not profile-level, differences in AC over time. In this situation, we would still likely retain AC- or AC/NC-dominant profiles or fully committed profiles. However, if AC tends to decline more steeply in some profiles than in others, we might begin to see certain profiles changing their form (e.g., from AC-dominant to a more AC/NC-dominant split). This would have implications for how profiles are understood and examined over time. In the current research, I based my hypotheses on the relevant variable-centred research where possible, however, in this new area of research, I added a research question into the stability of all three components over time and their impact on profile shape and membership.

Hypothesis 7: The results will demonstrate within-sample and within-person profile consistency.

a) I will find the same number of profiles across both time points.
b) I will find similarity in the shape of profiles extracted at each time point.
c) I will find similarity in the membership proportions of each profile across time.

Research Question 2: If profile consistency is not established, how does commitment change over time in newcomers?

Chapter VIII: Methodology

This study used archival data collected by the Canadian Armed Forces. The data were collected as part of a large study on factors that contribute to employee retention and attrition, such as work expectations, career intentions, commitment, value fit, and turnover intentions. The current project used a subset of the variables collected. Participants were given time during their Basic Training to complete the survey, and ID codes were used to ensure that data could be linked over time while remaining confidential. Participants were asked to give consent to link their surveys across measurement periods. All data were collected, linked, and shared by the Canadian Armed Forces.

Participants

Respondents were new recruits to the Canadian Armed Forces. Data were collected on a rolling basis starting in September 2014. The first data collection period used in this research was at the end of Basic Training. Basic Training is a mandatory course that teaches new recruits the basics needed for success in the military context. This program includes training on basic military skills, military ethics, and physical and technical training. Participants were given time at the end of their training to complete the survey.

In the Occupational Training sample, the first round of surveys was sent three months after the completion of Basic Training. At this point, participants had graduated from the Basic Training program and were beginning training in their occupations. Occupational training occurs within occupational stream and differs depending on whether individuals are with the Armed Forces, Navy, Air Forces, or Special Forces. Then, participants were contacted six months after the first Occupational Training survey. Although the data were collected on a rolling basis and more participants were added at the start of each round of Basic Training, the interval between collection periods remained stable.

Overall, a total of 5383 invitations to participate were sent at each time point. The data collected at the end of Basic Training resulted in 4023 completed responses. For the Occupational Training sample, only 636 participants completed responses at the next round of data collection, while 612 complete questionnaires were gathered in the final phase. Each participant was given the chance to complete each phase of the data collection. That is, if a participant did not complete the survey in the second phase of data collection, they were still invited to complete the third survey.

Although the data were collected on roughly the same sample of participants at each time point, the kinds of job demands experienced and resources available to personnel in Basic Training versus Occupational Training have the potential to be vastly different. To collapse the data across time points would be to ignore the contextual factors that may play into the development and stability of commitment in newcomers to the CAF. Therefore, for the purpose of analyses, the data were divided and examined through the lens of context. In the first sample, data collected during Basic Training were used to examine early commitment in newcomers and the relations between commitment and its antecedents and outcomes. The second sample, including data collected from participants undergoing Occupational Training, was used to examine the change in commitment over time in newcomers to their role, and to investigate the relations between profile membership and its antecedents and outcomes. Using both samples, I examined the relations between commitment profiles and predictors and outcomes. In the Occupational Training sample, I was also able to examine profile stability over time.

Study Design

Given the importance of context and tenure within this research, it is critical to consider how factors such as data collection frequency, timing, and spacing can influence results and interpretation. This study took place over the first year of employment with the military. The timing of each survey was intentional to answer the CAF's core questions of how employee attitudes and perceptions change over time, and how these variables would impact tenure in newcomers. By assessing participants both during Basic Training and Occupational Training, the study design allowed me to address how context influenced the relations between commitment and its covariates. Finally, for survey spacing, the measures were administered with at least three months between collection periods, to allow time for potential changes across variables, as well as to ensure participants were not fatigued with burdensome data collection.

Sample 1 (Basic Training) Measures

Commitment to the Organization. Commitment to the organization was measured at the end of Basic Training with the Organizational Commitment Scale (Meyer, Allen, & Smith, 1993). This measure assesses the three-components of the TCM on a six-point Likert-type response scale with anchors ranging from 1 (*Strongly disagree*) to 6 (*Strongly agree*). Items were modified from the original version to specifically ask about their commitment to the CAF. AC was measured with six items, and a sample item for this measure was "I would be very happy to spend the rest of my career with the CAF". NC was measured with six items, and a sample item was "I do not feel obligated to remain with the CAF" (reverse coded). CC was measured with five items, and a sample item was "Right now, staying with the CAF is a matter of necessity as much as desire".

Value Fit. Perceived value congruence was assessed with three items using a six-point Likert-type scale ranging from 1 (*Strongly disagree*) to 6 (*Strongly agree*). These items were adapted from work by Cable and DeRue (2002). A sample item for this scale was "My personal values match the CAF's values and culture".

Social Support. Level of social support was measured with a frequency scale assessing amount of social support from six targets using a shortened version of a similar measure used in studies of U.S. Navy recruits (e.g., Lucas et al., 2010). Responses were made on a rating scale from 1 (*Not at all*) to 5 (*All of the time*). Four items each were included to measure support from family, friends, partners, other recruits, and instructors. A sample item was "How often does/do your (family/friends/partner/other recruits/ instructors/supervisor) help you understand and sort things out?".

Training Satisfaction. Satisfaction with Basic Training was assessed with two 11-item scales created for this study, rated on a six-point scale from 1 (*Completely dissatisfied*) to 6 (*Completely satisfied*). These scales used the same set of items to assess satisfaction with two targets: field training and garrison training. Items assessed satisfaction with the components of training, such as "Satisfaction with the quantity of contact with loved ones".

Turnover Intentions. Intentions to leave the organization were measured with 10 items adapted from the CAF Retention Survey (Goldenberg, 2012), assessing at what stage participants intended to leave the CAF. Sample items included "I intend to leave the CAF after basic training" and "I intend to leave the CAF when I complete my terms of service". Responses were rated on a six-point scale from 1 (*Strongly disagree*) to 6 (*Strongly agree*).

Morale. Morale was assessed with six items from Britt and Dickinson (2006), asking participants to rate their motivation and enthusiasm during Basic Training. All responses were rated on a five-point scale from 1 (*Very low*) to 5 (*Very high*). A sample item was "Your level of drive".

Well-Being. Participants were asked to indicate how many days in a month they experienced anxiety as an indicator of their well-being using items from the Patient Health Questionnaire (Spitzer, Kreonke, Williams, & the Patient Health Questionnaire Primary Care Study Group, 1999). Responses were made on seven items using a three-point scale with the following anchors: 0 (*Not at all*), 1 (*Several days*), and 2 (*More than half the days*). A sample item was "How often do you feel nervous, anxious, on edge, or worried about a lot of different things?'.

As a second indicator of well-being, homesickness was assessed with six items adapted from the Homesickness Questionnaire (Longo, 2010). Responses were recorded on a six-point scale, from 1 *(Strongly disagree)* to 6 *(Strongly agree)*. A sample item was "I couldn't help thinking about my home.".

Sample 2 (Occupational Training Sample) Measures

Commitment to the Organization. As in Sample 1, commitment was measured with the Organizational Commitment Scale (Meyer, Allen, & Smith, 1993). The same items were used at each of the two Occupational Training sample time points, using the same six items to assess AC, six to measure NC, and five to measure CC.

Value Fit. Value fit was measured at both time points in the Occupational Training sample using the same three items and six-point scale as in the Basic Training sample.

Social Support. At the first collection point in the Occupational Training sample, social support was measured with eight items. Unlike other collection periods, the only target assessed as a source of social support was supervisors. The social support from supervisors items were rated on the same scale as in the Basic Training sample. At the second collection period in the Occupational Training sample, social support from all targets (family, friends, partners, other recruits, instructors, and supervisors) were rated the same as in the first sample.

Turnover Intentions. Turnover intentions were measured with nine items at each collection period in Sample 2. These items were the same as the items measured in the Basic Training sample with the exception of the removal of the items asking participants their intentions to leave after time-based milestones that had already passed (e.g., “I intend to leave the CAF upon completing basic training”).

Morale. Participant morale for their current work and training objectives was assessed with six items at each collection period. The same items and rating scale were used in the Basic Training and Occupational Training samples.

Well-Being. Homesickness was measured at both time points with the same six items assessment on the same six-point response scale as in the Basic Training sample. Anxiety was also measured at the first time point using the same six items and the same three-point response scale.

Data Analysis

The primary focus of this research was to further the literature on commitment to the Canadian Armed Forces and to organizations in general. A mix of variable-centred and person-centred approaches were used to address the hypotheses. The use of a longitudinal design allowed for the application of mixture modelling to understand how commitment developed and changed over time, and how a series of theoretically related predictors and outcomes were associated with the extracted profile structure and changes in profile membership. Analyses are discussed in two sections, related to the two contexts under investigation in this research.

The first sample was used to examine early commitment as it developed at the end of Basic Training, while the second sample was used to investigate how commitment changed over time as employees progressed through their first few months of employment with the CAF, including during Occupational Training. Data were provided by the Canadian Armed Forces, and prior to the any hypothesis testing, the data were prepared, matched across participants, and cleaned for analyses. Data cleaning, descriptives, and correlations were run using SPSS version 16 (IBM, 2016), while the confirmatory factor analyses, latent profile analyses, regressions, mean comparisons, and latent transition analyses were conducted using Mplus version 6.12 (Muthén & Muthén, 1998-2011). To ease with speed of running iterative analyses, an R code was used to automate running a series of finalized Mplus syntax (Hallquist & Wiley, 2018).

Sample 1 (Basic Training). The Basic Training sample was used to examine the shape and structure of early commitment profiles. The measure of commitment was first administered at the end of Basic Training; thus, this research used a cross sectional approach to commitment profiles. First, descriptive statistics, including means, standard deviations, and correlations between variables were calculated to describe the sample and to compare this sample to others. Then, I conducted confirmatory factor analyses (CFAs) on the commitment measures, antecedent variables, and outcome measures. In each of the analyses of the antecedent and outcome variables, I saved the factor scores for use in further analyses. For the commitment measures, I tested alternative models, including a one-factor, two-factor, and three-factor model, to ensure we found support for the three-component model before moving forward with latent profile analyses (LPAs).

Next, I used the factor scores for the TCM measures to conduct a latent profile analyses on the Basic Training data. Following the recommendations of Nylund, Asparouhov, and Muthén (2007), I used an iterative process for the LPA, comparing the model parameter estimates to determine the optimal profile solution. Although I predicted that the data would support the extraction of six profiles, I tested solutions with between two and nine profiles. The solutions were compared on the model fit statistics, including the Akaike information criterion (AIC), the Bayesian information criterion (BIC) values, and the sample-adjusted Bayesian information criterion (aBIC), the LMRT and BLRT, and finally on the proportion of individuals within each class. The optimal profile solution should have comparatively low AIC, BIC, and aBIC values, significant LMRT and BLRT values, and at least 5% of the sample in each profile group (e.g., Nylund, 2007). In a case where there was debate in the correct number of profiles, elbow plots were examined to ensure I extracted a solution with meaningful profile distinctions (e.g., Morin et al., 2011).

With the optimal solution extracted, predictors and outcomes were considered separately for their relations with early commitment. To test the predictive relations between commitment profiles and the study predictors, a multinomial logistic regression was used. This model results in regression coefficients that represent the effect of a predictor on the log odd value of a commitment profile comparison. That is, any one unit increase in a predictor is associated with a likelihood that an individual is classed in one profile vs. a comparison profile. Posterior probabilities are used to estimate the similarity of any given individual to a given class. In this analysis, there are k-1 log odd values for each profile, where k represents the number of profiles. These log odd values are difficult to interpret, and thus were converted into odds ratios, which allows for a direct investigation in the change in profile membership probability from one profile to another based on changes in the predictor values. This also allows for the direct comparison of odd ratios across profile comparisons.

I used the covariate factor scores saved from the earlier CFAs as predictors and outcomes of the latent profile variables. Start values were extracted from the best profile solution to ensure the profile structure and proportions were retained from the original retained LPA to the multinomial logistic regression. Each latent profile was first regressed on the factor scores of the predictors. Perceived value fit, satisfaction with Basic Training, and social support were included in the model.

To handle missing data on the predictors, a Monte Carlo integration was used to impute missing values. The amount of missing data varied across predictors, with most variables (e.g., social support from family, other recruits, instructors; satisfaction with training; value fit) demonstrating missing data in fewer than 10% of the cases. The only variable with a noticeably higher proportion of missing data was social support from partners, at around 22% missing data, however, this was likely due to the marital and relationship status of participants rather than due to an intentional lack of responding. Next, mean comparisons were used to understand how mean levels of the outcome variables differed across the profiles extracted. At this stage, well-being, morale, and turnover intentions were included in the model.

Sample 2 (Occupational Training Sample). The analyses used with Sample 2 were similar to those used with Sample 1. I began with descriptive statistics, then conducted CFAs to test the fit of the three-factor structure of commitment. I also examined the structure of the antecedents and outcomes included in this sample in two separate analyses. For each of these tests, I extracted the factor scores for later analyses.

After choosing the best-fitting model of commitment at both time points, I conducted measurement invariance analyses across time to assess the stability of the measure. Different levels of measurement invariance exist (e.g., Collins & Lanza, 2010), and it is important to choose the appropriate level on a case by case basis. Levels of invariance are tested by progressively adding constraints to the model and comparing fit between the more and less constrained model. If adding constraints does not reduce fit significantly from the model in the previous step, evidence is provided for weak, strong, and strict invariance, respectively (Vandenberg & Lance, 2000). The most basic tests of similarity are called weak invariance. Tests of weak invariance look to see if the number of factors as well as factor loadings are invariant across time points. The only assumption is that the same latent variables are being assessed across comparison groups. Although weak invariance is required for cross-group comparisons, more stringent similarity is required for comparisons across latent variables.

Strong invariance is supported if both factor loadings and item intercepts are not significantly different across groups. Demonstrating strong invariance indicates that the same latent variables are being measured across groups, and that any differences in observed means are attributable to differing levels of the latent variable. This level of invariance is required for testing latent solutions, such as in person-centred LPAs and LTAs (Morin et al., 2016).

Finally, strict measurement invariance is supported if factor loadings, item intercepts, and item uniqueness do not differ across comparison groups. This extension on strong invariance assumes that the same latent variables are being assessed across groups; that differences in mean observed variables are caused by differences in mean levels of the latent variable; and that differences in the variance of the observed variables are attributable to different variances in the latent variable. Although strict invariance provides the most rigorous test of similarity across groups, it is a highly constrained model that often does not hold in practice (Millsap, 2011). In the current investigation, however, it was important to test for strict invariance, as I planned to use the extracted factor scores from the invariance analyses as observed variables in further analyses. Therefore, I conducted tests of item loading, variance, and uniqueness differences to find a strictly invariant model of commitment over time.

Then, as with the Basic Training sample, I used an iterative process of latent profile analysis to find the best fitting profile solution. Using the Occupational Training sample, I conducted longitudinal LPAs, which allow for estimating profile solutions for both sets of commitment data across time within a single model. This method is generally recommended for non-independent LPA solutions, such as in longitudinal data (Ciarrochi, Morin, Sahdra, Litalien, & Parker, 2017). The best fitting profile solution was retained.

After choosing the best fitting profile solution, I tested the profiles for similarity over time using the method outlined by Ciarrochi and colleagues (2017) and elaborated on by Morin and Litalien (2017). This iterative process can be used to compare models with the same number of profiles using progressively more constrained parameters. The methodology, although similar to measurement invariance, does not indicate an issue if a model shows decreased fit – it merely indicates that there are some differences, whether in means, intercepts, or proportion of profile membership, across time. Finding the level of similarity, or dissimilarity, over time allows for further investigation into how constructs, in this case, organizational commitment, change over time. The best fitting similarity model also provides the basis for the latent transition analysis.

In this sample, four forms of similarity were examined: configural, structural, distribution, and dispersional similarity. Configural similarity was tested by assessing if the same number of profiles were identified at each time point. This involved conducting the LPAs at each time point and comparing these solutions with a multigroup model of configural similarity (Morin et al., 2016). The guidelines for extracting optimal profile solutions, as discussed above, were used to ensure strong configural similarity.

Structural similarity was used to determine whether the levels of commitment components were the same across time points. This was tested by fixing the means for the LPAs across time points and assessing the model fit of each. Next, dispersion similarity was used to test for differences between variances within profiles by fixing variances for both solutions across time. Finally, distributional similarity was used to assess whether the group size of each profile was similar across time. I tested this by constraining the relative size of each profile group for each phase's LPA and assessing model fit. These analyses were conducted to assess if there were homogenous profile numbers, structure, and distribution across the two time points. The model with the most similar form was retained for the investigation of the relations between profile membership and each of the antecedents and outcomes included in this sample.

Finally, I investigated a model of commitment with its antecedents using latent transition analysis (LTA). The most similar profile solution was used to create the LTA to assess the within-sample and within-person profile stability. I used this analysis to investigate whether there were individual- and population-level changes in profile membership. Using robust maximum likelihood estimation, LTA allows researchers to track individual movement across profile groups over time, and to assess if change in profile membership is associated with changes in other exogenous variables. Additionally, full information maximum likelihood estimation (FIML) was used to address missing data. Rather than using imputation, FIML estimates model parameter values based on the information available in the variance-covariance matrix (Kam et al., 2016). In longitudinal studies, FIML can be used to generate unbiased parameter estimates even in cases where there are large quantities of missing at random data, or under conditions of missing time points (e.g., Enders, 2010). Other longitudinal studies of commitment have used FIML in conjunction with robust maximum likelihood estimation (e.g., Kam et al., 2016).

To conduct the LTA, I used the three-step approach described by Asparouhov and Muthén (2014). Further, this three-step approach allows for the estimate of transition probabilities, while preventing any artificial "profile shifting" in the model (e.g., Morin & Litalien, 2017). Profile shifts occur when a specific profile (e.g., high AC, high NC, low CC) is output as Profile 1 in Time 1 of an LTA, but output as Profile 2 in Time 2, making it difficult to analyze and interpret the results. The use of the three-step approach allows for ease of interpretation of stable profile solutions over time.

The procedure is as follows: in the first step, the latent profile analysis is conducted with all profiles at all time points being assessed. This is the longitudinal profile analyses discussed above, using the fully invariant solution. Although the two time points were included in this first step, they are still independent, as a regression term has not been introduced. From this model, the measurement parameters from the Model Command section of the Output file are noted to be used in the next step. For the second step, the model is fixed using the extracted parameters from step one. The model is estimated separately for each of the time points, and values are saved using the Save function in Mplus. From this model, the most likely class membership and classification errors are retained from the Logits for the Classification Probabilities for the Most Likely Class Membership by Latent Class table to manually calculate log ratios. These ratios are used in the third and final step. At this last stage, the model is estimated as one holistic analysis, and the regression term is introduced. The log ratios obtained after step two are used to fix the model parameters in step three. As with the one-step approach, the measurement model of the LTA for commitment is conducted before introducing covariates.

I followed the recommendations by Collins and Lanza (2010) that the initial LTA model is run without covariates to establish the LTA structure. Once the LTA structure was established, I examined a model with antecedents and outcomes of latent transitions over time. In this case, some parameters were necessarily fixed (such as the item-response probabilities) to avoid underidentification of the complicated model. This not only reduced the number of parameters being estimated, but also improved the interpretability of the model. LTA models often suffer from issues of underidentification, regardless of the sample size, due to the complex computational nature of the model (Collins & Lanza, 2010).

The predictors and outcome variables included in the final LTA are those that have previously been related to each individual component of commitment in variable-centred research. I included social support, perceived value congruence, and satisfaction with training as predictors of latent transitions. Turnover intentions, morale, and employee well-being were included as outcome variables. For each, the factor scores extracted from earlier CFAs were used in the model.

Participant Retention

In longitudinal analyses, missing data can often be a major concern. It can be difficult to retain participants over time, either due to the logistics of maintaining up to date contact information, or due to a lack of participant interest in remaining involved in research. In the current sample, participant retention was not an issue. This may be due to the nature of the study design, where the employing organization recruited, tracked, and contacted participants over time. Perhaps the heavy involvement and interest from the CAF helped retain participants over time. It may also be aided by the relatively short time period (i.e., six months) between the two collections.

It should be noted, however, that the excellent retention was not consistent across all time points of the study. As described above, the current sample was divided into two samples based on context: one examining newcomers' experience at the end of Basic Training, and the other assessing new employees who were a few months into their new occupation and undergoing occupational training. However, respondents with these two samples were members of the same general sample of participants. In the Basic Training sample, 4 023 participants completed the measures. In the Occupational Training sample, 636 and 612 individuals completed the two time points, respectively. Thus, between the two time points, 3 387 participants were lost. This is a loss of 85% of the sample over only a three-month window.

There may be a few reasons for the large reduction of participation between the two studies. First, Basic Training data was collected in the last few days of training, where participants were given dedicated time to complete the survey as part of their workday. For the Occupational Training sample, participants had entered their occupations, and may not have had the appropriate time to complete the survey. A second, related, issue is that once individuals left training and began their occupation, they may have been more difficult to track and invite to the next survey. Individuals may have been relocated from their initial base, deployed to active combat, or otherwise been inaccessible to complete the survey. Given the sheer number of occupations, bases, and tertiary worksites for members of the CAF, retaining study participants past Basic Training is challenging. Finally, it is possible that many individuals exited the organization after Basic Training. Turnover at this time is a concern for the CAF and may have contributed to the large study drop-out rate.

Between the two time points collected with the Occupational Training sample, there was a very small proportion of missing data. Participants of different demographic characteristics (e.g., gender, rank, occupational stream) tended to drop out from the study in similar proportions across the two periods. However, this picture was slightly different when comparing the Basic Training and Occupational Training samples. Men tended to drop out approximately 12% more than women, and similarly, recruits tended to drop out approximately 11% more than officers. Naval and Air Force uniforms tended to drop out in similar proportions (~76%), while Military uniforms tended to drop approximately 12% more frequently than any other type of uniform. In sum, there is little evidence to suggest that the population characteristics change significantly between data collection periods in the Occupational Training sample, however, there were some concerns that the sample composition may have differed between the two studies. To determine the significance of drop-out rates across each demographic characteristic between the Basic Training and Occupational Training samples, I used independent chi-square analyses.

To conduct these chi-square tests, I calculated the number of individuals with a given demographic characteristic (e.g., number of males vs. number of females) and compared them to the number of individuals who dropped out of the study from each category. The results showed significant differences in the rates of dropouts based on demographics. Between collection of Basic Training and of Occupational Training data, men were significantly more likely to drop out than women ($x^2 = 44.02$, $p < .001$) and non-officer recruits were significantly more likely to drop out than officers ($x^2 = 50.59$, $p < .001$). Finally, land uniformed participants were more likely to drop out than either air or sea uniformed participants ($x^2 = 102.08$, $p < .001$).

In general, it can be difficult to say what role missing data and sample composition characteristics might play in testing a model of commitment. It is even more difficult to hypothesize how this may impact the results when comparing two related samples, distinguished by context. In the current investigation, I calculated the descriptive statistics for the constructs in the form of means, standard deviations, and correlations, to compare the data collected in each sample. Further, with the Occupational Training sample, I used measurement invariance to ensure the constructs measured within a sample were stable over time. The possibility that the sample characteristics were significantly different between the two contexts is an interesting question but was beyond the scope of the current investigation. See the Future Directions section for more discussion of this issue.

Chapter IX: Results

Descriptive information for all data collection periods can be found in Table 1. In both the Basic Training and Occupational Training samples, most of the participants were non-commissioned male recruits. There was representation from Sea, Land, and Air occupational streams in both samples, and the mean age was 26 years old. These proportions are representative of the CAF, which is approximately 85% male, divided between commissioned officers (~20%) and non-commissioned personnel (~80%), with most members between the ages of 25 and 39 years old (Park, 2008).

Correlations among the variables can be found in Table 2 for the Basic Training sample and Tables 3 and 4 for the Occupational Training sample. The patterns of correlations were similar across the two samples, with moderate correlations between AC and NC, weak non-significant correlations between AC and CC, and low but significant correlations between NC and CC. The patterns of correlations between each TCM component and the predictor and outcome variables were also similar across samples.

Finally, reliabilities for each scale can also be found in the diagonal of the correlation tables. Although the lowest reliability was for CC in all three surveys, all other scales obtained reliabilities of at least $\alpha = .70$ with many at $\alpha = .85$ or above. In both collection periods for the Occupational Training sample, CC reached acceptable reliabilities, but in the Basic Training sample, the reliability for CC was $\alpha = .64$. This was lower than expected, and there were some issues with the CC scale.

One of the CC items seemed to be particularly problematic. The item “If I had not already put so much of myself into the CAF, I might consider working elsewhere” may

Table 1

Descriptive Statistics for Each Data Collection Period

	BT Sample	OT Sample T1	OT Sample T2
N	3998	636	612
Age (M)	24.38	25.60	26.72
Sex			
Male	3448 (86%)	496 (74%)	464 (72%)
Female	548 (14%)	140 (21%)	151 (23%)
Rank			
Recruit	3430 (86%)	459 (69%)	423 (65%)
Officer	576 (14%)	143 (21%)	142 (22%)
Occ Stream			
Sea	478 (12%)	112 (17%)	97 (15%)
Land	2522 (63%)	289 (43%)	298 (46%)
Air	1003 (25%)	237 (36%)	220 (34%)
Marital Status			
Married/Partner	724 (18%)	178 (27%)	203 (31%)
Single	3215 (81%)	446 (67%)	401 (62%)
Separated	49 (1%)	12 (2%)	11 (2%)
Partner in CAF			
Yes	171 (24%)	59 (33%)	69 (34%)
No	543 (76%)	118 (67%)	132 (66%)
Children			
Yes	379 (9%)	97 (15%)	107 (17%)
No	3619 (91%)	540 (81%)	508 (79%)

Note. Occ Stream = Occupational stream; BT = Basic Training; OT = Occupational Training; CAF = Canadian Armed Forces

Table 2

Construct Reliabilities and Correlations Between Variables in the Basic Training Sample

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
1. AC	*.829*														
2. NC	.505**	*.775*													
3. CC	-.019	.226**	*.684*												
4. Fit	.489**	.360**	-.022	*.896*											
5. Support – Family	.145**	.057**	-.028	.126**	*.855*										
6. Support – Friends	.163**	.067**	-.047**	.153**	.596**	*.864*									
7. Support – Partners	.088**	.046*	-.060**	.029	.246**	.225**	*.952*								
8. Support – Recruits	.277**	.147**	-.049**	.173**	.349**	.396**	.150**	*.874*							
9. Support – Instruct.	.311**	.210**	-.011	.231**	.274**	.308**	.161**	.443**	*.874*						
10. BT Sat G	.296**	.158**	-.041*	.241**	.045**	.074**	.099**	.186**	.292**	*.824*					
11. BT Sat F	.270**	.160**	-.074**	.234**	-.045**	.003	.047*	.141**	.261**	.690**	*.888*				

Note. *N* = 2872-3679. * Correlation is significant at the .05 level. ** Correlation is significant at the .01 level. [a] The composite for continuance commitment was calculated with item CC_11 removed. AC = Affective Commitment; NC = Normative Commitment; CC = Continuance Commitment; Support = Social Support; Instruct. = Instructors; BT Sat G = Basic Training Satisfaction with Garrison Training; BT Sat F = Basic Training Satisfaction with Field Training

Table 2 continued

Construct Reliabilities and Correlations Between Variables in the Basic Training Sample

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
12. Morale	.448**	.258**	-.072**	.360**	.115**	.147**	.016	.232**	.284**	.340**	.306**	*.904*			
13. Anxiety	-.195**	-.014	.148**	-.112**	-.018	-.039*	-.014	-.098**	-.167**	-.333**	-.321**	-.339**	*.763*		
14. Hmsick	-.199**	-.111**	.124**	-.104**	.219**	.136**	-.042*	.031	-.092**	-.289**	-.347**	-.214**	.328**	*.769*	
15. TI	-.411**	-.252**	.036*	-.222**	-.051*	-.055*	-.025	-.105**	-.118**	-.175**	-.141**	-.235**	.146**	.189**	*.627*

Note. N = 2872-3679. * Correlation is significant at the .05 level. ** Correlation is significant at the .01 level. [a] The composite for continuance commitment was calculated with item CC_11 removed. AC = Affective Commitment; NC = Normative Commitment; CC = Continuance Commitment; Hmsick = Homesick; TI = Turnover Intentions.

Table 3

Construct Reliabilities and Correlations Between Variables in Time 1 of the Occupational Training Sample

	1.	2.	3.	4.	5.	6.	7.	8.
1. AC	*.849*							
2. NC	.558**	*.838*						
3. CC[a]	-.032	.269**	*.770*					
4. Fit	.556**	.447**	-.014	*.919*				
5. Support – Superv.	.439**	.253**	-.009	.303**	*.903*			
6. Morale	.514**	.365**	-.033	.350**	.470**	*.937*		
7. Homesick	-.176**	.126	.124*	-.110	-.056	-.228**	*.777*	
8. TI	-.474**	-.363**	.004	-.305**	-.296**	-.317**	.207**	*.623*

Note. *N* = 300-462 ** Correlation is significant at the .01 level. [a] The composite for continuance commitment was calculated with item CC_11 removed. AC = Affective Commitment; NC = Normative Commitment; CC = Continuance Commitment; Support – Superv. = Social Support from Supervisor; TI = Turnover Intentions.

Table 4

Construct Reliabilities and Correlations Between Variables in Time 2 of the Occupational Training Sample

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	12.	13.	14.
1. AC	*.880*												
2. NC	.630**	*.842*											
3. CC[a]	-.111*	.184**	*.781*										
4. Fit	.615**	.394**	-.091	*.908*									
5. Support – Family	.159**	.104*	-.132*	.043	*.806*								
6. Support – Friends	.190**	.122*	-.098	.148**	.568**	*.837*							
7. Support – Partners	.024	.054	-.075	.008	.134*	.048	*.938*						
8. Support – Recruits	.356**	.261**	-.071	.245**	.375**	.535**	.029	*.836*					
9. Support – Instruct.	.346**	.286**	-.065	.256**	.304**	.388**	.062	.664**	*.822*				
10. Support – Superv.	.446**	.377**	-.096	.333**	.102	.187**	.043	.372**	.548**	*.903*			
12. Morale	.541**	.417**	-.114*	.438**	.133*	.222**	.027	.366**	.415**	.495**	*.946*		
13. Homesick	-.193**	-.094	.136*	-.260**	.106	-.147*	-.116	-.130	-.204**	-.137*	-.240**	*.825*	
14. TI	-.443**	-.320**	.141**	-.340**	-.114*	-.202**	.008	-.240**	-.273**	-.309**	-.327**	.247**	*.555*

Note. N = 227-381. ** Correlation is significant at the .01 level. [a] The composite for continuance commitment was calculated with item CC_11 removed. AC = Affective Commitment; NC = Normative Commitment; CC = Continuance Commitment; Support = Social Support; Instruct. = Instructors; TI = Turnover Intentions.

not have been appropriate for a sample of new recruits. Examination into this item's psychometric properties showed extremely low endorsement rates and a below average mean rating, especially when compared to other continuance commitment items. Given this issue, this specific CC item was removed from future analyses in the Basic Training sample. In removing the item, the reliability increased from $\alpha = .64$ to $\alpha = .68$. This item was also problematic in the Occupational Training sample. Therefore, to retain only well-performing items and to remain consistent across samples, this item was removed from the examination of both contexts.

Basic Training Sample

Confirmatory Factor Analyses

To establish the factor structure of the commitment measure in the Basic Training sample, confirmatory factor analyses were used. I compared one-, two-, and three-factor models to test if the theoretical TCM of commitment demonstrated acceptable fit for this sample, or if a more parsimonious model was a better fit to the data. In the one-factor model, all commitment items were loaded on a single factor of overall commitment. In the two-factor model, AC and NC were combined on a single factor, while the four CC items were loaded on their own factor. In the three-factor models, the AC, NC, and CC items loaded on separate factors.

The fit statistics for the CFA models can be seen in Table 5 and item loadings and uniquenesses can be seen in Table 6. As demonstrated by these results, a three-factor model showed improved fit over the one- and two-factor models. According to Chen's

Table 5

Results of Factor Analyses of the Commitment Measure in the Basic Training Sample

Model	χ^2, *df*	*CFI*	*TLI*	*RMSEA [90% CI]*	*AIC*	*BIC*	*aBIC*
1. 1-Fac CFA	5531.060, 104	.613	.554	.118 [.115, .121]	180568.817	180867.846	180715.325
2. 2-Fac CFA	4088.108, 103	.716	.669	.102 [.099, .104]	178640.902	178946.161	178790.463
3. 3-Fac CFA	2523.267, 101	.827	.795	.080 [.077, .083]	176524.317	176842.035	176679.982
4. 3-Fac (CR) CFA	1593.382, 95	.893	.865	.065 [.062, .068]	17500.023	175655.121	175474.002

Note. Time 2 N = 3751. All models estimated using MLR. Fac = Factor (e.g., 1-fac = 1-factor); CFA = Confirmatory Factor Analysis; CR = Correlated Residuals; df = Degrees of freedom; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation, 90% CI = 90% confidence interval for RMSEA; AIC = Akaike Information Criterial; BIC = Bayesian Information Criteria; aBIC = Sample-sized Adjusted BIC.

Table 6

Standardized Factor Loadings (λ) and Uniquenesses (δ) for 1-Factor and 3-Factor CFA Models of Commitment

	BT 1-Fac		BT 3-Fac		OT_{T1} 1-Fac		OT_{T1} 3-Fac		OT_{T2} 1-Fac		OT_{T2} 3-Fac	
	Sλ	δ	Sλ	δ	Sλ	δ	Sλ	δ	Sλ	δ	Sλ	δ
Affective												
AC1	.614***	.623***	.606***	.633***	.643***	.587***	.668***	.554***	.678***	.540***	.687***	.528***
AC2	.573***	.671***	.534***	.715***	.642***	.588***	.668***	.554***	.661***	.564***	.651***	.576***
AC3	.532***	.717***	.691***	.523***	.516***	.734***	.683***	.533***	.669***	.553***	.739***	.454***
AC4	.651***	.577***	.804***	.354***	.607***	.631***	.775***	.399***	.795***	.368***	.878***	.229***
AC5	.691***	.523***	.671***	.550***	.688***	.526***	.720***	.482***	.740***	.452***	.731***	.466***
AC6	.579***	.665***	.728***	.471***	.489***	.761***	.661***	.563***	.720***	.482***	.799***	.362***
Continuance												
CC7	.383***	.853***	.655***	.571***	.397***	.842***	.704***	.505***	.239***	.943***	.637***	.594***
CC8	.327***	.893***	.831***	.310***	.425***	.819***	.847***	.283***	.221**	.951***	.821***	.327**
CC9	.173***	.970***	.500***	.750***	.122*	.985***	.589***	.654***	.090	.992***	.705***	.503***
CC10	-.033	.999***	.387***	.850***	.044	.998***	.498***	.752***	-.103	.989***	.586***	.657***
CC11 (REMOVED)			-	-			-	-			-	-
Normative												
NC12	.337***	.886***	.347***	.879***	.444***	.803***	.447***	.801***	.528***	.721***	.517***	.733***
NC13	.449***	.798***	.528***	.721***	.605***	.634***	.635***	.596***	.449***	.798***	.571***	.674***
NC14	.481***	.769***	.595***	.646***	.572***	.673***	.639***	.591***	.550***	.697***	.701***	.509***
NC15	.713***	.492***	.724***	.476***	.781***	.391***	.785***	.384***	.757***	.426***	.786***	.382***
NC16	.679***	.539***	.790***	.377***	.754***	.431***	.808***	.348***	.708***	.498***	.822***	.324***
NC17	.699***	.512***	.745***	.445***	.787***	.381***	.826***	.318***	.683***	.534***	.749***	.439***

Note. λ = standardized loading; δ = uniqueness. * $p < .05$, ** $p < .01$, *** $p < .001$. BT = Basic Training sample; OT = Occupational Training sample.

(2007) guidelines, significant model improvement is supported with an increase of .005 - .010 in CFI; an increase of .010 - .015 in RMSEA; and a decrease in AIC, BIC, and aBIC. Although it fit better than the other models, the three-factor model did not fit the data well. The CFI and TLI values were below the recommended cut-off of .90 (CFI = .827; TLI = .795), and the RMSEA was on the borderline of acceptable fit at .80. Therefore, I examined the modification indices for possible solutions to this degree of misfit.

One suggestion contained in the modification indices was to correlate the errors between items AC3, AC4, AC6, and NC12. These items were the only negatively worded items within the scale. To account for a potential influence of wording style, I tested a model correlating the residuals of these items. This three-factor correlated-residual model fit the data significantly better than the previous three-factor model. Still, the fit of the model was not excellent, as the CFI and TLI were slightly below .90 (CFI = .893; TLI = .865). However, the RMSEA reached acceptable levels (RMSEA = .065) and this model retained a balance of improved fit while remaining relatively faithful to its theoretical foundation. Additionally, to examine the reliability of the factor scores, McDonald's omega (1999) was used. This statistic assesses the reliability of a set of items combined to create a composite and relaxes some of the assumptions of item tau equivalence that are seen in Cronbach's alpha. An acceptable level for omega is $\omega = .50$, while $\omega = .75$ is considered excellent fit (Reise, Bonifay, & Haviland, 2013). The omega values for the three components in the correlated residual CFA were $\omega_{AC} = .67$, $\omega_{NC} = .68$, and $\omega_{CC} = .66$. Although these values did not demonstrate excellent fit, they were all above acceptable levels.

Another possible strategy to address differences in item keying within the same scale is to test a CFA model with a negative-wording factor (e.g., Marsh, 1996). This strategy can be used to partial out the variance associated with item keying, leaving the other factors in the model interpretable. I did test both a four-factor and a five-factor model (i.e., three TCM factors and a negative wording factor, and three TCM factors with a positive- and negative-wording factor), but neither of these models converged. Thus, the factor scores from the three-factor correlated residual model were retained for use in further analyses.

In addition to examining the factor structure of the focal commitment variables, I also tested the factor structure of the antecedents and outcomes included in the two studies. My primary interest was in demonstrating that my covariates, although related, are distinct and thus worth including in later models. Thus, I examined three competing models: a unidimensional model with all items loaded on one general antecedent factor, a three-factor model with similar constructs combined into separate latent factors (e.g., all targets of social support loaded on one factor), and an eight-factor model with all antecedents, including each of the subscales directed at different targets, on their own factors. In each of these multidimensional models, all latent factors were allowed to correlate.

As can be seen in Table 7, the best fitting model was the eight-factor structure (χ^2 = 22667.582, df = 917; CFI = .739; TLI = .718; RMSEA = .077 [.076, .078]). Further, examination of the correlations between latent antecedent variables showed that although constructs are related, these correlations were low to moderate in magnitude, with an average correlation between variables of r = .22. Thus, each of the

Table 7

Results of Factor Analyses of the Study Covariates in Basic Training Sample

Model	χ^2, *df*	*CFI*	*TLI*	*RMSEA [90% CI]*	*AIC*	*BIC*	*aBIC*
				Antecedents			
1. 1-Factor Model	62505.441, 945	.262	.227	.128 [.127. .129]	523698.860	524548.287	524119.317
2. 3-Factor Model	44016.063, 942	.484	.457	.107 [.106, .108]	501202.090	502070.392	501631.890
3. 8-Factor Model	22667.582, 917	.739	.718	.077 [.076, .078]	475314.311	476339.915	475821.974
				Outcomes			
1. 1-Factor Model	17710.932, 377	.448	.405	.108 [.107, .109]	250485.217	251031.749	250755.303
2. 4-Factor Model	4383.002, 371	.872	.860	.052 [.051, .054]	234000.325	234584.549	234289.037

Note. *N* = 3992. All models estimated using MLR. df = Degrees of freedom; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation, 90% CI = 90% confidence interval for RMSEA; AIC = Akaike Information Criterial; BIC = Bayesian Information Criteria; aBIC = Sample-sized Adjusted BIC.

following antecedents could be considered statistically distinct constructs: perceived value fit, social support from family, social support from friends, social support from partners, social support from other recruits, social support from instructors, satisfaction with garrison training, and satisfaction with field training.

Although the eight-factor model fit best, it did not fit the data well. There are a few reasons why this model was selected despite its below acceptable fit. First, compared to the other tested models, it was the best fitting of the models by far. RMSEA, CFI, and TLI all improved in the eight-factor model compared to the one- and three-factor models. Second, all the items loaded well onto their intended factor. Finally, modification indices were examined and there were no major modifications suggesting cross loadings or important changes to the structure of the model. Rather, the largest modifications suggested there were correlations among the residuals of items loaded onto the same factor, however, the modification were still small in magnitude. Again, McDonald's omega was calculated to assess the reliability of antecedent included in the eight-factor CFA, and all were above acceptable fit (ω_{fit} = .87; $\omega_{\text{family support}}$ = .80; $\omega_{\text{friend support}}$ = .81; $\omega_{\text{partner support}}$ = .92; $\omega_{\text{recruit support}}$ = .82; $\omega_{\text{instructor support}}$ = .76; $\omega_{\text{satisfaction with garrison training}}$ = .61; $\omega_{\text{satisfaction with field training}}$ = .69). Thus, I concluded that this model demonstrated support for measuring each of the antecedents independently and used the factor scores extracted from this model in subsequent analyses.

Similar results were found for the outcome variables used in the Basic Training sample (see Table 7). In these analyses, I compared a unidimensional model to a four-factor model with turnover intentions, homesickness, morale, and anxiety. Although the four-factor model did not fit the data well (χ^2 = 4383.002, df = 371; CFI = .872; TLI = .860; RMSEA = .052 [.051, .054]), it was an improvement over the one-factor model. Again, the items typically loaded well onto their home factor, and the largest modification indices suggested correlations between item residuals, rather than loading items into different latent factors. Omega coefficients were all above acceptable levels ($\omega_{\text{turnover intentions}}$ = .57; $\omega_{\text{homesickness}}$ = .69; ω_{morale} = .80; ω_{anxiety} = .62). Finally, the correlations between factors were low, indicating that each of the constructs was related to, but conceptually distinct from all other outcomes.

Latent Profile Analyses

Using the factor scores retained from the adjusted three-factor CFA for commitment, I ran LPAs on the Basic Training sample. These analyses were conducted to investigate the profile structure of commitment in newcomers, which was the focus of Research Question 1.

The results of these analyses can be seen in Tables 8 and 9, and in Figure 1. As seen in Table 8, the AIC, BIC, and aBIC continued to decrease with each iteration. An elbow plot showed a bend at the five-profile solution, with smaller bends at the three- and four-profile solutions (see Figure 2). In the five-profile solution and for each of the iterations that followed, there were profiles with fewer than 5% of the sample present. For example, the five-profile solution had a profile with only 2% of the sample as members, translating to 77 members out of the sample of 3751 participants. This issue only became more pronounced as the number of profiles was increased. For example,

Table 8

Basic Training Latent Profile Analyses

	AIC	BIC	aBIC	Entropy	LMRT	*p*	BLRT	*p*
2 Classes	18394.462	18456.760	18424.985	.764	2726.405	.0000	2809.226	.0000
3 Classes	17069.276	17156.493	17112.007	.798	1293.882	.0000	1333.187	.0000
4 Classes	16368.566	16480.702	16423.507	.805	687.816	.0027	708.710	.0000
5 Classes	15969.814	16106.869	16036.964	.834	394.760	.0000	406.752*	.0000
6 Classes	15813.163	15975.137	15892.521	.815	159.797	.0039	164.651*	.0000
7 Classes	15667.588	15854.481	15759.155	.793	149.048	.0057	153.575*	.0000
8 Classes	15529.412	15741.225	15633.189	.805	141.866	.0706	146.175*	.0000
9 Classes	15428.724	15665.456	15544.710	.818	202.964	.0110	209.130*	.0000

Note. N = 3751 *Best log likelihood value was not replicated. AIC = Akaike Information Criterial; BIC = Bayesian Information Criteria; aBIC = Sample-sized Adjusted BIC; LMRT = Lo-Mendell-Rubin adjusted test; BLRT = Bootstrapped Likelihood Ratio Test.

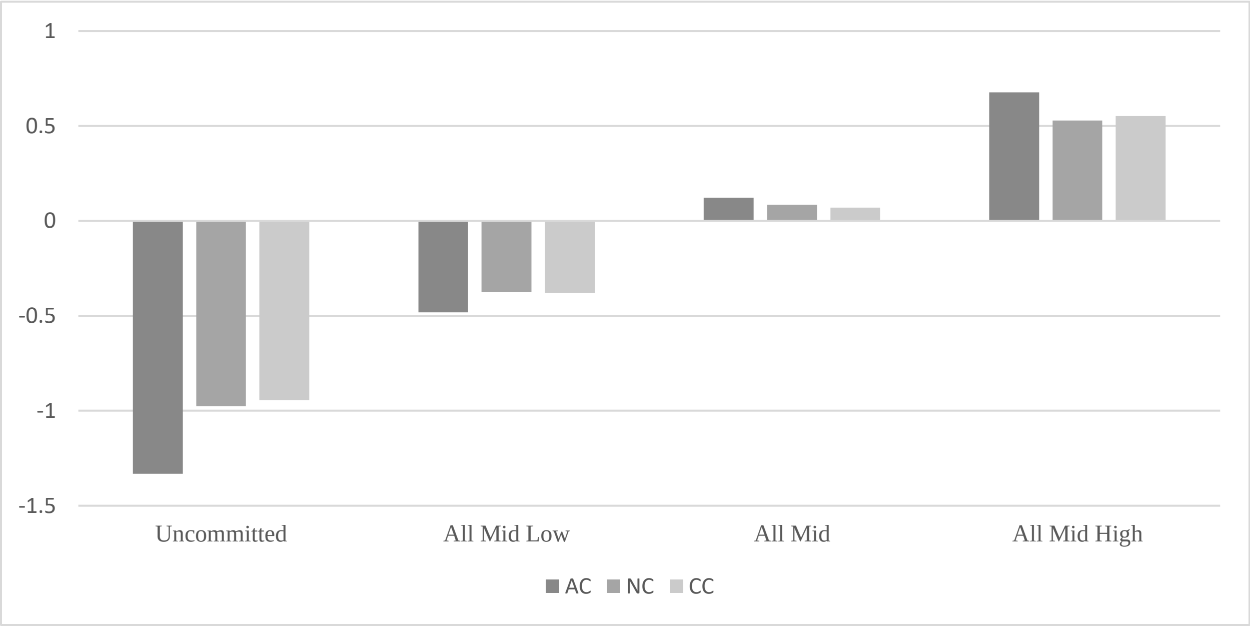
Table 9

Final Class Proportions Based on Estimated Posterior Probabilities in the Basic Training Sample

	1	2	3	4	5	6	7	8	9
2 Classes	.64898	.35102							
3 Classes	.10539	.46909	.42552						
4 Classes	.42367	.23857	.27767	.06008					
5 Classes	.27956	.09248	.01972	.21942	.38883				
6 Classes	.01967	.27557	.35177	.20746	.05425	.09129			
7 Classes	.01910	.08746	.19846	.34095	.06821	.08659	.19924		
8 Classes	.01744	.19736	.06685	.02560	.09070	.33275	.07408	.19522	
9 Classes	.09252	.19509	.01754	.19453	.07350	.00744	.32997	.07037	.01903

Figure 1

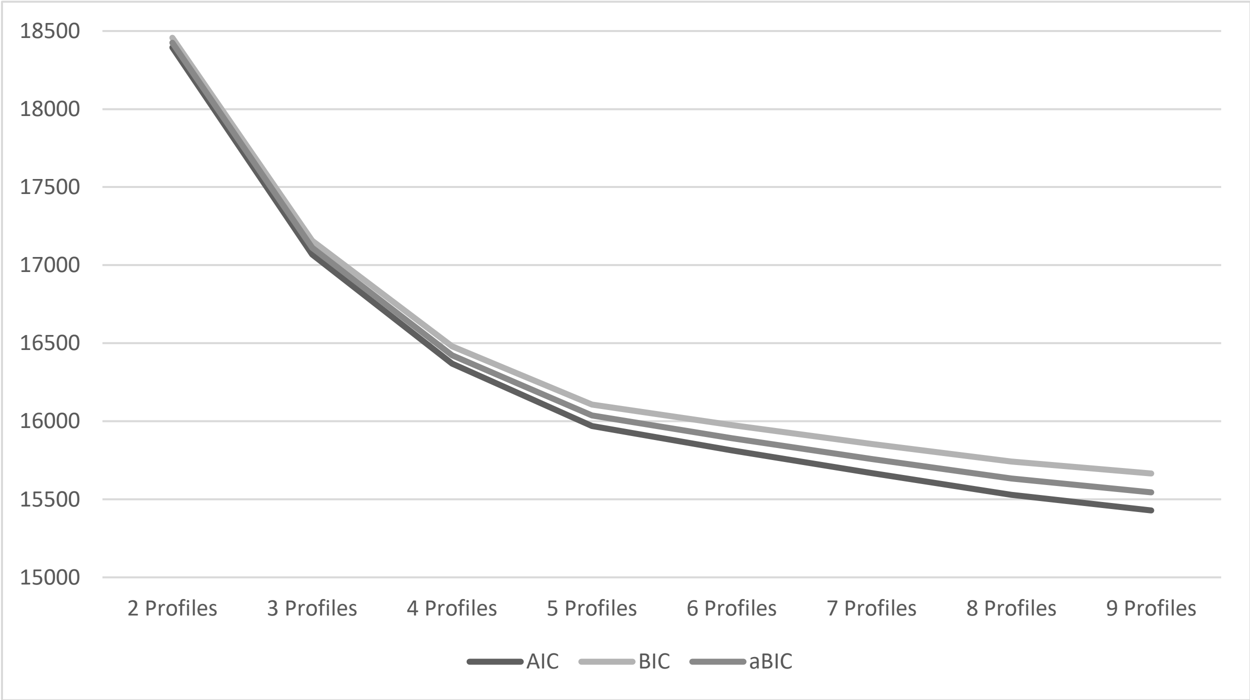
Basic Training LPA – Retained Four-Profile Solution



Note. The retained LPA four-profile solution in the Basic Training sample.

Figure 2

Basic Training LPA – Elbow Plots



Note. Elbow plots of the AIC, BIC, and aBIC values from the iterative 2- to 9-profile LPAs.

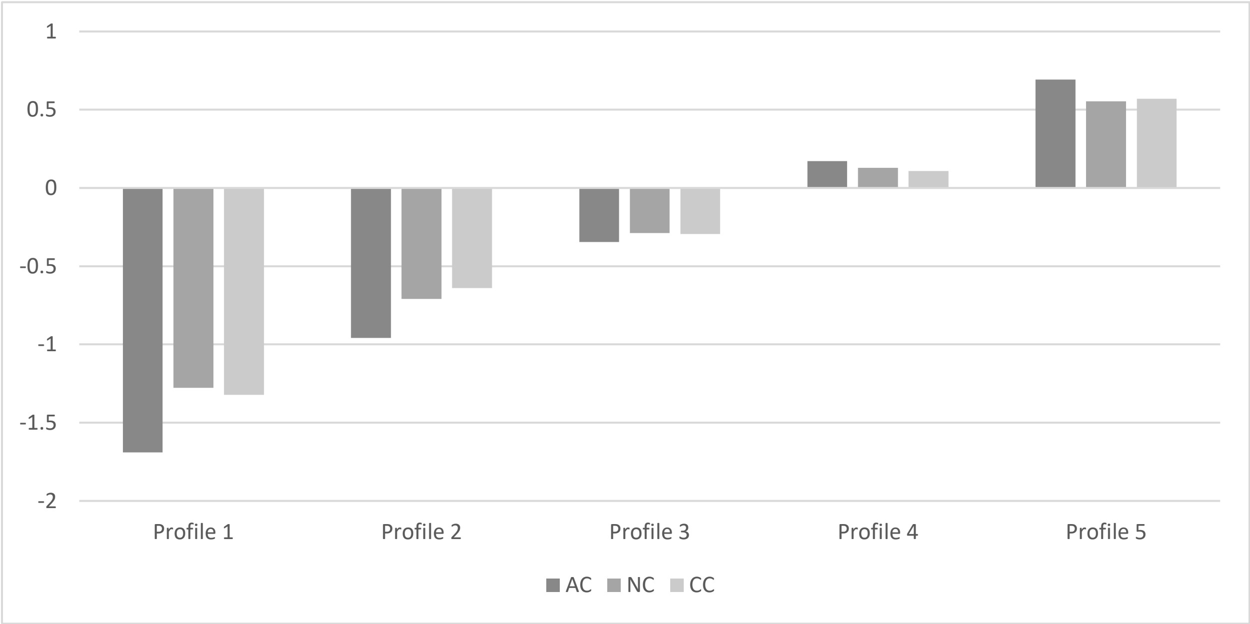
while the five-profile solution had one class with less than 5% membership, the nine-profile solution had three classes with unacceptably small proportions of individuals.

Further, I plotted the profiles solutions for each of the eight models and found that many of the profiles extracted using the Basic Training sample were similar in shape and differed only in elevation. See Figures 1, 3, and 4 for a comparison of the four-, five- and six-profile solutions. Although the six-profile solution showed more qualitative differences across profiles, it suffered from low membership proportions in some profiles and was not chosen. This pattern persisted, where solutions with more profiles showed a more interesting and distinctive structure, but many of the profiles were not meaningful due to their small size. In keeping with Nylund's (2007) recommendations, the four-profile solution was selected as the final model. This solution had lower AIC, BIC, and aBIC values than previous models. It also demonstrated acceptable values for entropy, LMRT, and BLRT. Finally, all profiles had at least 5% membership.

Once the best fitting profile solution was determined, the profiles were reordered from the original output to a more interpretable order to aid with profile comparisons and discussions. The four profiles extracted were labelled as follows: Uncommitted (Profile 1), All Mid Low (Profile 2), All Mid (Profile 3), and All Mid High (Profile 4). There was no evidence of typical qualitatively distinct profiles, such as AC/NC-Dominant. Because these profiles demonstrated quantitative, but not qualitative differences across classes, I could not use this sample to test my hypotheses regarding predictors and outcomes. Each hypothesis focused on distinguishing between value-based, exchange-based, and weak profiles. However, I conducted the analyses on an exploratory basis to investigate the

Figure 3

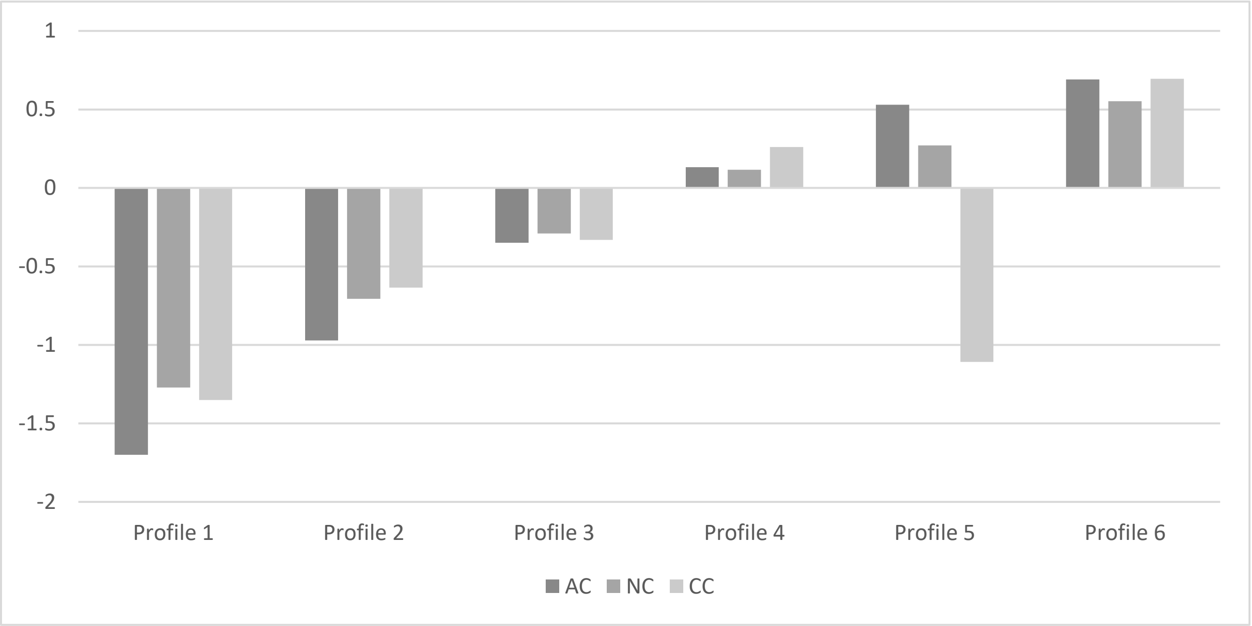
Basic Training LPA – Unselected Five-Profile Solution



Note. The unselected five-factor LPA solution in the Basic Training sample.

Figure 4

Basic Training LPA – Unselected Six-Profile Solution



Note. The unselected six-factor LPA solution in the Basic Training sample.

possibility that the antecedents predicted profiles defined by quantitative differences (see *Multinomial logistic regression* section below). Some potential explanations for these findings are discussed in Chapter X: Discussion.

Multinomial Logistic Regression

The results of the multinomial logistic regression (see Table 10) were interpreted in relative terms. Odds ratios of above 1.0 can be interpreted to mean higher values of a predictor are associated with an increased likelihood of being similar to the target profile rather than the comparison profile, while odds ratios below 1.0 indicate that an individual is less likely to be similar to the target group than the comparison profile. As an example, see Table 10 for the odds ratio values for perceived fit. Perceived fit was predictive of the posterior probabilities of profile membership in that those with higher fit were 50% less likely to be similar to the Uncommitted profile (Profile 1) than the All Mid Low profile (Profile 2). The pattern of results for perceived fit suggested that greater fit with the organization was associated with an increased likelihood of being similar to a profile with higher commitment than one with weaker commitment.

As can also be seen in Table 10, for the most part, social support was not a significant predictor of commitment profiles in the Basic Training sample. Family, friend, and partner support were all nonsignificant predictors of profile membership posterior probabilities. However, support from other recruits and from instructors was predictive for some profile comparisons, such that those with recruit support were 76% more likely to be similar to an All Mid profile than an Uncommitted profile, and 85% more likely to be similar to an All Mid profile than an All Mid Low profile. Instructor support was

Table 10

Multinomial Logistic Regression Results for Basic Training Predictors of Ordered Profile Membership

	Profile 1 vs. 2		Profile 1 vs. 3		Profile 1 vs. 4	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Fit	-.734 (.123)**	.480	-1.680 (.144)**	.186	-3.038 (.186)**	.048
Family Support	-.050 (.123)	.951	.076 (.124)	1.079	.000 (.137)	1
Friend Support	.050 (.135)	1.051	.038 (.137)	1.039	.183 (.153)	1.201
Partner Support	-.031 (.061)	.969	-.043 (.061)	.958	-.094 (.073)	.910
Recruit Support	-.118 (.139)	.889	-.278 (.135)*	.757	-.277 (.153)	.758
Instructor Support	-.187 (.137)	.829	-.512 (.134)**	.599	-.742 (.150)**	.476
Satisfaction G	-.499 (.279)	.607	-.681 (.279)*	.506	-.956 (.321)*	.384
Satisfaction F	.150 (.212)	1.162	.260 (.209)	1.297	.188 (.241)	1.207

	Profile 2 vs. 3		Profile 2 vs. 4		Profile 3 vs. 4	
	Coef. (SE)	Coef. (SE)	Coef. (SE)	OR	Coef. (SE)	OR
Fit	-.946 (.091)**	.388	-2.304 (.141)**	.131	-1.357 (.126)**	.257
Family Support	.127 (.078)	1.135	.051 (.092)	1.052	-.076 (.086)	.927
Friend Support	-.012 (.084)	.988	.133 (.100)	1.142	.145 (.093)	1.156
Partner Support	-.012 (.039)	.988	-.063 (.053)	.939	-.051 (.049)	.950
Recruit Support	-.159 (.076)*	.853	-.159 (.097)	.853	.000 (.090)	1
Instructor Support	-.325 (.076)**	.723	-.555 (.095)**	.574	-.230 (.087)*	.795
Satisfaction G	-.182 (.170)	.834	-.457 (.215)*	.633	-.275 (.195)	.760
Satisfaction F	.110 (.130)	1.116	.038 (.164)	1.04	-.072 (.148)	.931

Note. Profile 1 = Uncommitted; Profile 2 = All Mid Low; Profile 3 = All Mid; Profile 4 = All Mid High associated with increased probability of being like either the All Mid or All Mid High profiles over the Uncommitted or All Mid Low profiles, and an increased probability of being more similar to the All Mid High than the All Mid profile.

Finally, there were two targets of satisfaction assessed in the Basic Training sample – satisfaction with training in the garrison, and satisfaction with training in the field. Field training satisfaction was not a significant predictor of the posterior probabilities of profile membership. Garrison satisfaction was associated with an increased probability of being similar to either the All Mid or All Mid High profiles over the Uncommitted or All Mid Low groups, and an increased likelihood of being like the All Mid High group rather than the All Mid profile. This pattern suggests that being more satisfied with garrison training was predictive of profiles with higher levels of commitment.

Mean Comparisons of Outcome Variables

Lastly, I examined the mean differences of the outcomes, using factor scores, across each of the four profile groups identified in the Basic Training sample. Namely, these included turnover intentions and well-being as measured by morale, anxiety, and homesickness. As seen in Table 11, the tests of mean differences demonstrated that the means between each of the profile groups on all predictors were significant. That is, profiles categorized by high levels of commitment had higher mean levels of well-being (in the form of less anxiety and homesickness, and higher morale), while those in profiles with lower means on the three commitment components demonstrated more anxiety and homesickness. Further, those in profiles with higher levels of commitment had lower

Table 11

Characteristics of Basic Training Reordered Profiles on Outcomes

	Profile 1	Profile 2	Profile 3	Profile 4	Tests of Significance
TI	.435**	.127**	-.044**	-.180**	4<3<2<1
Morale	-.598**	-.235**	.037*	.360**	1<2<3<4
Anxiety	.178**	.054**	-.007	-.095**	4<3<2<1
Homesick	.649**	.199**	-.048	-.311**	4<3<2<1

Note. Values represent mean differences on outcomes across profiles, using retained factor scores for each of the outcomes.

Profile 1 = Uncommitted; Profile 2 = All Mid Low; Profile 3 = All Mid; Profile 4 = All Mid High.

mean levels of turnover intentions at the end of Basic Training than their less strongly committed counterparts.

Occupational Training Sample

Confirmatory Factor Analyses

To examine the factor structure of the commitment measure used for the Occupational Training sample, I conducted the same analyses as with the Basic Training data. I repeated these analyses with both the Time 1 and Time 2 data.

As used in the Basic Training sample, the three-factor model including correlated residuals was the best fitting model (Table 12). In the Time 1 data, this model reached acceptable values for CFI and RMSEA. Following the same pattern as the Basic Training data, however, the TLI was below the cut off for acceptable fit (χ^2 = 334.270, df = 95; CFI = .908; TLI = .884; RMSEA = .068 [.061, .076]). This model was still selected, however, as it was the best fitting model of those examined here. Further, I examined the modification indices and did not find any suggestions for model changes that would create significant improvements in fit. The omega coefficients also suggested that each factor reached acceptable levels of reliability (ω_{T1AC} = .70; ω_{T1NC} = .73; and ω_{T1CC} = .71). Similar results were obtained in the Time 2 data (χ^2 = 354.678, df = 95; CFI = .893; TLI = .865; RMSEA = .077 [.069, .086]; ω_{T2AC} = .75; ω_{T2NC} = .73; and ω_{T2CC} = .72). Whereas the three-factor correlated-residual model provided the best fit to the data, some of the model fit indices fell below the standard acceptable cut off values. These models were retained due to their theoretical relevance, small modification indices, acceptable

Table 12

Results of Factor Analyses of the Commitment Measure in the Occupational Training Sample

Model	χ^2, *df*	*CFI*	*TLI*	*RMSEA [90% CI]*	*AIC*	*BIC*	*aBIC*
1. Time 1 1-Fac CFA	1047.091, 104	.637	.582	.130 [.123, .137]	26658.439	26864.256	26711.887
2. Time 1 2-Fac CFA	738.218, 103	.756	.715	.107 [.100, .114]	26239.582	26449.687	26294.145
3. Time 1 3-Fac CFA	481.381, 101	.854	.826	.084 [.076, .091]	25893.604	26112.285	25950.394
4. Time 1 3-Fac (CR) CFA	334.270, 95	.908	.884	.068 [.061, .076]	25705.851	25950.259	25769.322
5. Time 2 1-Fac CFA	1034.908, 104	.618	.559	.140 [.132, .147]	23164.504	23362.698	23210.360
6. Time 2 2-Fac CFA	704.823, 103	.753	.712	.113 [.105, .121]	22710.266	22912.589	22757.078
7. Time 2 3-Fac CFA	444.243, 101	.859	.833	.086 [.078, .094]	22354.526	22565.108	22403.249
8. Time 2 3-Fac (CR) CFA	354.678, 95	.893	.865	.077 [.069, .086]	22246.244	22481.599	22300.698

Note. Time 1 *N* = 538; Time 2 *N* =459. All models estimated using MLR. Fac = Factor (e.g., 1-fac = 1-factor); CFA = Confirmatory Factor Analysis; CR = Correlated Residuals; df = Degrees of freedom; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation, 90% CI = 90% confidence interval for RMSEA; AIC = Akaike Information Criterial; BIC = Bayesian Information Criteria; aBIC = Sample-sized Adjusted BIC.

RMSEA, acceptable factor reliability coefficients, and proximity to reaching acceptable CFI and TLI values.

I also examined the factor structure of the antecedents and outcomes used in the Occupational Training sample (see Table 13). As in the Basic Training analyses, I tested a unidimensional model, a condensed four-factor model combining related constructs (e.g., all targets of social support), and a full nine-factor model examining each construct as its own latent factor. The nine-factor model was the best fitting model. Again, it did not reach the acceptable levels to be considered good fit. However, I proceeded with this nine-factor model as it was the best fitting model of the structures examined. Similar to the Basic Training results, each had high loadings on its home scale. Additionally, modification indices did not suggest any cross loadings of concern. Omega coefficients for each of the antecedents were above acceptable values (ω_{T1fit} = .89; $\omega_{T1supervisor\ support}$ = .77; ω_{T2fit} = .89; $\omega_{T2supervisor\ support}$ = .78; $\omega_{T1family\ support}$ = .76; $\omega_{T2friend\ support}$ = .78; $\omega_{T1partner\ support}$ = .90; $\omega_{T2recruit\ support}$ = .78; $\omega_{T1instructor\ support}$ = .77). In this final model, the antecedents for Time 1 were perceived fit and supervisor support. The antecedents for Time 2 were perceived fit and social support from supervisors, family, friends, partners, other recruits, and instructors.

Only two models were contrasted for the outcome variables using the Occupational Training sample (see Table 13). I compared a unidimensional model to a seven-factor model that included Time 1 homesickness, morale, and turnover intentions, as well as Time 2 homesickness, morale, turnover intentions, and job satisfaction. This multidimensional model demonstrated a better fit to the data. The model approached

Table 13

Results of Factor Analyses of the Study Covariates in Occupational Training Sample

Model	χ^2, *df*	*CFI*	*TLI*	*RMSEA [90% CI]*	*AIC*	*BIC*	*aBIC*
				Antecedents			
1. 1-Factor Model	7879.744, 819	.338	.304	.099 [.097, .101]	58026.455	58627.718	58227.572
2. 4-Factor Model	5245.980, 813	.584	.560	.079 [.077, .081]	54840.180	55470.076	55050.875
3. 9-Factor Model	2051.386, 783	.881	.869	.043 [.041, .045]	51124.284	51987.337	51382.386
				Outcomes			
1. 1-Factor Model	5728.205, 944	.552	.530	.081 [.079, .083]	5336.402	53968.664	53536.801
2. 7-Factor Model	2634.673, 924	.840	.828	.049 [.047, .051]	49830.858	50556.100	50060.727

Note. *N* = 874. All models estimated using MLR. df = Degrees of freedom; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation, 90% CI = 90% confidence interval for RMSEA; AIC = Akaike Information Criterial; BIC = Bayesian Information Criteria; aBIC = Sample-sized Adjusted BIC.

acceptable fit and showed improved fit over the unidimensional model. The omega coefficients for each of the seven factors were all within the acceptable range ($\omega_{\text{T1homesickness}}$ = .68; $\omega_{\text{T1turnover intentions}}$ = .57; ω_{T1morale} = .86; $\omega_{\text{T2job satisfaction}}$ = .85; $\omega_{\text{T2homesickness}}$ = .71; $\omega_{\text{T2turnover intentions}}$ = .50; ω_{T2morale} = .87). Correlations between factors were in the expected directions. In general, these correlations were low (average r = .29), suggesting factors were related but conceptually distinct. Additionally, all items loaded well onto their home scales. The factor scores were retained for further analyses.

Measurement Invariance

As can be seen in Table 14, I found support for strict invariance. Two models are considered invariant if they demonstrate change of .01 or less in the CFI, .015 in RMSEA, and relative stability in AIC, BIC, and aBIC (Chen, 2007). Although the fully unconstrained model demonstrated the best fit, the differences in these model fit indices was below Chen's (2007) suggested thresholds, and thus could be considered invariant. The model retained had invariant factor loadings, item intercepts, item uniquenesses, variance covariance matrices, and latent means over time. Factor scores from this model were retained for use in further analyses.

Latent Profile Analyses

As with the Basic Training sample, I examined the profile structure of the Occupational Training sample data. However, unlike in the Basic Training analyses, in samples of longitudinal data it is possible to use longitudinal LPAs to investigate and compare profile structures across time (Ciarrochi, Morin, Sahdra, Litalien, & Parker,

Table 14

Measurement Invariance in Commitment Measure in the Occupational Training Sample

Model	χ^2, *df*	*CFI*	*TLI*	*RMSEA [90% CI]*	*AIC*	*BIC*	*aBIC*
1. Freely Estimated Model	966.924, 421	.914	.898	.041 [.038, .045]	47194.668	47837.782	47396.400
2. Fixed Factor Loadings	982.702, 434	.913	.901	.041 [.038, .044]	47189.021	47771.988	47371.886
3. Fixed Item Intercepts	1064.908, 450	.903	.893	.043 [.039, .046]	47245.414	47754.353	47405.058
4. Fixed Uniquenesses	1099.925, 466	.900	.893	.042 [.039, .046]	47268.367	47703.278	47404.790
5. Fixed Variance Covariance	1108.893, 469	.899	.893	.043 [.039, .046]	47273.525	47694.557	47405.595
6. Fixed Latent Means	1108.893, 469	.899	.893	.043 [.039, .046]	47273.525	47694.557	47405.595

Note. All models estimated using MLR. df = Degrees of freedom; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation, 90% CI = 90% confidence interval for RMSEA; AIC = Akaike Information Criterial; BIC = Bayesian Information Criteria; aBIC = Sample-sized Adjusted BIC.

Table 15

Occupational Training Sample Longitudinal LPAs

	AIC	BIC	aBIC	Entropy
2.2 Classes	8388.821	8509.116	8426.555	.700
3.3 Classes	7742.036	7927.105	7800.088	.781
4.4 Classes	7360.293	7610.136	7438.664	.819
5.5 Classes	7219.810	7534.427	7318.499	.820
6.6 Classes	7107.309	7486.700	7226.316	.813
7.7 Classes*	7030.712	7474.876	7170.037	.836
8.8 Classes	6973.538	7482.477	7133.182	.812
9.9 Classes	6925.627	7499.340	7105.589	.806

*Note.** This model had a non-positive definite first-order derivate matrix, and standard errors may not be trustworthy. AIC = Akaike Information Criterial; BIC = Bayesian Information Criteria; aBIC = Sample-sized Adjusted BIC.

2017). Using a longitudinal LPA approach outlined by Morin and Litalien (2017), I investigated the structure of profiles across time, allowing participants to have membership probabilities on each profile at both time points. As seen in Table 15, I used an iterative process, testing for the possibility of two through nine profiles across time.

Based on the AIC, BIC, aBIC values, and profile membership size, the optimal solution from these sets of analyses was one with six profiles at each time point (see Tables 16 – 23). Given that these analyses were conducted to create a foundation for the LTA, the results of the LPA were not interpreted. Rather, the profiles were examined for similarity across time, then retained for examination and interpretation with the LTA.

Profile Similarity

The profile similarity results were mixed, as can be seen in Table 24. Although BIC and aBIC scores decreased as more model constraints were introduced, AIC increased from the configural model to the structural, dispersion, and distributional model, and the distributional model AIC was lower than the AIC in the dispersion model. Further, entropy values continued to decrease across models, although the values remained around .80 for all models tested. For each of the four types of similarity tested, proportional membership for each profile at both time points remained at or above the standard 5% cut-off (see Tables 25 – 28).

A disconnect between the AIC and BIC, and their related adjusted counterparts, is not uncommon in assessing models of profile similarity. In fact, AIC has been shown to

Table 16

Longitudinal LPA 2.2 Classification of Individuals Based on Most Likely Class Membership

	1	2
Time 1	.44	.56
Time 2	.68	.32

Note. 2.2 = An LPA with two profiles extracted at each time point. Values represent the proportion of individuals within a class at each time.

Table 17

Longitudinal LPA 3.3 Classification of Individuals Based on Most Likely Class Membership

	1	2	3
Time 1	.14	.51	.35
Time 2	.33	.53	.14

Note. 3.3 = An LPA with three profiles extracted at each time point. Values represent the proportion of individuals within a class at each time.

Table 18

Longitudinal LPA 4.4 Classification of Individuals Based on Most Likely Class Membership

	1	2	3	4
Time 1	.11	.37	.36	.16
Time 2	.30	.43	.16	.10

Note. 4.4 = An LPA with four profiles extracted at each time point. Values represent the proportion of individuals within a class at each time.

Table 19

Longitudinal LPA 5.5 Classification of Individuals Based on Most Likely Class Membership

	1	2	3	4	5
Time 1	.11	.04	.40	.18	.27
Time 2	.11	.33	.10	.12	.35

Note. 5.5 = An LPA with five profiles extracted at each time point. Values represent the proportion of individuals within a class at each time.

Table 20

Longitudinal LPA 6.6 Classification of Individuals Based on Most Likely Class Membership

	1	2	3	4	5	6
Time 1	.12	.31	.30	.09	.04	.14
Time 2	.10	.24	.19	.32	.04	.11

Note. 6.6 = An LPA with six profiles extracted at each time point. Values represent the proportion of individuals within a class at each time.

Table 21

Longitudinal LPA 7.7 Classification of Individuals Based on Most Likely Class Membership

	1	2	3	4	5	6	7
Time 1	.31	.12	.01	.10	.31	.03	.13
Time 2	.04	.22	.19	.33	.12	.01	.10

Note. 7.7 = An LPA with seven profiles extracted at each time point. Values represent the proportion of individuals within a class at each time.

Table 22

Longitudinal LPA 8.8 Classification of Individuals Based on Most Likely Class Membership

	1	2	3	4	5	6	7	8
Time 1	.16	.10	.12	.05	.11	.04	.26	.17
Time 2	.32	.05	.09	.16	.07	.10	.19	.02

Note. 8.8 = An LPA with eight profiles extracted at each time point. Values represent the proportion of individuals within a class at each time.

Table 23

Longitudinal LPA 9.9 Classification of Individuals Based on Most Likely Class Membership

	1	2	3	4	5	6	7	8	9
Time 1	.06	.10	.22	.04	.19	.13	.16	.06	.04
Time 2	.04	.07	.11	.20	.10	.16	.20	.04	.08

Note. 9.9 = An LPA with nine profiles extracted at each time point. Values represent the proportion of individuals within a class at each time.

Table 24

Profile Similarity Based on Longitudinal LPA with 6 Profiles at Each Occupational Training Sample Collection Period

	AIC	CAIC	BIC	aBIC	Entropy
Configural 6.6	7107.309	7568.700	7486.700	7226.316	.813
Structural 6.6	7125.531	7485.641	7421.641	7218.415	.808
Dispersion 6.6	7114.126	7372.955	7326.955	7180.886	.805
Distributional 6.6	7114.411	7345.106	7304.106	7173.914	.806

Note. N = 755. AIC = Akaike Information Criterial; CAIC = Corrected Akaike Information Criterial; BIC = Bayesian Information Criteria; aBIC = Sample-sized Adjusted BIC.

Table 25

Configural LPA 6.6 Classification of Individuals Based on Most Likely Class Membership

	1	2	3	4	5	6
Time 1	.12	.31	.30	.09	.04	.14
Time 2	.10	.24	.19	.32	.04	.11

Note. 6.6 = An LPA with six profiles extracted at each time point. Values represent the proportion of individuals within a class at each time.

Table 26

Structural LPA 6.6 Classification of Individuals Based on Most Likely Class Membership

	1	2	3	4	5	6
Time 1	.31	.28	.10	.07	.14	.10
Time 2	.32	.30	.12	.04	.13	.10

Note. 6.6 = An LPA with six profiles extracted at each time point. Values represent the proportion of individuals within a class at each time.

Table 27

Dispersion LPA 6.6 Classification of Individuals Based on Most Likely Class Membership

	1	2	3	4	5	6
Time 1	.10	.31	.13	.10	.07	.28
Time 2	.10	.31	.14	.13	.04	.29

Note. 6.6 = An LPA with six profiles extracted at each time point. Values represent the proportion of individuals within a class at each time.

Table 28

Distributional LPA 6.6 Classification of Individuals Based on Most Likely Class Membership

	1	2	3	4	5	6
Time 1	.10	.07	.31	.10	.14	.29
Time 2	.12	.04	.32	.10	.14	.29

Note. 6.6 = An LPA with six profiles extracted at each time point. Values represent the proportion of individuals within a class at each time.

be less effective at detecting goodness of fit for profile models, and some researchers consider a model to be acceptably similar if two of CAIC, BIC, and ABIC decrease (A. Morin, personal communication, May 7, 2019; Morin, Meyer, Creusier, & Biétry, 2016).

With those guidelines in mind, I found support for a fully similar model across means, intercepts, and proportions of profile membership. This evidence of profile stability across samples lent support to Hypothesis 7(a). Further, the finding of profile stability meant Research Question 2, which sought to investigate any systematic differences in profiles over time, was not relevant and could not be examined in this sample.

Across both time points, there was similarity in the number of profiles extracted and in the proportions of individuals in each of these profile groups. This indicated support for within-sample stability of the profile solution, similar to those results obtained by Kam et al. (2016). The full-similarity model extracted during the test of distributional similarity was used as the base for the latent transition analysis.

Latent Transition Analysis

As with the latent profile analyses, a latent transition analysis is an iterative process. First, a base model must be investigated, including only the focal variables of choice. In this model, the probability of membership, using posterior probabilities, in commitment profiles at Time 2 was regressed on Time 1 commitment profile posterior probabilities. Only following the demonstration of a sufficient base LTA should covariates be added to the model.

LTA Base Model. In cases where distributional similarity of profiles is retained, simply converting a longitudinal LPA into a latent transition analysis is impractical and introduces the possibility of altering the meaning of the base LPA model (e.g., Morin & Litalien, 2017; Vermunt, 2010). The syntax to create such a model requires the specification of the relative size of profiles between the time points, and these parameters must be individually fixed using Model Constraint functions. Adding statements to constrain relative profile size to be the same across multiple time points is computationally heavy, increasing the time required to run models and decreasing the likelihood that models will converge. These problems increase when the transition probabilities between profiles are zero, which is likely in a very stable model. Therefore, use of the three-step approach (e.g., Asparouhov & Muthén, 2014) was required. The three-step approach to LTA allows users of Mplus to regress latent variables on other latent variables over time in cases where measurement invariance is fully supported.

In the first step, the latent model is specified using two LPAs, one for each time point. In the second step, the most likely class variable, indicating class assignment, is calculated based on the posterior probabilities for each latent profile, and the measurement error values are retained. In the third step, the measurement error values are fixed based on the values from Step 2, and the transitions between latent profiles are calculated. By estimating the most likely class probabilities and fixing these values in the final model, researchers can estimate transition probabilities across two LPAs that are extremely stable and reach distributional similarity.

The model results for the base LTA can be found in Table 29. Given that the LTA with six profiles at each time point was chosen from iterative testing of longitudinal

Table 29

Profile Similarity Based on Longitudinal LPA with 6 Profiles at Each Occupational Training Sample Collection Period

	AIC	CAIC	BIC	aBIC	Entropy
6.6 LTA	4829.853	4886.120	4876.120	4844.366	.720
6.6 LTA with Predictors	4366.069	4534.831	4504.831	4409.568	.745
6.6 LTA with Outcomes	12710.509	12762.509	12952.324	12787.199	.766

Note. N = 755. AIC = Akaike Information Criterial; CAIC = Corrected Akaike Information Criterial; BIC = Bayesian Information Criteria; aBIC = Sample-sized Adjusted BIC.

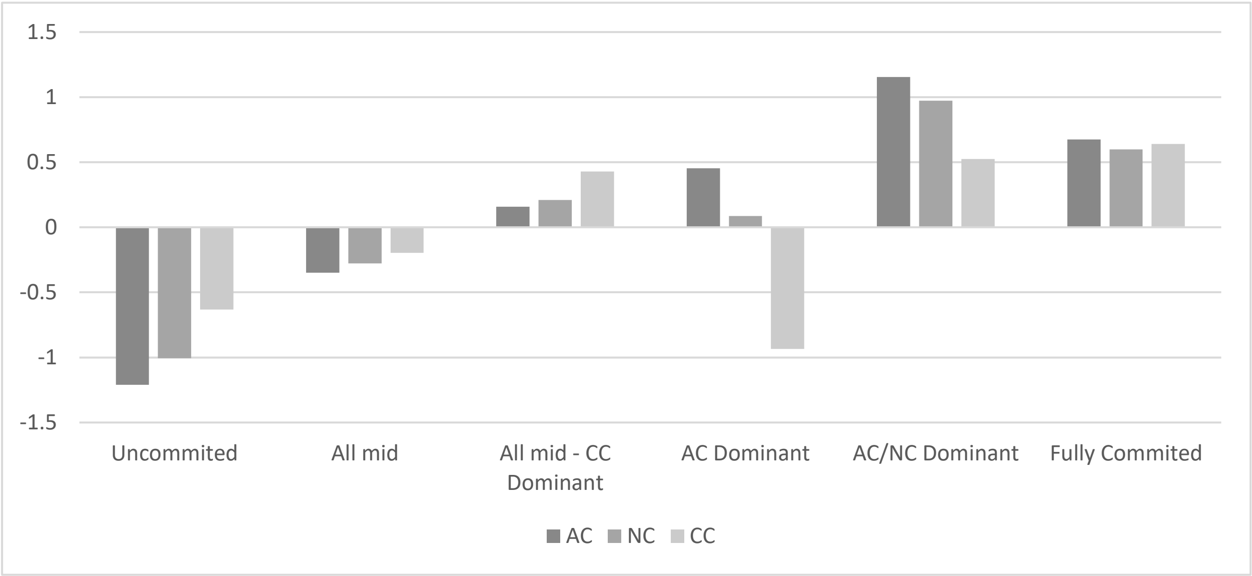
LPAs in the tests of profile similarity, no other LTA models were tested, thus, there was no model for comparison. Figure 5 demonstrates the six profiles extracted, including: Uncommitted (Profile 1); All Mid (Profile 2); All Mid/CC-Dominant (Profile 3); AC-Dominant (Profile 4); AC/NC-Dominant (Profile 5); and Fully Committed (Profile 6). The Uncommitted group (Profile 1) was used as a referent class in subsequent analyses. These results supported Hypothesis 1, which predicted a combination of value-based, exchange-based, and weak profiles.

The results showed a high degree of within-person stability. By examining posterior probabilities, I assigned individuals to classes based on their highest probability class membership. I repeated this exercise for Time 1 and Time 2 profile membership. A total of 68% of participants remained in their original class over time. The latent transition patterns can be seen in Table 30. For most profiles, more participants could be classed as stable than as "movers" to another class. For example, 81% of the participants who started in the All Mid profile remained in the same group. In these cases, the individuals who did move tended to move to adjacent profiles. In the All Mid group (Profile 2), those who moved were most likely to move either to the Uncommitted profile (Profile 1) or the All Mid/CC-Dominant (Profile 3) group. These results were supportive of Hypothesis 7(b) and Hypothesis 7(c), which predicted similarity in profile shape and membership proportions over time.

However, for some classes, there was more movement. Only 7% of participants in the AC/NC-Dominant group remained there across time, with 65% moving from this profile to the Fully Committed group. Moreover, in the Fully Committed profile,

Figure 5

Occupational Training LTA – Final Retained Model



Note. The retained six-factor LPA for the Occupational Training sample.

Table 30

Classification of Individuals Based on Most Likely Latent Class Pattern

	T1 Uncommitted	T1 All Mid	T1 All Mid/CC-Dom	T1 AC-Dom	T1 AC/NC-Dom	T1 Fully Committed
T2 Uncommitted	**57**	19	2	0	0	1
T2 All Mid	25	**192**	22	6	2	4
T2 All Mid/CC-Dom	1	16	**161**	7	7	52
T2 AC-Dom	0	9	5	**51**	7	6
T2 AC/NC-Dom	0	0	0	3	**4**	8
T2 Fully Committed	0	0	6	0	37	**48**

Note. Dom = Dominant.

while 40% remained in the same profile over time, another 44% moved to the All Mid/CC-Dominant group. This transition not only demonstrated a high degree of instability of membership in the Fully Committed profile, it also represented a change from a value-based to an exchange-based profile. Therefore, I found mixed support for Hypothesis 7.

LTA Full Model. Following the completion of the base LTA, covariates were included in the model. For the predictors, each of the three models were conducted independently. First, I examined the potential predictive effects of demographic variables, where age, sex, and occupational stream were entered as a block to predict Time 1 commitment profile posterior probabilities. Second, I tested a model with the Basic Training commitment components predicting profile posterior probabilities in the Occupational Training sample. Finally, the antecedents were all included as predictors of each the posterior probabilities of profile membership from both time points.

As seen in Table 31, sex and occupational stream did not predict the probability of being similar to any of the profile groups over being in the Uncommitted profile. Age predicted a slightly higher probability of commitment similar to that of an AC/NC-Dominant profile than an Uncommitted one. For all other profiles, age was not a significant predictor of commitment profile.

I also found that commitment in Basic Training was predictive of posterior probabilities of commitment in the Occupational Training sample. First, AC predicted higher likelihood of being similar to the AC-Dominant, AC/NC-Dominant, or Fully Committed profiles over being similar to the Uncommitted group in the Time 1 data.

Table 31

Prediction of Profile Membership at Time 1 and Time 2

	All Mid (Profile 2)		All Mid/CC-Dom (Profile 3)		AC-Dom (Profile 4)		AC/NC-Dom (Profile 5)		Fully Committed (Profile 6)	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Effects of Demographics on Time 1 Profiles										
Age	-.039 (.025)	.96	-.045 (.026)	.96	.019 (.029)	1.02	-.156** (.040)	.86	-.006 (.027)	.99
Sex	-.301 (.391)	.74	-.123 (.392)	.88	.215 (.448)	1.24	-.194 (.4600)	.82	-.659 (.455)	.52
Occ Stream	.121 (.452)	1.13	.347 (.446)	1.41	.208 (.508)	1.23	.502 (.510)	1.65	.294 (.448)	1.34
Effects of Basic Training Commitment on Time 1 Profiles										
AC	-.062 (.457)	.94	.691 (.554)	2.00	3.883** (.963)	48.57	3.707** (.857)	40.73	2.826* (.989)	16.88
NC	1.705* (.639)	5.50	2.340* (.742)	10.38	.767 (.984)	2.15	5.592** (1.175)	268.27	4.799** (1.231)	131.39
CC	.089 (.235)	1.09	.819* (.265)	2.27	-.716* (.300)	.49	-.120 (.367)	.89	.450 (.327)	1.57
Effects of Basic Training Commitment on Time 2 Profiles										
AC	.528 (.524)	1.70	2.117* (.655)	8.31	4.691** (.933)	108.96	3.339 (1.714)	28.19	4.019** (.994)	55.65
NC	1.764* (.686)	5.84	2.332* (.769)	10.30	.927 (.982)	2.53	7.322* (3.015)	1513.23	4.257* (1.481)	70.60
CC	.079 (.259)	1.08	.592* (.277)	1.81	-.666 (.336)	.51	-.951 (.512)	.39	.679 (.411)	1.97
Effects of Time 1 Predictors on Time 1 Profiles										
Fit	1.375** (.361)	3.96	2.194** (.506)	8.97	4.055** (.727)	57.69	4.858** (.998)	128.77	4.227** (.603)	68.51
Sup Support	.240 (.237)	1.27	.651* (.302)	1.92	.489 (.403)	1.63	2.353** (.574)	10.52	.807 (.411)	2.24
Effects of Time 1 Predictors on Time 2 Profiles										
Fit	.514* (.259)	1.67	2.198** (.386)	9.01	3.493** (.521)	32.88	4.557** (.686)	95.30	3.906** (.525)	49.70
Sup Support	.484* (.224)	1.62	.511 (.252)	1.67	.390 (.339)	1.48	.850 (.920)	2.34	1.407** (.387)	4.08

Note. All classes are compared to the referent profile: Occ Stream = occupational stream; Uncommitted (Profile 1). Dom = Dominant.

Similarly, AC predicted a higher probability of being similar to the AC-Dominant and Fully Committed profiles at Time 2, although the effect fell just below significance for the AC/NC-Dominant group. It also predicted a higher probability of being like the All Mid/CC-Dominant profile rather than the Uncommitted profile.

NC was a predictor of higher posterior probabilities for the All Mid and All Mid/CC-Dominant profiles at Time 1 and Time 2 when compared to the Uncommitted profile. Higher NC was related to being approximately five times more likely to be similar to the All Mid profile over the Uncommitted profile, and 10 times more likely to be more like the All Mid/CC-Dominant than Uncommitted group (see Table 31). However, NC was a much stronger predictor of likely membership in the AC/NC-Dominant and Fully Committed profiles. Participants with high NC were much more likely to be similar to either of these two profiles than an Uncommitted profile at both time points.

CC was not as strong of a predictor of posterior probabilities as AC and NC. In both Time 1 and Time 2, one unit increase in CC predicted being more similar to the All Mid/CC-Dominant profile than the Uncommitted group. Higher CC predicted a slightly lower probability of being similar to the AC-Dominant profile over the Uncommitted profile at Time 1, but it was not predictive of any value-based profile in Time 2.

As can be seen in Table 31, perceived fit was a predictor of posterior probabilities of profile membership for all profiles at both time points. The odds ratio values ranged from 1.67 to 128.77, and the pattern of results indicated that higher levels of perceived fit predicted a greater probability of being more like any of the other profiles than the referent Uncommitted profile. In fact, the odds ratios were much higher for the comparison between the Uncommitted profile and the value-based profiles than for the comparison between the Uncommitted group and the exchange-based profiles. Because higher value fit predicted greater probabilities of being more like the value-based profile groups than either moderate or weakly committed groups, I found support for Hypothesis 2. Interestingly, the results indicated that the likelihood of profile membership relative to the Uncommitted profile was highest for the AC/NC-Dominant profile, rather than the Fully Committed group. This may be because, although the Fully Committed profile demonstrated relatively high levels of commitment across all three components, the AC/NC-Dominant profile had higher mean levels of AC and NC than in the Fully Committed profile. This pattern was seen for both Time 1 and Time 2 profiles.

Supervisor support was a weaker predictor than perceived fit at both time points, but as seen in Table 31, it did predict the probability of being similar to certain groups. At Time 1, high supervisor support predicted that an individual would be twice as likely to have a profile similar to the All Mid/CC-Dominant profile, and 10 times more likely to be similar to the AC/NC-Dominant profiles than the Uncommitted profile. At Time 2, supervisor support predicted being just under twice as likely to be like the All Mid group, and four times as likely to be similar to the Fully Committed profile rather the Uncommitted group, lending some support to Hypothesis 3. However, overall support for Hypothesis 3 support was mixed, as social support was not predictive of likelihood of being more similar to the AC-Dominant profile compared the Uncommitted group at either time.

Finally, I tested a model of commitment profile membership over time and its relations to the outcome variables: homesickness, morale, and turnover intentions. Table 32 shows that people with the Uncommitted profile had the highest mean level of homesickness and turnover intentions and the lowest levels of morale at both time points. These results also show that homesickness and turnover intentions are lower in profiles categorized by higher levels of value-based commitment, including AC-Dominant, AC/NC-Dominant, and the Fully Committed profile, and morale is higher in these profiles. Combined, these results lend support for Hypotheses 5 and 6 and suggest that profiles with higher levels of commitment, including different combinations of high AC, NC, and CC, were associated with higher mean levels of positive outcomes.

It should be noted that the means of homesickness for the three profiles with the highest levels of commitment (AC-Dominant, AC/NC-Dominant, and Fully Committed) were not significantly different at either time point. The means between the AC-Dominant and the Fully Committed groups were also not significantly different for turnover intention and morale in both collection periods. Finally, it is interesting to note that the mean for homesickness was not different between the All Mid and the AC-Dominant profiles.

Table 32

Within-Time Comparisons of Commitment Profiles on Homesickness, Morale, and Turnover Intentions

	Uncommitted	All Mid	All Mid/CC	AC-Dom	AC/NC-Dom	Full
	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)
			Homesickness			
Time 1	.530 (.146)	-.042 (.046)[a]	.117 (.056)	-.216 (.080)[ab]	-.290 (.112)[b]	-.222 (.061)[b]
Time 2	1.017 (.171)	.096 (.052)[f]	-.032 (.058)[fg]	-.441 (.072)[h]	-.407 (.247)[gh]	-.412 (.056)[h]
			Morale			
Time 1	-1.078 (.121)	-.125 (.045)[c]	-.042 (.054)[c]	.405 (.085)[d]	.823 (.086)	.461 (.086)[d]
Time 2	-1.424 (.133)	-.204 (.040)	.146 (.054)	.547 (.080)[j]	.881 (.215)[j]	.566 (.070)[j]
			Turnover Intentions			
Time 1	.636 (.052)	.134 (.029)	-.068 (.027)	-.251 (.038)[e]	-.419 (.033)	-.256 (.032)[e]
Time 2	1.018 (.104)	.238 (.033)	-.189 (.033)	-.398 (.043)[k]	-.667 (.057)	-.466 (.032)[k]

Note. Means with the same subscripts within time are not significantly different from one another. Dom = Dominant.

Chapter X: Discussion

General Discussion

In the current research, I sought to investigate the nature, development, implications, and temporal stability of commitment profiles in a sample of newcomers. Commitment is most frequently studied in samples of employees with mixed tenure, making it difficult to understand how commitment may form as individuals enter a new organization and how this commitment may change over time. Further, I used a person-centred approach to examining commitment to investigate the nuanced ways in which the three components of commitment may differ across individuals. Finally, I included several predictors and outcomes to understand how commitment profiles relate to important covariates, both within and across time in a sample of newcomers. These predictors and outcomes were also relevant from an operational perspective to the Canadian Armed Forces.

To investigate the development of commitment, I used archival data collected by the Canadian Armed Forces on new recruits to the military. My first sample was composed of participants completing Basic Training, and my second sample included participants undergoing occupational training. Although this context is specific to the military, previous findings suggest that commitment profiles within the military are similar to those found in civilian populations (e.g., Meyer et al., 2013). The onboarding process, both within the military and in civilian organizations, is often underexamined but may have important implications for commitment.

In the investigation of Basic Training commitment, the results of the LPA demonstrated support for a four-profile solution. This profile solution demonstrated little qualitative distinction across profiles. That is, these profiles were generally the same shape, with the three components of commitment at similar levels within a profile (e.g., little differentiation between AC, NC, or CC), and only differed on their strength of commitment. Despite the relatively uninteresting profile solution, I found support for fit between personal and CAF values to be a strong predictor of profile membership. Social support and training satisfaction also partially predicted profile membership. The source of social support was important for predicting the probability of being in any given class, with sources internal to the organization acting as stronger predictors than sources outside of the organization. Additionally, I found that individuals with high commitment profiles had more favourable outcomes than those with profiles demonstrating lower levels of commitment.

Using the Occupational Training sample, I extracted a six-profile solution with LPA, and this structure was in line with my hypotheses and with similar research. This profile structure was found to be fully invariant over time, suggesting it is stable across the two time points. The results of an LTA demonstrated that approximately a third of participants changed profile membership across the two time periods. As in the Basic Training sample, I found that perceived value fit was a strong predictor of profile membership, supporting my hypothesis, while social support was less consistent in predicting the probability of membership in any given profile. Additionally, turnover intentions were lower in profiles with value-based commitment, while well-being was higher in these groups. These results were generally in line with my hypotheses and provided support for the importance of these covariates in investigations of commitment.

Dimensionality of Commitment

As a precursor to the LPAs, CFAs were conducted with both the Basic Training and Occupational Training samples. The factor scores from these CFAs were retained for use as input variables in subsequent analyses. The results of the CFAs were not fully aligned with expectations and had implications for the LPAs run with both samples and the LTA conducted with the Occupational Training sample. Therefore, they are discussed below.

Basic Training Sample

In investigating the dimensionality of commitment using the Basic Training sample, I found support for a three-factor model with correlated residuals between negatively worded items. However, the fit was still below typically acceptable cut-off values. The below-acceptable fit paired with the need to include correlated residuals that are not a part of the typical three-factor model raised questions about the measurement of commitment in this sample.

Previous research has found instability in AC and CC over time in newcomers and suggests that perhaps time or experience in the role is required for commitment to develop (Vandenberg & Self, 1993). It may be that commitment measured too early – in this case, before individuals had even begun their role within the organization – does not provide individuals with a frame of reference for their experiences, making it difficult for them to rate items pertaining to their perceived obligation to, or affiliation with, the organization. In fact, some items did not load well onto their intended scale, with an average loading of .62 for AC, .62 for NC, and .59 for CC. Further literature on newcomer commitment is sparse and cannot provide much evidence on this front. More research may be required to evaluate the fit of the three-factor model in newcomers.

It is important to note that removal of one item from the CC scale (i.e., “If I had not already put so much of myself into the CAF, I might consider working elsewhere”) led to improvement in fit. This item does not seem relevant to a Basic Training sample given that they have not had a chance to invest much of themselves in the role at this point. It may be that other items reflecting accumulated costs are also not particularly relevant for this sample. To the extent that new recruits do perceive costs associated with leaving the Canadian Forces, it might be the threatened loss of the experiences that are contributing to their desire to remain (affective commitment). This could help to explain why continuance commitment scores tend to mirror those for affective commitment across profiles in the context of Basic Training.

Perhaps three months with the organization is too soon for participants to feel certain aspects of CC. This is not to say that three months is too short of a time in *any* role to feel that one is giving significantly to the organization. It may be that, because military personnel spend their first three months in Basic Training, the feelings of investment do not grow until they have begun their occupational training and spend significant time in their role. However, these are assumptions that require future investigation. It is important to understand if this item only performs well in certain conditions or in samples that meet specific requirements (e.g., with longer-tenured employees).

The issues with this specific item also raised a few other questions about commitment that deserve further attention. Are there other items that perform differently, depending on the time at which they are assessed? How can we determine at what time point any given item becomes more or less relevant? Time is an important variable to consider when investigating employee attitudes, beliefs, and motivations, and commitment is no exception. Previous research has found that continuance commitment in particular may be less stable over time than affective commitment (Vandenberg & Self, 1993). The current research only investigated commitment in the first few months of employment. Further studies may wish to use a longer time interval to understand the nature of commitment, paying close attention to measurement structure and invariance over time.

Practically, commitment may be less relevant for organizations to study within the first months of employment. Although this research suggests a multidimensional construct of commitment is still an improvement over a unidimensional measure, the nature of AC, NC, and CC might depend on an individual's stage of employment. Further research is required to explore this possibility. Alternative conceptualizations, such as commitment propensity (e.g., Cohen, 2007), may also be considered in samples of individuals with very short tenure.

Occupational Training Sample

Similar to the Basic Training analyses, a three-factor correlated residual factor structure was retained as the best fitting model for the Occupational Training sample. Despite the fact that participants had spent more time with the organization, including a few months in training in their role, the model still demonstrated less-than-acceptable fit. This subpar model fit further supports the need to investigate the longitudinal change in commitment over employment tenure, including expanding beyond the first year with the organization. Although Xu and Payne (2018) began to investigate this issue, following new recruits for four years, their use of only two components of commitment limits our ability to generalize the results to studies using the full Three Component Model. However, it is possible that if the current sample was reassessed years into their role, the CFA without correlated residuals would provide an acceptable fit to the data, as it did in the Xu and Payne (2018) study. It may also be that these results were idiosyncratic to this population. Replications of this research is required to draw further conclusions. Despite the issues with model fit, correlated residuals, and the continuance commitment items, the three-factor model was fully invariant over time in the Occupational Training data.

Retaining the three-factor correlated residual model raised some concerns about the measurement and interpretation of the analyses. Not only did the CFA demonstrate less-than-ideal fit, but these factor scores were retained and used in further analyses. The goal of retaining the factor scores was to correct for measurement error, however, the below-acceptable model fit makes interpretation more complicated. At this time, results should be considered preliminary. Replication of these results, both with a similar study design or using different time points, would lend support to the reliability of these results.

Structure of Commitment Profiles

Basic Training Sample

Contrary to research in mixed tenure samples, the results found with the Basic Training data did not support a typical five- to seven-profile structure. The best fitting LPA model was one with four profiles, and these groups differed only in level, not shape. As noted earlier, it may be that time in the organization is required for meaningful profiles to emerge, and this sample may have been collected too early. At this stage, the only differences found in the profiles were based on the level of commitment.

In addition to selecting the best fitting profile solution, I also examined alternative profile solutions (e.g., solutions with more than four profiles). These models were not selected due to small proportions of individuals in one or more classes (Nylund, 2007); however, their structure can provide insight into how commitment may begin to develop over time. In the six-factor solution, for example, an AC/NC-Dominant profile was identified. It appears that, in this sample of recruits, the distinction between AC, NC, and CC was not particularly salient for the majority, however, it may have been meaningful for a small group of individuals. In fact, the unselected six-profile solution was more in line with the profiles extracted in the Occupational Training data. In future research, more frequent measurements of commitment and examination of profiles might help to establish timelines for the development of commitment profiles.

Occupational Training Sample. The profiles obtained with the Occupational Training sample were more in line with my hypotheses. Six profiles were extracted, three of which were value-based (Fully Committed, AC-Dominant, and AC/NC-Dominant), one of which was exchange based (All Mid/CC-Dominant), and two of which were weak (All Mid and Uncommitted). These classes were in line with previous findings in both civilian and military contexts (e.g., Kam et al., 2016; Meyer et al., 2015).

Perhaps the timing and context of the Occupational Training data collection allowed for further development of commitment profiles. The CFA demonstrated better fit than in the Basic Training results, suggesting greater differentiation of components in this later sample and/or greater relevance of item content in this context. Either way, the passing of only a few months resulted in a change in the number and qualitative distinctiveness of profiles extracted. Future researchers may wish to conduct longitudinal studies using different data collection intervals, to test the impact of timing and tenure on how commitment develops and changes, and whether these effects build slowly or are sparked by context or important events, such as graduating training.

Stability of Commitment Profiles

Occupational Training Sample

Six profiles were extracted at each time point and my profile similarity analyses demonstrated that they were similar over time. That is, at both Time 1 and Time 2 for the Occupational Training sample, distributional similarity was reached, as the same number of profiles were extracted with roughly the same shape and same proportion of individuals in each class (e.g., Morin et al., 2016). It is important to note that extracting a similar solution across time points does not mean that there was not movement between classes. Rather, it suggests that the profiles themselves were stable over time. This is consistent with previous research (e.g., Kam et al., 2016; Meyer et al., 2018). For example, Kam et al., found stability in the commitment structure over time during an organizational change, and Meyer et al. (2018) found a stable structure prior to and following a major economic crisis.

I found that approximately 32% of the sample changed profile groups between the two time points. For the most part, participants who changed profile membership moved to similar profiles. For example, participants in the All Mid group were most likely to move to the Uncommitted or to the All Mid/CC-Dominant profiles. This suggests either that changes in commitment are small, resulting in movement between similar profile groups, or that some individuals may have been misclassified in either of the two time points. Of the 242 participants who changed profiles, 79 had a 65% or less probability of being a member of the assigned class in either their Time 1 or Time 2 profiles. That is, 33% of the movers could be considered “borderline” for membership in their profile at either time point, suggesting their most probable profile may not have been an accurate representation of their commitment.

Overall, this research found a higher proportion of participants who moved profiles than some previous research but was consistent with other studies (Xu & Payne, 2018). Kam et al. (2016) found that only 3% of their sample changed profile membership over time. There are a few reasons why the proportion of people changing profile membership over time may be greater than in Kam’s study. The Kam et al. (2016) study used a very different population than the one included in this research. Kam’s research focused on a civilian population undergoing organizational change. It may be that there are differences in the likelihood of profile membership stability in civilian vs. military populations. Further, it may be that specific circumstances, such as tenure, organizational climate, and stability in the workplace, are associated with different individual patterns of commitment over time.

In the one previous study that has investigated the stability of profile membership in military personnel, Xu and Payne (2018) found that movement between profiles was rare. Approximately 72% of their sample did not change profile membership over time, which is in line with the findings of the Occupational Training sample. They also found differences in the amount of movement between different profile types. For example, individuals in profiles with high AC and low CC were less likely to move than individuals with high AC and high CC. This suggests that the nature of the profiles extracted may influence how much movement is present in any given sample. This may indicate that some profiles are less stable than others, or that some expressions of commitment (e.g., high CC) may be more open to change over time than others. Although the current results suggest a relatively high degree of stability, there is not yet enough research to draw firm conclusions about how much movement should be considered “normal” for any given profile in any given population. Further research that helps establish how much movement between profiles should be considered normal for a given sample or context would provide a baseline for understanding the impact of specific workplace conditions (e.g., organizational change) or interventions (e.g., onboarding programs) on commitment stability over time.

Tenure may be a critical factor in the stability of commitment profiles. This research was unique in its use of a newcomer population, and it may be that commitment profiles are less stable in the first year of employment but become more stable over time. Perhaps as individuals begin a new role, attempt to learn the values, procedures, and standards of the organization, and interact with their leaders and fellow coworkers, their commitment is more open to change. Although more research is required to understand the mechanisms of the development and stability of commitment in the first few months of employment, this research suggests that early job experiences may be important contributing factors in long-term organizational commitment.

Predicting Profile Membership

Basic Training Sample

Perceived value fit with the CAF was a significant predictor of profile membership in the cross-sectional Basic Training data. In fact, it was one of the best predictors of probability of commitment profile membership, despite the four profiles demonstrating differences only in elevation. Perceived value fit was sensitive enough to distinguish between the probabilities of membership in similar profiles (e.g., between the All Mid Low vs. All Mid profile), indicating that it is a useful predictor of level-based classes of commitment. This is in line with previous variable-centred research, which finds perceived fit is a significant predictor of AC and NC (e.g., Kristof-Brown et al., 2005). However, previous research had found non-significant relations between fit and CC (e.g., Amos & Weathington, 2008), further suggesting that CC in this sample of new recruits may not be interpreted in the same manner as in long-tenured samples. Although fit was the best predictor of commitment profile posterior probabilities, these findings again raise questions in the conceptualization and interpretation of CC in newcomer populations.

Social support, on the other hand, was not a consistent predictor of profile membership. In this sample, five sources of social support were included: family, friends, partners, other recruits, and instructors. Family, friend, and partner support were not significant predictors of profile membership probabilities. In fact, only recruit and instructor support were significant predictors of probabilities of profile membership. The latter supports helped to distinguish those who were more committed versus less committed but did not distinguish between levels for those who had below-average commitment.

It is interesting to note that only social supports internal to the organization were predictive of profile membership probabilities. The three external social supports did not distinguish between any of the four profiles extracted in the Basic Training sample. This is in line with previous research, which found that sources of social support had differential relations with each component of commitment (e.g., Simosi, 2012), and provides evidence for the discriminant validity of different forms of social support. These findings suggested that during Basic Training, only those supports available *within* the organization were relevant to the probability of being classed in any given profile. This may be due to the intensive nature of the training program, with its focus on educating and onboarding new personnel in a short period of time. Support from others in the same situation may be more salient than support from those external to the organization. It further suggests that the source of social support is salient to new recruits, and that participants were able to meaningfully distinguish between internal and external support.

Two forms of satisfaction with Basic Training were included. First, I examined the impact of satisfaction with the field training. This was not a significant predictor of membership in any of the four profiles. Satisfaction with the garrison, however, was a significant predictor of membership in some profiles. Although it was effective in distinguishing the probability of being in profiles with low vs. higher commitment, it was not sensitive enough to predict the probability of a given individual being in one of two profiles with below average commitment.

These results were novel, as little research has examined training satisfaction with commitment. Although one previous study found that training satisfaction was a significant predictor of commitment components in military personnel (Booth-Kewley et al., 2017), no research thus far has examined it as a predictor of profile membership. More research is required to investigate how satisfaction with training might predict profile membership. For example, researchers might consider if satisfaction with different components of training (e.g., with course materials, instructors, length, and conditions of training) have differential relations with commitment profiles. Further, research could examine the lasting impact of training satisfaction on commitment over time using longitudinal data.

Occupational Training Sample

As with the Basic Training sample, perceived fit with the values of the CAF was the strongest predictor of profile membership probabilities in the longitudinal Occupational Training context. Fit measured at Time 1 was used to predict the probability of profile membership at both Time 1 and Time 2. In both measurement points, it predicted a significantly higher probability of being in value-based profiles, such as the AC/NC-Dominant group and the Fully Committed class, over the

Uncommitted class. These findings support both JD-R theory, suggesting value fit is a resource employees can draw upon in their role (e.g., Yoo et al., 2014), and previous research that has found support for value fit as a predictor of affective commitment in new military personnel (e.g., Holtom et al., 2014).

It also expands the literature by including value fit as a predictor of commitment, both in terms of the individual commitment components, as well as commitment profiles. As noted above, value fit positively predicts AC and NC, but has previously been shown to be unrelated to CC (e.g., Amos & Weathington, 2008). The finding that fit predicts an increased likelihood in being similar to the Fully Committed class, which is characterized by relatively high CC with high AC and NC, suggests that fit and CC are not necessarily independent, but that they may be related when high AC and/or NC are also present.

Again, social support was not a consistent predictor of profile membership. In the Occupational Training results, only supervisor support was included as a source of social support, and it did predict membership in some profiles at both time points. For exchange-based or weakly committed profiles, supervisor support predicted a small increase in the probability of being in the All Mid group in Time 1. Further, it predicted an increase in the likelihood of being similar to the All Mid/CC-Dominant group in both Times 1 and 2 over the Uncommitted profile. These results were somewhat surprising, as little research on the relation between CC and social support has been conducted, with most previous studies only including AC and sometimes NC. We have only a preliminary understanding of how social support may relate to both CC and CC-dominant profiles.

Unfortunately, these different sources of social support measured during Basic Training were not included in the Occupational Training measures, so this research cannot determine if the importance of internal vs. external social support changes over time, or how these five supports compare to supervisor support as a predictor. Future research should consider including multiple sources of social support in their investigations of commitment to better understand these nuanced results. For example, if internal support is particularly relevant for new recruits, does the importance of external support grow as their time away from family lengthens? Does the importance of internal and external support begin to balance out as individuals become more settled in their role? As military personnel are deployed, does family and partner support become more salient, or do fellow recruits remain a larger source of support? These questions may have implications for social support theory (e.g., Eisenberger et al., 1986), and more theoretical and empirical work is required to fully explore these possibilities.

Further research is required to understand why supervisor support was not better able to predict the probability of membership in more value-based profiles. Although supervisor support was a significant predictor of being in the Fully Committed profile, it did not predict a difference in probability in membership in either the AC-Dominant or AC/NC-Dominant groups. This may be because value fit, also included in this analysis, was such a strong predictor of membership in these profiles, potentially mitigating the contribution of social support, or it may be that the sample size included in value-based profiles was too small to detect the incremental effect of social support on posterior probabilities. Although the overall sample was relatively large, the number of individuals classed in the value-based profiles was smaller than the number classed in exchange-based or weak profiles. It is also possible that other sources of social support, such as from family, friends, or other recruits would be more salient in this sample. Future research might consider adding more forms of social support (e.g., from friends, family), as examined with the Basic Training sample, to provide further insight into the commitment of recruits in this phase of Occupational Training. In addition, future research could examine if supervisor support is perhaps more relevant for commitment to the supervisor, team, or occupation rather than to the organization, and the implications these relations have on recruit outcomes.

Overall, demographic variables did not predict membership in the commitment profiles for the Occupational Training sample. Only one difference was significant, the decreased likelihood of being in the AC/NC-Dominant profile vs. the Uncommitted profile with greater age. Given that this relatively weak finding was the only significant difference observed in a single comparison, it may well be spurious and requires replication before making any efforts at interpretation. Future research should investigate if there are any systematic differences in profile membership across demographic characteristics in samples of newcomers or military personnel. Although previous research has not found demographic variables to be good predictors of commitment (e.g., Meyer et al., 2002), there is little research examining their relationship with commitment in a military context. More research is needed before firm conclusions are drawn.

Cross Sample Comparisons

The relation of Basic Training commitment with profile membership in the Occupational Training sample was interesting. Higher levels of AC in Basic Training were predictive of an increased likelihood of being in a value-based profile than in an Uncommitted profile in both Time 1 and Time 2 of the Occupational Training sample. It was also a moderate positive predictor of the exchange-based All Mid/CC-Dominant profile. It is perhaps not surprising to see that AC was predictive of profiles defined by high AC.

Further, higher NC was a somewhat weak predictor of being in an exchange-based profile compared to the Uncommitted group but was a much stronger predictor of two of the value-based profiles compared to the Uncommitted profile. Participants with high NC during basic training were 1513 times more likely to be in the AC/NC-Dominant group and 70 times more likely to be similar to the Fully Committed profile than the Uncommitted class. In fact, these two profiles were the groups with the highest mean levels of NC at both time points, and their strong presence of NC in the profile structure may explain why NC predicted membership in these profiles but not the AC-Dominant profile, which is also value-based. The implications of these findings are discussed in the Practical Implications section below.

Finally, CC was a largely non-significant predictor of profile membership. It was a weak predictor of the exchange-based All Mid/CC-Dominant profile compared to the Uncommitted group, but to a much lesser extent than, for example, AC was predictive of value-based profiles. However, CC was not a significant predictor for profiles like the Fully Committed profile, where CC is above average. It may be that AC and NC were excellent predictors of membership in this profile, reducing the relation of CC with membership in this profile. Further, the level of CC, while above average, is not exceptionally high in terms of mean level. However, this finding may also lend further support to my earlier suggestion that CC, as measured in the Basic Training data, was not an accurate reflection of the concept. The measurement of CC in this sample, with its reduced item pool and lower reliability, may indicate that the nature of the construct in newcomers is not the same as in samples of longer-tenured employees. Future studies may wish to examine the conceptualization of CC in newcomer samples to better understand how it is interpreted in by new recruits and to examine its impact in predicting long-term profile membership.

Outcomes of Profile Membership

Basic Training Sample

I examined two classes of outcome variables in this sample. First, I looked at turnover intentions with a single scale. Second, I looked at well-being via three variables: anxiety, homesickness, and morale. As expected, the Basic Training participants had better outcomes in profiles with higher levels of commitment, such as the All Mid High profile. That is, those with higher mean levels of commitment had lower turnover intentions, lower anxiety and homesickness, and higher morale than their less committed counterparts. It should be noted that, because the expected value-based and exchange-based profiles did not emerge at this time, I could not directly test my hypotheses using the Basic Training sample. However, the results did suggest that commitment may be important for personnel outcomes, even early in their tenure with the organization before qualitatively different profiles may have formed.

These results also highlight another important finding of this research. Profiles such as the All Mid High group were categorized by relatively high levels of all three forms of commitment – AC, NC, and CC. This profile was associated with higher mean levels of well-being and lower mean levels of turnover intentions than in the other three profiles. This lends support to previous findings (e.g., Gellatly et al., 2006; Meyer et al., 2012) that typically less desirable components of commitment, namely CC, can be associated with positive outcomes when paired with high AC and NC.

Occupational Training Sample

When looking at outcomes of commitment, a similar pattern was seen in the Occupational Training sample. In this sample, I included turnover intentions, as well as homesickness and morale as indicators of well-being. Anxiety was not measured at this time. Those in value-based profiles had lower turnover intentions and homesickness, and higher morale than individuals in exchange-based or weak commitment profiles. For example, not only were turnover intentions lowest in value-based profiles compared to exchange-based or weak profiles, but within value-based profiles, mean levels of turnover intentions were lower for the Fully Committed group than the AC/NC-Dominant group.

These results were in line with my predictions of better outcomes for individuals in value-based profiles than those in exchange-based or weak profiles. It is also in line with the Basic Training findings, that profiles characterized by higher levels of commitment demonstrate better outcomes. Although I could not test differences between exchange-and value-based profiles with the Basic Training sample, these two studies together suggest that commitment level and profiles both have implications for outcomes, highlighting the value of person-centred commitment research.

Theoretical Implications

This research adds to the literature in several ways. First, it contributes to the ever-growing body of research using a person-centred approach to examine organizational commitment. Using latent profile analysis, these two studies add to previous findings on the number, forms, and development of commitment profiles. The Occupational Training results in particular lends support to previous findings of five to seven meaningfully distinct, stable profiles in samples of employed adults.

These studies add to the small literature on commitment profiles within a military context (e.g., Bremner et al., 2015; Meyer et al., 2013; Xu & Payne, 2018), and the results found during Occupational Training mirror the findings of these previous studies. As in the previous research, the Occupational Training findings demonstrated evidence of a profile solution containing uncommitted, exchange-based, and value-based commitment profiles. Further, these results are similar to what has been reported in previous civilian samples (e.g., Kabins et al., 2016; Meyer & Morin, 2016).

The research on newcomer commitment is relatively scarce. Few studies have focused on this population. The results found with the Basic Training sample added to our understanding of the commitment profiles that exist in a military newcomer population. It also added to our understanding of the predictors and potential outcomes of these commitment profiles. However, the results suggest that commitment may not have formed at this point in time for many of the participants. This may be because Basic Training precedes placement in an occupation in the organization, and commitment may be less likely to form during the onboarding experience.

Despite the relatively undifferentiated profile structure found with the Basic Training sample, this research does suggest that commitment profiles may emerge and develop over time. Preliminary investigation of profiles in unselected solutions (e.g., a six-profile solution in the Basic Training sample) suggests more nuanced profiles may be emerging, but that they are not represented in meaningful proportions of the population until individuals have gained more experience on the job. However, the typical profile structure did emerge for the Occupational Training sample, suggesting that time, training, work experiences, or some combination of factors, may facilitate the development of commitment profiles in the first year on the job. Further research and theoretical development in both a military and civilian context are needed to better understand these findings.

Additionally, few studies have examined predictors and outcomes of commitment profiles. Examining commitment within a framework of antecedents and outcomes helps to further our knowledge of the factors that contribute to an individual's probability of being classed in a profile, and of the consequences of commitment profile membership. It is also highlighted the importance of examining commitment using a person-centred approach, as this research demonstrated that value-based profiles, which can include high levels of CC, are positively related to value fit, training satisfaction, and social support. When examined independently, CC has been found to relate negatively to positive work resources and outcomes such as these, and the results demonstrate that the context of AC and NC is critical for understanding the relations of CC with other constructs.

Practical Implications

The results of this research suggest that commitment may change and develop over time in military personnel. This can have implications for how policy makers and leaders in the Armed Forces conceptualize and foster commitment in new recruits. The finding of only quantitatively distinct profiles using the Basic Training sample suggest that the forms of commitment may not be well differentiated in new recruits, and that any factors influencing commitment may impact all three components in a similar manner. However, this does not mean that early interventions seeking to increase commitment components would not have an effect. The results of the LTA suggest that early commitment in Basic Training may predict commitment profiles in Occupational Training months later. Basic Training AC predicted an increase likelihood of membership in value-based profiles in Occupational Training. Further, high Basic Training NC predicts both increased probabilities of being in exchange-based and value-based profiles, with stronger positive prediction for value-based profiles. These findings together suggest that attempts to increase any one component of commitment may increase all components, but that this might have implications for commitment over time.

We also see from these results that although commitment is largely stable, some individuals will change profile membership over time. This suggests that commitment is open to influence by external factors, such as training, social support from within the company, and potentially from other policy decisions within the organization. What is more, changes in profile membership were seen in both directions, to more or less value-based profiles. Therefore, it is important to understand and consider those factors that foster positive commitment profiles in the first year of employment.

The results of these findings can be used to inform practices in training and onboarding that may help foster value-based commitment profiles in new personnel and employees. For example, based on these results, we can conclude that increasing social supports from sources internal external to the organization (e.g., quality time with other recruits, or positive relations with instructors) may be more important than facilitating external supports (e.g., time with friends and family) when it comes to predicting membership in profiles with higher levels of commitment. Leaders and decision makers may want to consider the positive impact of internal social supports on the long-term commitment of their staff when designing training programs.

The results on perceived value fit with the CAF are also interesting for the organization from a recruitment and selection perspective. This research demonstrated that perceived fit with the values of the CAF was a significant and strong predictor of profile membership. Increased levels of fit were associated with increased probability of being classed in value-based profiles. Clearly stating the values of the organization in recruitment materials can help attract those who have better fit with the organization. Then, organizations may wish to screen for and select those candidates whose values align with those of the company. Reinforcing these values during training and encouraging individuals to reflect on their own values within the context of the organization’s values may help bolster a sense of perceived fit and encourage the development of value-based profiles. Research is required on the impact of interventions to foster fit and, as a result, value-based commitment profiles, but this is a potentially fruitful area of investigation, especially for companies with strong, salient value codes.

Further, this research shows that commitment profile membership is relevant to mean levels of turnover intentions and well-being in military recruits, and thus commitment may be valuable in retaining healthy, motivated personnel. Turnover and ill health are costly to an organization, and the development of positive, value-based commitment may be a valuable method of avoiding the consequences of each.

Limitations

The present research had some notable limitations. First, as is common in longitudinal and workplace samples, this research suffered from high levels of missing data and participant attrition. That is, the same participants were asked to complete the measures in both the Basic Training and Occupational Training contexts. However, between these two studies, the number of participants who were unreachable or who did not respond was very high. In fact, the attrition rate was well above what is typically seen in longitudinal research (e.g., Gustavson, von Soest, Karevold, & Roysamb, 2012). Between studies, the overall participant pool was decreased by more than 3000 participants, which translates to over 80% of the original sample.

This may have been due to the changing circumstances between the Basic Training and the Occupational Training contexts, namely graduating from training into their occupational roles. Participants may have left the organization, moved to different military sites, or been deployed into active duty. In such circumstances, it is perhaps unsurprising that so many participants did not complete the Occupational Training surveys. However, it is noteworthy that retention within the two time points of the

Occupational Training sample was very high (> 90%), suggesting those who did complete both studies were motivated participants.

Next, this research suffered from the inherent limitations of survey administration. In any workplace sample, survey lengths and the time required to complete a survey are of increased importance and attention. Thus, in some cases, measures that were administered at earlier time points were altered, shortened, or excluded at other time points. These decisions, made for operational reasons, were beyond my control. This made it difficult to compare results in the Basic Training and Occupational Training samples for some analyses.

Additionally, this research exclusively used self-report data. Although many of the variables included in this sample were asking about participant experiences and attitudes, there were some opportunities for additional sources of data. For example, one of the predictors included was perceived value fit with the CAF. It may have been interesting and informative to understand what values participants thought their organization held and then contrasted self-reported values with company standards. Then, I could have compared perceived fit to “actual” fit and investigated the impact of both on commitment profile membership (see Edwards, Cable, Williamson, Lambert, & Shipp, 2006 for more). This research might also have benefited from other-ratings (e.g., instructor, supervisor) of health or well-being for an outside perspective of well-being.

The nature of the analyses limited my ability to make causal statements about a model of commitment with predictors and outcomes included. As a result of using non-experimental data, I could not examine the predictive nature of commitment profiles on outcomes. Further, the three-step latent transition analysis required the use of a multi-stage process to examine the base model and each of the sets of covariates in separate estimations. Future research should make use of sophisticated statistical techniques, such as growth mixture modelling, and multiple time points to test a comprehensive model of predictors, commitment profiles, and outcomes in a single estimation.

Additionally, these results were relevant to a military context. That said, the military onboarding procedure is a unique situation, and it is difficult to say how likely it is that these findings would generalize to other work contexts. As noted, the development of commitment may be sensitive to contextual factors, such as timing and on-the-job experiences. Although previous research has shown that military and civilian samples demonstrate similar profile structures (e.g., Bremner et al., 2015; Meyer et al., 2018), it is possible that the manner in which these profiles develop differ across groups. Replication of these studies in a sample of civilian newcomers would help to determine the generalizability of these results.

Future Directions

This research should be considered a preliminary investigation of the stability of commitment in newcomers to a military organization. Many of the results found in this investigation should be validated and replicated with future studies, including the profile structure of new personnel and civilian employees early in their tenure with an organization, the predictors of profile membership, and the mean differences of commitment outcomes across profiles.

This research also suggests many other avenues of research. First, I included only a small subset of the possible predictors of commitment profile membership. It would be interesting to investigate the impact of individual difference variables on the formation of commitment profiles, including personality or core self evaluations. Additionally, there are many contextual variables that may be important to examine, such as the resources available to new members of the organization and the specific demands involved in Basic Training and other onboarding or training experiences. As the commitment literature evolves and researchers move forward with a relatively standard set of profiles, we can begin to examine what factors drive membership in these profiles, and there are any number of constructs we might consider in the formation and evolution of organizational commitment over time.

The same can be said for outcomes of commitment. This research only examined a limited number of outcomes, and although this is more than typically included in commitment profile research, there is much still to be discovered. Turnover intention is one of the most commonly studied outcome variables in the field, but it may be interesting to examine how profile membership relates to other variables such as job satisfaction, organizational citizenship behaviours, and counterproductive workplace behaviours. In certain populations, like military personnel, it might also be interesting to look at constructs such as safety behaviours and rule compliance. Finally, actual retention data could supplement the investigations of turnover intentions. The CAF is currently collecting data from those participants of the study who exit the organization. Given the nature of this data, gathered only during exit surveys, collection of an appropriately sized sample can be slow, but future researchers may wish to re-examine the current data once enough turnover data can be added.

Further, well-being was included as an outcome of profile membership, however these studies took a very traditional approach to well-being. That is, the measures of well-being looked at the absence of illness, such as low anxiety, rather than looking to positive, eudemonic factors of well-being, such as personal growth and development (e.g., Anderson, Meyer, Vaters, & Espinoza, 2019). Future researchers may wish to expand the definition of well-being before drawing firm conclusions about its relations with commitment profile membership.

Beyond the constructs of choice, there are many future directions in the research design and methodology of commitment profile research. First, I used two time points in my longitudinal sample. An interesting future direction would be to replicate these findings using more than two time points. This would not only add further data on the stability of commitment over time but would allow for the investigation of the development of commitment over longer time periods. Latent transition analyses can incorporate more than two time points, although it becomes a significantly more complex model to run and interpret.

Future researchers may also want to experiment with the timing of measuring commitment. In these two studies, I looked at commitment at the end of Basic Training and at three and nine months into Occupational Training. Future research may want to test a model with shorter time lags, or time points chosen based on other important milestones, such as around performance evaluations or other training opportunities.

Additionally, future research should consider expanding beyond the first year of employment, investigating how commitment changes as individuals transition from being “newcomers” to more experienced personnel in their roles.

In terms of methodologies, there are always several ways to approach data analysis, and these should be investigated more fully. Although this research used a latent transition analysis, to examine movement between profiles over time, LTA can also be used to include predictors and outcomes of this movement. Additionally, there are other approaches to examining longitudinal data that may provide new insights. For example, growth mixture modelling uses change in a variable over time as a latent construct that can be used in regression analyses with predictors and outcomes. This type of analysis would not only show, for example, how individuals move between commitment profiles over time, but also how these changes are predicted by certain variables, and how movement between profiles influences outcomes (see Morin, 2016 for more). As with latent transition analysis, more than two time points can be incorporated in this analysis for a more nuanced understanding of how commitment may change or remain stable across time lags. Both person- and variable-centred analyses can, and should be, used to further understand how commitment profiles develop and change over time.

Conclusions

This research sought to increase understanding of the development of commitment over time. The findings suggested that although commitment profiles in newcomers differ primarily in elevations, with little differentiation between the three components, over the course of only a few months, more traditional commitment profiles emerge. The results of the Occupational Training data revealed a six-profile solution similar to that found in other studies of military commitment (e.g., Bremner et al., 2015). Additionally, this research added to our understanding of the antecedents and outcomes of commitment profiles. Unsurprisingly, value-based commitment profiles were associated with more positive predictors such as value fit with the organization and internal social support, and outcomes such as turnover intentions and well-being, and uncommitted or exchange-based profiles showed weaker relations with these constructs. Further, these results highlighted the importance of a person-centred approach to examining commitment, as the relation of any one component of commitment with antecedents and outcomes was influences by the context of the other two commitment components.

Together, these two studies have both theoretical and practical implications relevant to a military sample. Theoretically, the studies add to the literature on commitment in using a longitudinal sample of newcomers to the CAF. Although these results warrant replication with a civilian sample to understand the generalizability, this furthered understanding on early profiles of commitment, and on the development of and stability of profiles over time. Practically, this research may have implications for how we understand and seek to develop and foster positive forms of commitment in a military context. Practitioners may wish to consider these results when designing onboarding or training programs for new members of the organization, especially when commitment and turnover intentions are of interest to the organization.

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Publications:

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